initiate tracking of the target and simultaneously request local assets to launch weapons, allowing the remote assets to take the lead in tracking and intercepting the target. These two CE strategies maximize cooperation between various assets, thereby enhancing target interception performance.

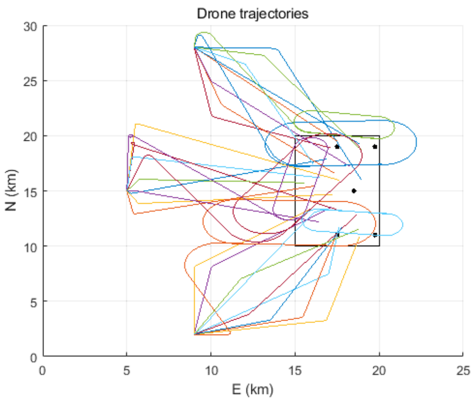

Fig. 1. Drone trajectories.

The structure of the heuristic algorithm [3] performs assignments on an anti-aircraft gun to target basis. After determining the assignment of anti-aircraft guns and radars to each target using the heuristic algorithm, the expected value of interception for each target is calculated. The expected value of interception is calculated by multiplying the value of target *j* with the earliest possible firing time. Based on the results of this calculation, targets to be eliminated are prioritized in a list, optimizing resource allocation. Anti-aircraft shell units are then allocated to targets in order of engagement value, allowing for efficient engagement.

To set priorities, the allocation of armament is varied based on the number of anti-aircraft gun types, employing the armament allocation plan at the battery level. For instance, if more than two types of anti-aircraft guns can be assigned to a target, it enables follow-up responses even if the initial interception attempt fails, eliminating the need for excessive armament allocation in the initial response.

Based on these rules, the optimal combination of anti-aircraft guns, targets, and radars is selected for the given situation. Finally, batteries and radars are assigned to targets, and the allocation process is repeated for a predetermined number of iterations until completion.

3. Result

The results of the interception simulation under the assumed problem environment are shown in Fig. 2. In the graph, the "O" marks indicate the state where the assets are tracking the drone, and the "X" marks represent points where interception was successfully achieved. In this simulation, a total of 30 drones were deployed, of which 26 were intercepted. Thus, the simulation shows an interception success rate of approximately 87 % for this defense system.

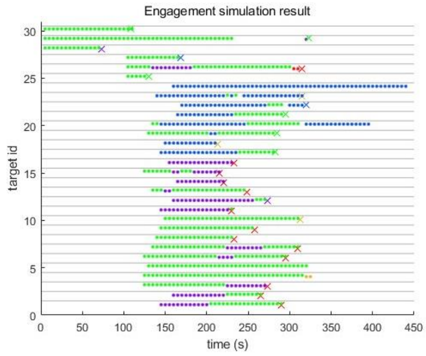

Fig. 2. Engagement simulation result.

4. Conclusion

This study proposed resource management and scheduling strategies within a multi-layered defense system to effectively counter advanced UAV threats, such as suicide drones. By applying the CE concept, resource allocation among defense assets was optimized, and suicide drone interception scenarios were simulated to analyze defense efficiency. The study confirmed that effective cooperation between remote and local assets is achievable through the use of precision cue and forward pass approaches within the CE strategy. This demonstrated that each defense asset could perform intercepts efficiently, minimizing assets damage even within resource constraints. Additionally, incorporating precise calculations of interception points for each defense asset and continuous target tracking during interception is expected to further enhance the precision and responsiveness of the defense system. These future improvements will support the multi-layered defense system in responding more effectively to various threat scenarios.

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Handling Uncertainty in UAV Sensor Information using Bayesian Belief Network and Large Language Model

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Summary: This paper describes how UAVs can handle uncertainty in information collected from UAVs with heterogenous sensors. The approach reported here combines Bayesian Belief Network (BBN) with a Large Language Model (LLM). Our primary use case concerns the detection of forest fires but we also report laboratory experiments that are conducted using non-combustible objects. Objects' colour, shape, are detected and interpreted using on-board sensors. Images from the UAV are also passed for interpretation to an LLM. None of the sources is perfectly applicable in all situations, as such, the UAV requires situation-based confirmation. Each of the sources is mapped to a node in BBN node with relations between nodes pre-defined through a Conditional Probability Distribution (CPD) created with input from Subject Matter Experts. We demonstrate the approach using DJI Ryze Tello programmable UAV and PyBBN scripts. The approach shows flexibility, adaptability, real-time analysis, and data saving (little data is required).

Keywords: Uncertainty handling, UAV, LLM, Forest fire.

1. Introduction

Unmanned Aerial Vehicles (UAVs) or drones have been extensively applied in the detection of forest fires [1]. The drones are equipped with various sensors to detect, monitor, and report the presence and movement of fire. A key problem in using multiple sensors arises from detection uncertainty [3, 4]. For example, detecting forest fire using colour could be incorrect when there is a presence of fire-like objects (e.g., dried grass covered with dust). To address this, multiple sensors need to be coordinated to handle various sensors operating in varying situations.

We have developed an approach to handling uncertainty in data from multiple sensors using a Bayesian Belief Network (BBN) [5, 6]. We have also developed an approach to path planning using a version of Delaunay triangulation [2] that simplifies on-broad processing and supports a semi-random search pattern (which we believe to be more efficient when searching for targets over a large area than the existing fixed pattern methods e.g., parallel track, creeping line, sector search, expanding square, etc. or random search e.g., Levy flight [1-9]). In this paper, we implement these solutions on a DJI Ryze Tello using PyBBN in an easy-to-implement, flexible (easy to update), real-time (non-post-hoc), and adaptable(situation-aware) fashion.

1.1. Bayesian Belief Network (BBN) for Handling Information Uncertainty

In Fig. 1, information from onboard sensors is used to infer the presence of objects (balloon or fire) from features in an image taken by the UAV (in terms of colour and shape of the spreading fire). It is possible that these sensors could misinterpret the image, e.g., the colour analysis could 'see' an orange surface as fire, or the shape analysis could fail to spot the full extent of the fire. In our approach, we complement the sensor analysis using off-board image interpretation. This could be evoked when the recognition confidence is below a threshold and could use a human Subject Matter Expert or, in this instance, a Large Language Model, to interpret the image. We assume that there will be circumstances in which this off-board processing could fail, e.g., when a fire is obscured by tree cover. The sensors could be supplemented with sensors for temperature, smoke analysis, etc. The output of the analysis nodes is weighted by time of day and weather conditions, and this weighted information is combined to produce a Situation Awareness report ('fire_final_SA') as represented by the BBN in Fig. 2.

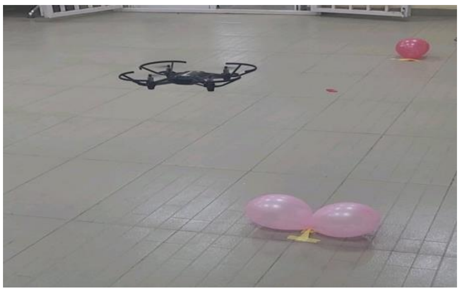

Fig. 1. Example of BBN.

The 'fire_final_SA' is derived using a Conditional Probability Distribution (CPD) of the decision parent nodes (Table 1) of the Bayesian Belief Network (BBN). Each distinct combination of the states of the parent nodes has a probability input in the decision node CPD. The inputs of the CPD can be seeded by a Subject Matter Expert (e.g., Table 1) or learned [6] or a combination of both. In Table 1, each information source reports whether it believes that fire is present (P) or absent (A). Where there is disagreement between the sources, the CPD proposes a probability of fire presence. The CPD in Table 1 is an assumed SME input e.g., #1 indicates an agreement between all sensors that fire is present. On the other hand, #2 shows a situation when shape-based fire input disagrees with the colour-based sensor. A probability value of 0.1 for fire absence was allocated because the time of the day is night and the weather is foggy which could possibly affect shape visibility. Hence, the change in weather and time of the day could improve the uncertainty (e.g., having time of the day as "Day" and weather "Clear" could lead to a higher uncertainty depending on the LLM input). This clearly shows the input of the CPD can be learned based on previous encounters with the objects by the sensors. In previous work [10], the Expectation-Maximisation algorithm (EM) was used to demonstrate the learning process. The number of inputs of the CPD can be calculated using Equation (1) and hence Table 1 shows the summary of the input.

$$N_{inputs} = \left(\prod_{i=1}^{n} S_i\right) S_\alpha, \quad (1)$$

where N_{inputs} is the number of the CPD inputs, S_i is the number of states of the parent nodes, S_α is the number of states of the deciding node (child node).

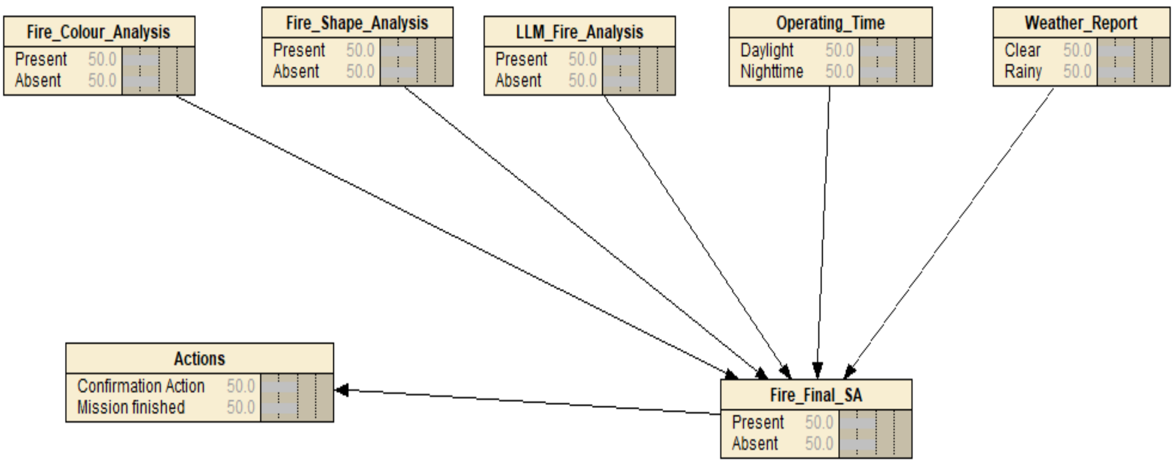

Fig. 2. Example of the UAV BBN.

Table 1. Example of CPD (Present = P, Absent = A) of the BBN Decision Node.

#	Colours indicate	Shape of fire	Time of day	LLM	Weather conditio	Fire final SA	
						P	**A**
1	P	P	Day	P	Foggy	1	0
2	P	A	Night	A	Foggy	0.1	0.9
…	…	…	…	…	…	…	…
3	P	A	Day	A	Windy	0.7	0.3

1.2. Delaunay-inspired Area Coverage Planning Algorithm

The Delaynay-inspired algorithm systematically selects seed waypoints (highly separated points within the searching space) and generates the remaining waypoints based on angle, direction, and distance differences. The seed waypoints are spread across the searching space (this can be systematic e.g., selecting from each angle). The seed waypoints serve as layer 1 waypoints of the search. Having the seed waypoints, then number of waypoints to be visited in layer two are then generated based on Delaynay triangulation number of triangles theorem (i.e., by taking each waypoint as a centre of triangle). As such the higher the number of seeds waypoints the higher the number of places to be visited. The search continues by visiting each waypoint in a layer and generating the next layer waypoint. Each layer of waypoints has a common angle, edge distance, and direction values. The choice of angle (direction) is based on the four quadrants and is systematic to stay around the search space and being non-repetitive. The number of waypoints and edges in a layer is controlled by the Delaunay triangulation number of triangles theorem [2] i.e., a mapping of points with the number of triangles that will be produced. This makes it look like a pseudorandom (in terms of coverage) approach while it is predictable and controllable.

2. Implementation

A DJI Ryze Tello programmable drone was tasked to explore an area based on a predefined path using a Delaunay-inspired path planning algorithm [11]. The drone is connected to the computer using the drone's WIFI. A Python script is written to generate a Delaunay-inspired path using distance and direction variation. The implementation of the Delaunay-inspired path planning approach uses simple distance (x meters) and direction (based on angle) variation.

The task is to detect an object from analysis of images captured using the on-board camera. Images are analysed using the OpenCV library to analyse the colour and shape of an object, and also an LLM interpreter (through Hugging Face Transformers). The LLM function is designed to output a Boolean result based on target presence or absence. This information (colour, shape, LLM output) is fed to nodes in the BBN (Fig. 2), and implemented on the connected PC using PyBBN. Each of the functions will return true (when an item is present) or false (when an item is absent). The received value will then be judged based on the assigned CPD of the deciding node.

For safety reasons, the experiment in the laboratory detected balloons (Fig. 1) in different colours. When an object was detected, the drone changed its behaviour from an area search to a local search, i.e., it changed from the Delaunay path to circling clockwise at a set height if the object is a specific colour, or circling at a lower height if it is another colour. The purpose of these circling paths was to create different actions for the drone depending on the object's colour, shape, or LLM interpretation. The analogy with operational conditions would be the need under some conditions, to fly closer to the fire in order for specific sensors (e.g., temperature, smoke analysis) to be more effective. A later replacement with real fire images was conducted.

3. Discussion

The proposed method offers the following benefits:

a. Real-time application i.e., non-post hoc: the interpretation is real-time on the connected hosting machine i.e., without the need for a vision-based training process (which is time and data-consuming) [12, 13];
b. Uncertainty: the proposed BBN-based model uses probabilities. This allows uncertainty modelling [10,14,15], e.g., #2 of Table 1 shows fire:absent = 90 %, fire:present = 10 %;
c. Learning: the model can be trained to handle various forms of uncertainty as described in [10];
d. None situation training approach: the model does not require a training process using situation data e.g., different parent nodes to ascertain the group of nodes information;
e. Multi-hierarchy: it allows multi-hierarchy solutions;
f. UAV action control: based on the output of the deciding node, the UAV can select confirmation action.

4. Conclusions

We demonstrate how BBN can be applied to handle the issue of uncertainty in UAV sensors. The BBN shows a potential to control UAV actions. The approaches require no large datasets for training and real-time sensor data analysis using LLM and object characteristics features. In the future, the work will look at CPD training and dynamic BBN.

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