Trusted Artificial Intelligence for Armaments in Uncertain Environments

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Abstract— **With the integration and greater reliance on autonomous methods in armament systems, accountability, trust, and reliability are critical in ensuring the safety of human life. Autonomous systems, especially those built on artificial intelligence (AI) subsystems, often face high levels of uncertainty due to the black box nature of AI. This paper introduces various techniques to build greater trust in autonomous systems as explored through the context of mine-field traversal. In this paper, we propose various techniques to address each aspect of a trusted autonomous mine-field traversal method. Among methods introduced, we explore regression modeling of AI and human mine identification accuracy, Reinforcement Learning methods for optimal UAV and UGV routing, and optimal system design to ensure maximum trust. Solutions will be analyzed through a set of criteria that include expected human safety, traversal time, variance in system accuracy, and performance across different environments. Ideal performance in these metrics is defined and used to facilitate an iterative design process allowing for the broadening and synthesis of candidate solutions. While this paper simply acts as a proposal of possible solutions awaiting data and simulations, our proposed criteria will guide future testing and optimization. Ultimately, this paper recommends a combination of mine identification improvement strategies and optimal routing techniques to maximize safety and minimize traversal time. This paper also outlines a plan for the next challenge phase and ideas on how to test and analyze alternative solutions.**

I. Introduction

With the rapid development of Artificial Intelligence (AI) systems, AI is positioned to play a role in countless aspects of our everyday lives. AI has demonstrated superiority over human control across various fields, making the adoption and integration of intelligent solutions a requirement to maintain superiority in commercial, industrial, and adversarial applications. As AI systems become more complex, it is critical to integrate trust and accountability deep within these systems to ensure accuracy and optimal performance, even in previously unseen conditions. This need is especially crucial when human lives and critical infrastructure are under the control of autonomous systems. One area that can greatly benefit from the integration of AI is troop routing through dangerous situations. With the scale of the United States military, the complexity of moving troops, supplies, and other goods from point A to B becomes a logistical challenge that is compounded by potentially hazardous terrain, inaccurate and delayed evaluation systems, and the countless environmental conditions encountered across all seven continents. Integrating AI can significantly enhance

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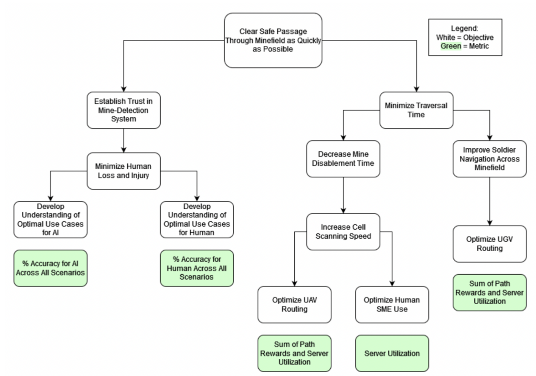

Fig. 1. This figure shows the various objectives of the future state system with the broadest objective at the top and then narrowing down each branch. Metrics for success associated with each objective are listed below the bottom node.

the efficiency of these operations; however, without the trust and accuracy of these systems fully known, it is crucial to have a system robust to unseen conditions, and resilient to potential inaccuracies. The goal of this work is to devise a system that can efficiently route mine-defusing Unmanned Ground Vehicles (UGVs) and troops through mine-laden terrain under various environmental conditions as quickly as possible. The complexity of this problem stems from the varying accuracy of mine detection methods. In this work, two systems are employed: a human observer and an AI. These methods have different accuracies depending on environmental factors such as visibility, time of day, and precipitation. Additionally, the processing times differ significantly, with the AI able to evaluate a cell in one minute, whereas the human takes 30 minutes to evaluate the same cell. To enable the mine detection methods, a routable Unmanned Aerial Vehicle (UAV) is utilized to provide aerial reconnaissance of each possible traversal location. Thus, the overall problem of this challenge can be broken down into several parts:

1) Routing of the UAV
2) Evaluation of which method (human or AI) should scan the potential location
3) Routing the UGV and troops

As this system functions on two semi-unreliable subsystems, a key aspect of this work is creating a trusted and reliable system, from less reliable subsystems. This paper acts as the first of three that explore various techniques to bring troop routing into the modern world. We aim to specifically integrate a variety of techniques to leverage AI and human methods to evaluate the efficiency and safety when traversing mine riddled terrain. A systems engineering approach will introduce all methods considered and enable future exploration to improve accuracy and safety. The remainder of this study is formatted into problem and objective formulation, a description of the criteria evaluation methods, proposed solutions as broken down by subsystem, and future work.

II. Problem Definition

The challenge of safely navigating warfighters across dangerous mission terrain requires a system that prioritizes trust and reliability, optimizing route planning to minimize traversal time while ensuring safety and mission security. This challenge is compounded by the introduction of uncertainty, both in environmental conditions and in the accuracy of safety systems. The primary goal is to develop a robust system that can integrate environmental data, accuracy metrics from AI and human detection methods, and positional data to minimize the probability of encountering mines along the chosen route. Ensuring confidence in the performance of this system, particularly in minimizing false negatives, is paramount.

A key aspect of this project is building reliable systems from less reliable components. This involves assessing the accuracy of AI and human predictions, optimizing UAV and UGV routing, and efficiently utilizing resources to adapt to dynamic and uncertain environments. The overall solution is architected on top of existing systems, requiring the leveraging of their capabilities while enhancing overall functionality. The solution needs to be capable of learning and adapting to unforeseen metadata and situations within the existing autonomous infrastructure. This adaptability is crucial for maintaining reliability and effectiveness in diverse and evolving operational contexts, ensuring that the system can continuously improve its performance and provide safe, efficient navigation through all complex and hazardous terrains and environmental conditions. To supplement our problem definition, we define the following analysis in (Figure 1).

III. Criteria for Candidate Ranking

In order to effectively rank candidate solutions for navigating warfighters across the mission terrain, several key criteria must be considered. The primary criterion is trust and reliability. Ensuring the system's reliability includes making sure that the system functions as intended and that warfighters are able to trust and therefore use the AI system, providing them a competitive advantage on the battlefield. This will look different depending on whether the UGV is 100% effective or not. By analyzing metrics such as the system's accuracy, false positive and false negative rates, and the consistency of its performance across different conditions, we can assess the reliability of a solution.

The next important criterion is traversal time. Minimizing traversal time is essential for reducing exposure to potential threats and improving overall mission efficiency. This metric includes the expected time, which is the estimated duration to complete the mission under normal conditions, and the variance, which accounts for potential delays caused by obstacles such as mines or changing environmental conditions. Additionally, movement time and delay time provide further insights into the efficiency of route traversal.

The variability of system performance across different environments must also be considered, as varying environmental conditions can impact the accuracy of mine detection. Understanding how these conditions affect system performance ensures that the system remains reliable under diverse and changing conditions. Key metrics include the impact of environmental conditions on performance, the variation in confidence levels of detection accuracy across different conditions, and the system's resilience to novel and unforeseen environments.

Resource utilization is a significant factor, involving the efficient use of both human and autonomous resources. This includes optimizing processing times and efforts through parallel processing, allowing AI and human systems to operate simultaneously. Efficient parallel processing is crucial for leveraging the strengths of both AI and human detection methods, speeding up the overall decision-making process and improving system responsiveness. Furthermore, it is essential that human and AI processing occurs concurrently with troop routing to ensure real-time adjustments and efficient resource allocation. One of the key metrics for this criterion is the average number of processes being done concurrently, which measures the extent to which parallel processing is being utilized. Additionally, the server utilization rate of the various subsystems will help identify inefficiencies in the identification, routing, and mine removal processes.

By considering these criteria, the system can prioritize routes that ensure safety by accurately predicting mine encounters and minimizing risk, reduce both the expected traversal time and its variance, optimize resource utilization through parallel processing, account for environmental variability, and maintain mission security and operational efficiency.

IV. System Evaluation

Given the complexity of safely navigating warfighters across dangerous terrain, it is essential to consider this problem as a system of systems. This section explores various methodologies for accuracy determination, UAV routing, and UGV routing. In the context of this project, the control of these subsystems culminate in the design of a Command and Control (C2) system. This C2 system represents the complete system and acts as the main director of each subsystem. By addressing each subsystem individually, and their context together, we can propose targeted approaches to solve specific aspects of the overall mission and evaluate each component's effectiveness and cost.

The first major subsystem involves Accuracy Determination, which is crucial for identifying the accuracy of mine detection methods. This process involves utilizing environmental metadata to determine the accuracy of both AI and human predictions for a given cell. As each prediction method has an associated probability of failure, falsely detecting no mine is of great consequence. By using statistical and machine learning techniques such as regression analysis, decision trees, random forests, and neural networks, we can calculate the probability that a given prediction method will minimize a false negative and a potential mine encounter. Each method offers distinct benefits and limitations, and as an added component we will incorporate techniques such as anomaly detection.

The second subsystem focuses on UAV Routing, where the UAV must be efficiently routed to optimize the detection process. We consider two primary routing methods: full observation, where the entire map is considered and a comprehensive route is planned, and partial observation, where each move is treated as a transition from the current location to adjacent cells. This section discusses the use of Deep Reinforcement Learning (RL) to dynamically adjust the path of the UAV based on real-time data, leveraging AI and human detection methods in parallel to minimize false negatives and enhance overall mission efficiency. We also discuss alternative methods like decision trees and random forests for their interpretability and reliability in route planning.

The third subsystem addresses UGV Routing, which is critical for the safe and efficient traversal of the vehicle through hazardous terrain. The routing decisions of the UGV depend on the scanned data provided by the UAV, factoring in the probability of encountering mines and the associated traversal costs. We explore various approaches, including decision trees, Q-Learning, and the concept of secondary routing where the UGV acts as a follower to the path of the UAV. This strategy simplifies the UGV's decision-making process, reduces computational load, and ensures that the UGV navigates the safest and most efficient route based on the latest data.

By considering each of these subsystems individually and proposing a range of possible approaches for each aspect, we aim to develop a comprehensive and robust solution to the overall challenge. The integration of these methods ensures that the system can adapt to dynamic and uncertain environments, maintain high levels of accuracy and reliability, and optimize the safety and efficiency of the mission.

V. Methods

A. Accuracy Determination

Accurately determining the presence of mines is a crucial aspect of navigating warfighters safely through dangerous terrain. The first major step in this process is the deployment and scheduling of the UAV system, which involves deciding which cells to navigate to and selecting the appropriate mine detection method. Each potential cell is provided with environmental metadata such as temperature, visibility, precipitation, terrain, and other relevant factors. These environmental variables significantly impact the performance of both AI and human predictions for mine detection. Therefore, it is essential to understand the relationship of these variables and the accuracy of each prediction method to inform optimal path selection.

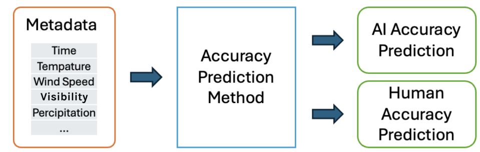

Fig. 2. Outline of accuracy prediction method

To assess the accuracy of human and AI predictions, we need a method that can take in the environmental metadata and provide a confidence score and interval for each individual cell. This can be achieved through either full or partial observation of the map. Several approaches, including regression and machine learning techniques, should be evaluated to determine the most effective method. Each of these approaches has benefits and limitations that must be carefully considered.

Regression involves using statistical techniques to model the relationship between the environmental variables and the accuracy of mine detection. This method can provide clear and interpretable results, making it easier to understand how each environmental factor impacts prediction accuracy. Interpretation is an important factor with clearly established relationships leading to better accuracy and understanding in novel environments. However, regression models may struggle with complex, non-linear relationships and may not perform as well when dealing with high-dimensional data or interactions between multiple variables.

Machine learning approaches, such as decision trees, random forests, and neural networks, can capture complex patterns and interactions in the data. These methods are often more flexible and can handle large, high-dimensional datasets more effectively. However, they may require more computational resources and can be less interpretable compared to regression models, making it harder to understand the influence of individual environmental factors.

To address the limitations of both prediction methods in novel out-of-sample conditions, incorporating techniques such as anomaly detection can help identify when predictions are significantly out of line, enabling real-time adjustments. Introducing a confidence score or detection method for out-of-sample data can indicate when input data may lead to less confident results. This anomaly detection can flag unconfident predictions, allowing for additional scrutiny and adjustments as needed. Without knowing the true accuracy of both prediction methods, trust in the mine detection methods is greatly reduced. This approach ensures that the system can adapt to unknown situations and metadata, maintaining reliability and accuracy even in unpredictable environments. By combining the strengths of both methods and incorporating these adaptive techniques, the system can better handle unknown metadata and ensure consistent performance across diverse conditions.

After a scan is completed, Bayes' Theorem can be applied to update the probability of a cell containing a mine based on the predicted accuracy and the observed results. For instance, if a mine is detected, the updated probability takes into account the false positive rate, while the absence of a detection considers the false negative rate. By weighting false positives and false negatives equally, we can determine the adjusted likelihood of a mine being present. This probabilistic approach allows for more nuanced decision-making, enhancing the overall reliability and trust in the mine detection process.

Evaluating these approaches allows for the determination of which method provides the most reliable and accurate confidence scores for each cell. This, in turn, ensures that the UAV system can make informed decisions about its path and scanning strategy, ultimately improving the safety and efficiency of the mission.

B. UAV Routing

With an understanding of the potential accuracies of human and AI methods for each cell, the UAV must be routed to optimize the detection process. The primary objectives are to minimize warfighter encounters with mines, reduce uncertainty, and efficiently utilize human and AI detection. An added level of complexity is introduced by the ability to scan cells using AI and human methods in parallel. This allows for scenarios where cells are being evaluated by AI simultaneously with other cells being processed by a human, optimizing the overall detection process. With the significantly higher assessment time of a human, the UAV must be active at all times to maximize route planning and efficiency. It may also be more efficient for the UAV to first scan cells that are to be analyzed by a human due to the human's longer assessment time. However, this approach could lead to a less efficient UAV flight path.

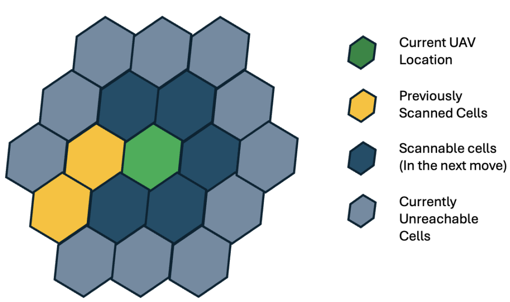

Fig. 3. Representation of Partial Observation for UAV Routing

To achieve these goals, two different methods of routing can be employed: full observation and partial observation. In the full observation method, the entire map is considered the state, allowing for a comprehensive route to be planned from start to finish. This method evaluates all possible routes and their associated risks, using the predetermined accuracy and confidence intervals for both AI and human prediction methods across the entire map.

Alternatively, the partial observation method treats each move as a transition from the current location to adjacent cells. In this context, the system state is defined by the current location and the eight possible cells bordering it in the cardinal and diagonal directions. Each of these locations has a predetermined accuracy and confidence interval for both AI and human prediction methods. This method simplifies the routing process to an 8x2 system, where the UAV makes decisions based on the immediate surrounding cells.

A potential approach could involve combining these two methods to capitalize on their respective strengths. The UAV could initially use the full observation method to determine a comprehensive pathway across the map, providing a strategic overview that accounts for all potential risks. As the UAV proceeds along this path, the partial observation method could be employed to make real-time adjustments, refining the route based on updated information from the immediate surroundings. This hybrid approach allows for an optimal initial plan while maintaining the flexibility to adapt to new data, ensuring both efficiency and safety as the mission progresses.

By leveraging the strengths of both AI and human detection methods, both routing strategies aim to minimize false negatives and ensure the highest possible accuracy. This approach not only enhances safety by reducing the risk of undetected mines but also improves overall mission efficiency by making the best use of available resources. The routing method must use these scores to decide which locations should be scanned with each method, dynamically adjusting the path based on real-time data and parallel processing capabilities.

With each move, a given cell has three possible actions: it can be scanned by the AI agent, reviewed by a human, or ignored. While state information is instantaneous, as it was predetermined by our accuracy methodology, mine detection has varied time components depending on the method selected. Each cell scanned by AI incurs a cost of one minute. Human reviews, although potentially more accurate, take 30 minutes per cell.

To find a solution to the UAV routing problem, several methods can be considered. One promising approach for routing in dynamic and uncertain environments is Deep Reinforcement Learning (RL), a subfield of Machine Learning. RL optimizes policies through interactive "play" with the environment, requiring minimal human intervention to learn optimal strategies. In this context, the UAV routing and evaluation method problem is formulated as a Markov Decision Process (MDP), consisting of states, actions, and rewards. States represent the current environment, including UAV location, detected mines, and environmental conditions. Actions involve moving to different cells, choosing human or AI scanning methods, or skipping scans. Rewards provide feedback on the outcome of actions, encouraging safer and more efficient routes. Rewards can be designed to encourage a balance between the selection of high safety and high speed routes.

The RL agent interacts with the environment by making decisions based on the current state, transitioning to new states, and receiving rewards or penalties. The goal is to learn a policy that maximizes cumulative rewards over time. Balancing exploration and exploitation is crucial, and techniques like Deep Q-Networks (DQNs) or Actor-Critic methods are used to optimize the policy. Practical implementation steps include defining the environment and reward function, developing the RL agent, simulating interactions, training the model, and evaluating and optimizing the policy. Once the policy is reliable in simulations, it can be deployed and continuously monitored in real-world operations.

Deep Reinforcement Learning offers a robust framework for solving the UAV routing problem in dynamic and uncertain environments. Deep RL extends upon the traditional RL paradigm by leveraging the power of neural networks to model more complex, high-dimensional interactions. Additionally, Deep RL has been shown to be resilient and robust to high uncertainty and noisy environments with incomplete data as seen in this challenge. By formulating the problem as an MDP and training an RL agent, the system can navigate safely and efficiently, adapting to real-time data and changing conditions, leveraging the strengths of both deep learning and reinforcement learning. As an added benefit, RL algorithms are able to learn optimal solutions without full environmental knowledge through continuous feedback from the environment. These factors indicate RL's ability to successfully route the UAV, even with untrusted and incomplete underlying information.

Alternative methods which can be considered are decision trees, which are a simple yet powerful statistical method for decision-making and routing. They work by splitting the data into branches based on feature values, making decisions at each node until reaching a final decision at the leaf node. In the context of UAV routing, decision trees can help determine the best path by evaluating the environmental conditions and prediction accuracies for each cell. This method is easy to interpret and understand, making it suitable for applications where transparency and trust are critical. However, decision trees can become complex with many features and may overfit the data if not pruned properly.

Random forests are an ensemble method that builds multiple decision trees and combines their outputs. This method extends the abilities of decision trees by creating a collection (or "forest") of trees, each trained on different subsets of the data and features. This greatly increases the accuracy and confidence in decision making compared to using a single decision tree, as each tree provides a different perspective on the data. In the context of UAV routing, random forests can enhance decision-making by considering multiple possible routes and their associated risks. Each decision tree in a random forest can handle different aspects of the routing problem, such as the accuracy score for each cell, distance to the goal, and the accuracy of surrounding cells. This comprehensive analysis allows for more informed decision-making. Random forests improve accuracy and reduce overfitting by averaging the predictions of multiple trees, thus generalizing better to unseen data. They handle large datasets well and provide insights into feature importance. However, random forests are less interpretable than single decision trees and can be computationally intensive, which may pose challenges in real-time applications.

An efficient system must leverage parallel processing, utilizing both AI and human processing simultaneously with the UAV, and coordinating with the UGV's movements. Given the UGV's minimum traversal time of 20 minutes per cell, it is crucial that adjacent cells are processed during transit to minimize downtime. This requirement becomes even more critical when mine removal is involved, as it triples the traversal time to 60 minutes. To mitigate this additional delay, the UAV should broaden its scanning scope to consider more potential routes while mines are being removed.

By comparing these alternative methods, we can determine the most suitable approach for UAV routing in various operational contexts. These statistical and traditional methods offer interpretable and reliable solutions, potentially enhancing trust and reducing the variance associated with black-box machine learning models.

C. UGV Routing

The routing of the Unmanned Ground Vehicle (UGV) is a critical component of the mission to navigate warfighters across dangerous terrain while minimizing traversal time and avoiding mines. Each move of the UGV takes 20 minutes under normal conditions, but encountering a mine increases traversal time to 60 minutes per cell. The goal is to use the scanned cells' data to make informed routing decisions that minimize the total route distance and minimize the number of mines encountered. Effective UGV routing is essential for ensuring mission success and the safety of both warfighters and equipment.

The decision-making process for UGV routing involves evaluating the predictions for each adjacent cell that was scanned by the UAV, considering the direction and distance to the end goal, and selecting the optimal next cell to traverse. This process requires a method that can balance the need for quick traversal with the imperative to avoid mines. Various approaches can be employed to achieve this balance, including decision trees, reinforcement learning techniques, and algorithms for pathfinding.

One approach to UGV routing is through decision trees. These methods take in the predictions of all surrounding cells, the direction, and the distance to the end goal, and use a structured decision-making process to select the optimal next cell to traverse. Decision trees can evaluate the likelihood of encountering a mine in each adjacent cell based on the predictions and environmental factors. By comparing these probabilities and considering the shortest path to the goal, the decision tree can guide the UGV along the safest and most efficient route. This approach is straightforward and interpretable, making it easy to understand and trust the routing decisions.

Q-Learning, a model-free reinforcement learning algorithm, can also be applied to UGV routing. In this approach, the UGV learns a Q-value for each state-action pair, representing the expected utility of taking a particular action in a given state. The UGV updates these Q-values through exploration and exploitation, aiming to maximize cumulative rewards over time. In this context, the reward structure would penalize encountering mines and reward reaching the destination quickly. Over time, the UGV learns the optimal policy for routing through the terrain by minimizing the expected traversal time and the probability of encountering mines. Q-Learning is well-suited for dynamic environments, can adapt to changing conditions and new data, and is particularly effective in scenarios with limited information, where the UGV must learn optimal strategies through continuous interaction with the environment.

A major factor in routing is the concept of primary routing, which determines which method directs troop movement. Since the routing process impacts both the UAV and UGV, an independent routing system for each could introduce complexity and points of failure. Thus, an optimal solution involves a primary routing method for either the UAV or UGV, with the other system dependent on the path determined by the primary router. For example, the UAV could scan all surrounding cells, and the UGV could follow the path with the lowest probability of encountering a mine.

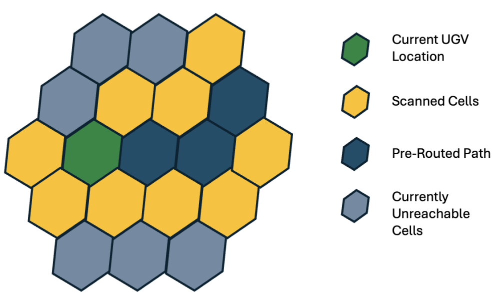

Fig. 4. Representation of Secondary Routing for UGV Traversal

In this context, the UGV can be treated as a secondary router, acting as a follower to the lowest cost path of all currently scanned cells by the UAV. The UAV continuously scans the environment, updating the probabilities of mine presence in each cell. The UGV then uses algorithms like A* to navigate through the shortest and lowest-risk path identified by the UAV. The cost associated with each node (cell) for the UGV includes the base traversal time of 20 minutes, plus an additional time cost based on the probability of encountering a mine. This is calculated by multiplying the probability of there being a mine by the added time of mine removal (40 minutes). For example, if there is a 100% probability of a mine, the total time cost for that cell would be 60 minutes (20 minutes base time + 40 minutes for mine removal). If the probability is 50%, the additional time cost would be 20 minutes (0.5 * 40 minutes), making the total time cost 40 minutes. This approach simplifies the UGV's decision-making process, reduces its computational load, and enhances overall efficiency by relying on the route already generated by the UAV.

By employing these approaches, the UGV can effectively navigate through hazardous terrain while minimizing the risk of encountering mines and optimizing traversal time. Whether using the adaptive learning capabilities of reinforcement learning, the interpretability of decision trees, or the follower strategy with the UAV as the primary router, each method offers distinct advantages tailored to different operational requirements and constraints.

D. Future Considerations

Considering this problem in the context of the real world, this challenge leads to several thoughts of future exploration. With the size and vastness of the United States military, a hidden requirement to this problem is scalability. Minefield traversal is a complex enough issue when dealing with a single UAV, UGV, and set of warfighters, but in the real world, thousands of these systems may be employed at any one time. With current technological limitations, it is reasonable to expect humans to be responsible for the majority of decision making in our current age, but the future has much uncertainty. As a bridge from this challenge into the real world, it would be realistic to consider more than a single UGV or destination for troops. In the above described methodology, in the event multiple UGVs are employed, a secondary routing method would be optimal. With minimal added compute, assuming the UAV is successful in scanning enough of the map for routes to be determined, a purely statistical or algorithmic approach could be utilized to find the shortest, lowest risk path. This would provide the highest trust system in giving a deobfuscated path a human could review and verify to be the most optimal. The only uncertainty in the system now comes from the scanning methods of the UAV.

One potential improvement to the proposed troop rerouting system could include allowing for calculations of whether continuing down a path if a mine is identified partially through a cell is optimal. For example, if troops have traversed a certain number of minutes across a cell and hit a mine, could the optimal troop or UGV routing policies allow troops to turn around and use a different path. This could be incorporated by adding additional paths and rewards to an MDP in a reinforcement learning model. Rerouting mid cell will add additional costs and risks. These could include having to reroute the UAV to scan new cells or, if troops encounter additional mines along the new path, wasting more time than if the original mine had been defused in the first place.

Another consideration for future development is the unreliability of battery and power systems. The UAV system contains a "battery" system and the UGV contains a "power" system. While, for this stage of the project, both systems are assumed to have infinite charge, this could change in future stages. If these systems have finite power supplies, recharging could generate significant monetary costs. Additionally, troops may incur the time costs of having to wait for mine identification or removal. To ensure that power resources do not have a substantial effect on mission outcomes and goal achievement, all models must consider the physical limitations of subsystem devices. Additionally, the UGV system contains a suite of sensors and a mine neutralization system. For this stage, these subsystems are assumed to be 100% effective. However, in future iterations, the UGV may not always be able to defuse a mine properly or sense a mine's location. This could include false positive sensing by the UGV, leading to inaccurate removal sites and wasted time. Future models must account for limited accuracy in physical systems and devices.

The reliability and accuracy of images sent over Wide Area Networks (WANs) provides another opportunity for future improvements. The UAV will utilize a WAN to send images of the minefield back to the command center for them to be analyzed before the UAV returns. Images sent over WAN have lower resolution than images downloaded directly off UAVs at a command center, which may lead to a lower accuracy of mine detection for both humans and AI that are analyzing the images. In the future, the possibility of rerouting UGVs and troops, based on the new analysis of the sharper downloaded images, while they are already in the minefield may provide ways to improve solution systems. WAN accuracy can also be included as a variable in decision models, as improvements to the technology will most likely occur in the future. These considerations could make a solution more trustworthy and reliable.

VI. Future Plans

The action taken in the next phase of the project will rely heavily on the additional information and resources provided. With larger data sets or a simulation system, the alternative solutions outlined in this paper can be easily tested. The various learning models for UAV and UGV routing outlined above can be developed and trained using additional data. A larger data set will also improve the regression analysis that can be done to identify the most critical environmental variables to UAV and human mine-detection accuracy. As the amount of data increases, the variance in regression estimators will decrease, allowing for stronger claims from model results. After testing and model design, experimentation on combinations of the candidate solutions will be performed. This can be done through the use of a simulation system which will be built if not provided. One interesting idea will be testing how various approaches perform on different subsets of data. For example, are certain learning algorithms better at identifying optimal policies for particular geographic conditions? Another potential subject of testing could be how well systems perform when the underlying system is changed. Some changes to consider could be an increased number of resources, such as additional UAVs and UGVs, and the possibility of multiple destinations through one minefield. The overarching goals of the next phase will be to build out proposed models, perform testing and simulations, and find creative ways to utilize limited amounts of information and data.

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