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A novel approach to detect lightning strike ignitions with a swarm of uncrewed aerial vehicles

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Abstract

Algorithms for lightning strike investigation and ignition detection with an uncrewed aerial vehicle (UAV) swarm are proposed. This approach is scalable to cover large bushfire prone areas with rapid ignition detection times and little human intervention. Key insights provided by the approach include real-time drone assignment to minimise inspection time and repulsive swarming behaviour of unassigned UAVs to maintain uniform distribution. The algorithms also have capacity to prioritise strikes with high ignition risk to lower their inspection time.

Several severe lightning storms from the 2019-20 bushfire season were simulated over a 100,000 square kilometre region along the east coast of Australia. These simulations indicate that with 100 UAVs across the region, mean inspection times of under 30 minutes can be achieved. If the locality of high-risk storm events can be predicted an hour in advance to allow a pre-emptive increase in UAV density over that region, the inspection time can be reduced further to 12 minutes with 100 UAVs or just 6 minutes with 500 UAVs. This demonstrates the feasibility of a UAV solution for rapid ignition inspection, which in combination with a similar water-bomber fleet could drastically reduce the time to extinguish remote strike ignitions at the source.

1 Introduction

Dry lightning strikes are a primary bushfire ignition source in Australia, thus rapid strike ignition inspection followed by suppression would significantly improve a response program. The location of these strikes can already be accurately determined in real time using a network of low frequency receivers [1]. However, these strikes often occur densely in remote regions with limited accessibility, making rapid responses difficult.

It is thus proposed that a swarm of uncrewed aerial vehicles (UAVs) could be used to investigate and detect lightning strike ignitions. UAVs have countless advantages over crewed aircraft as a single human operator can manage multiple UAVs, thus reducing human injury risk and financial cost. UAVs have been utilised previously for frontier monitoring [2] and bushfire assessment [3], however the group is unaware of any previous attempts to use UAVs for lightning strike ignition inspection.

2 Methodology

To simulate the use of UAVs for lightning strike investigation and ignition detection, a python application was developed which provides simulation and visualization for each of the algorithms described below. The source code and documentation for the software is available at https://github.com/ANUBushfireInitiative/bushfire-drone-simulation.

2.1 Allocation algorithm

To minimize inspection times, UAVs must be assigned to lightning strikes as efficiently as possible in real time. The UAV allocation algorithm implemented and analysed in this report is designed on the premise that each UAV has a queue of strikes that are currently assigned to them, and they inspect each of the strikes in the queue sequentially. When a new strike is detected, it is inserted anywhere into a UAV queue that minimizes the total increase in mean inspection time provided the assigned UAV has sufficient fuel.

2.2 Prioritisation

The ignition risk of a lightning strike depends on numerous local factors such as the fuel load and associated rain events [4, 5] as well as the nature of the strike itself [6]. There is significant past and ongoing research into identifying this ignition risk, which may allow higher risk strikes to be prioritised and inspected sooner than low risk strikes.

Prioritisation was implemented by adjusting the minimization heuristic so that it depends not only on the inspection time of the strike as discussed in section 2.1, but also on the strike's risk. This risk could be calculated using a combination of the potential burn area and ignition risk. Some example prioritization heuristics tested in this study are shown in Table 1. It was assumed that the risk rating is normalized to be between 0 and 1.

Prioritisation name	Prioritisation function
Inspection time	t
Product	$t \cdot r$
Risk rating squared	$t \cdot r^2$
Risk rating cubed	$t \cdot r^3$
Threshold	$\begin{cases} 100t, & r \geq 0.8 \\ t, & r < 0.8 \end{cases}$

Table 1: Prioritisation heuristics (value to minimize) implemented in the modelling software. t is the inspection time of a strike and r is the strike's risk rating.

2.3 Swarming Behaviour

Ideally, unassigned UAVs (empty inspection queues) should maintain a uniform distribution over the region, and congregate towards busier areas where other UAVs are already occupied by lightning strike inspections. It was hypothesized that this "swarming" behaviour could be achieved using repulsion "forces", in which unassigned UAVs are repelled from each other. UAVs are also repelled from a boundary polygon to keep them contained in the region of interest. By repelling only from other unassigned UAVs, there is no repulsion from regions where the UAVs are currently occupied, which causes the unassigned UAVs to move towards these regions. This increases UAV density in lightning dense regions whilst maintaining a roughly uniform density over the remainder of the region.

The magnitude of the repulsion varies with distance such that UAVs that are close together are repelled strongly while the repulsive force between UAVs on opposite sides of the region are negligible. This causes the UAVs to behave as a swarm, spreading out from high density regions (where there will be greater repulsion) into lower density regions.

2.4 Forecasting

Forecasting regions of higher lightning strike density would allow unassigned UAVs to be pre-emptively clustered over regions which are expected to receive a large number of strikes to reduce inspection times. For simplicity, it was assumed that a forecast would consist of several locations where it is anticipated that there will shortly be a high density of lightning strikes. The unassigned UAVs can then be directed towards these forecast points by adding an attractive force to the swarming algorithm described in section 2.3.

To simulate a lightning forecast, regions of high lightning strike density over a future time frame (e.g. next hour) were identified using a Mean Shift Clustering algorithm. The forecast look-ahead time and resolution can both be adjusted with this method by varying the time window of strikes to use for the forecast and clustering hyper-parameters.

2.5 Test region

The algorithms described above have been tested on two severe lightning events from the 2019-20 bushfire season across a region of approximately 100,000 square kilometres in south-eastern Australia pictured in Figure 1.

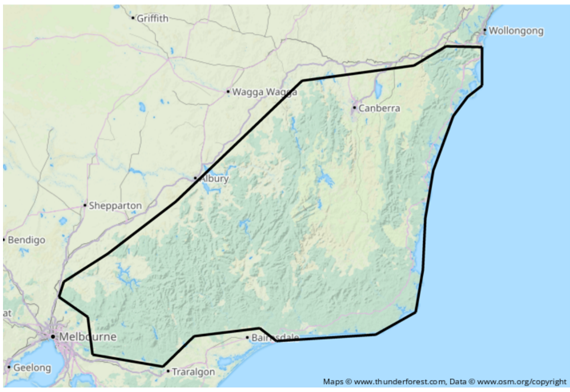

Figure 1: Boundary polygon surrounding a region of approximately 100,000 square kilometres on the south-east coast of Australia. Map data from OpenStreetMap [7].

2.6 Lightning Dataset

The data for the two lightning storms simulated in this report were obtained from Blitzortung.org. Storm 1 consists of 4567 strikes from the 24 hour period between 6:00am 19/01/20 to 6:00am 20/01/20. Storm 2 consists of 4257 strikes in a separate 24 hour period during the 2019/2020 bushfire season. Unfortunately, the exact date of this 24 hour period is unknown. The nature of the storms differ significantly with Storm 1 exhibiting a long storm front that moves across the entire region while Storm 2 has three disconnected storm events.

2.7 Assumptions

As part of the ANU bushfire initiative, prototype UAVs for lightning strike ignition inspection are being developed which form the basis for the modelling in this study. These UAVs have a range of approximately 650km travelling at 85 km/hr. The inspection time required is assumed to be 1 minute per strike and they will take approximately 15 minutes to refuel and perform pre-flight checks at a UAV base. These values have been used to describe the parameters of the UAVs for all tests in this report, however they can be easily adjusted in the simulation software.

To simulate real world fuel constraints, 58 UAV bases were randomly distributed throughout the region shown in Figure 1. It is assumed that the UAVs can refuel at any of these bases which have unlimited fuel and can accommodate any number of UAVs simultaneously.

Each UAVs initial fuel was randomly sampled from a uniform distribution between 50 and 100% of a full tank. Unless otherwise indicated, each of the simulations hereafter use 100 UAVs initially distributed evenly across the region.

3 Results

The effectiveness of the basic allocation algorithm was evaluated via simulations of an 100 UAV fleet on both storms and the results are presented in Table 2. This achieved mean inspection times that were less than half an hour for both storms.

Lightning Storm	Mean	Maximum	99th Percentile	90th Percentile	50th Percentile
Storm 1	0.45 hr	3.25 hr	1.77 hr	0.95 hr	0.35 hr
Storm 2	0.42 hr	3.06 hr	1.55 hr	0.87 hr	0.35 hr

Table 2: Basic allocation algorithm inspection times

3.1 Swarming

Table 3 demonstrates swarming behaviour for unassigned UAVs improves all metrics. Swarming brought the mean inspection time down to approximately 24 minutes with 100 UAVs. The maximum time is also decreased by approximately half an hour due to the more uniform distribution of unassigned UAVs across the region reducing outliers.

Lightning Storm	Mean	Maximum	99th Percentile	90th Percentile	50th Percentile
Storm 1	0.43 hr	2.89 hr	1.64 hr	0.95 hr	0.31 hr
Storm 2	0.38 hr	2.41 hr	1.49 hr	0.81 hr	0.28 hr

Table 3: Inspection times with swarming

3.2 Forecasting

To determine the impact of forecasting on inspection times, the simulated lightning forecasting described in section 2.4 was generated for both storms. The forecasting was implemented with a look ahead of 1 hour and resolution of 30 minutes requiring at least 25 strikes in a 50km radius to be considered a storm. Table 4 demonstrates this forecasting yields a significant improvement to the inspection times of Storm 2, almost halving the mean time to just 13 minutes. However, little difference is seen in the inspection times of Storm 1.

This is due to the different nature of the two storms. Storm 1 has a long front that moves across the entire region. The UAVs follow the front across and are not 'surprised' by new clusters of strikes popping up independently of the main front. Storm 2, however, has several disconnected storm events, so forecasting and increasing UAV density over these storms before they occur was greatly beneficial.

Lightning Storm	Mean	Maximum	99th Percentile	90th Percentile	50th Percentile
Storm 1	0.46 hr	2.90 hr	1.64 hr	0.95 hr	0.31 hr
Storm 2	0.21 hr	1.99 hr	1.05 hr	0.46 hr	0.14 hr

Table 4: Inspection times with swarming and forecasting

It is important to note that the generated forecast did not have any uncertainty associated with its location or time. Therefore, the inspection times may not decrease as much if real-world forecasting is used which may not be as accurate. However, it is clear that accurate forecasting could be extremely beneficial for spontaneous storm events.

3.3 Prioritisation

To evaluate the effectiveness of prioritisation, the strikes from both lighting storms were randomly assigned a risk rating from a uniform distribution between 0 and 1 with 0 indicating no risk. These storms were then simulated using swarming behaviour and forecasting with each of the prioritisation heuristics discussed in section 2.2. A summary of inspection times for Storm 1 using all tested prioritisation heuristics is displayed in Table 5.

Prioritisation	Mean	Maximum	99th Percentile	90th Percentile	50th Percentile
Inspection time	0.46 hr	2.90 hr	1.64 hr	0.95 hr	0.31 hr
Product	0.61 hr	6.34 hr	3.38 hr	1.45 hr	0.35 hr
Risk rating squared	0.83 hr	8.32 hr	4.79 hr	2.26 hr	0.42 hr
Risk rating cubed	1.04 hr	8.58 hr	5.63 hr	2.86 hr	0.53 hr
Threshold	0.62 hr	4.07 hr	1.89 hr	1.19 hr	0.57 hr

Table 5: Inspection times of Storm 1 with swarming and forecasting for various prioritisation functions. Prioritisation functions are defined in Table 1.

Prioritisation method	Mean inspection time risk rating ≥ 0.8
Inspection time	0.46 hr
Product	0.49 hr
Risk rating squared	0.60 hr
Risk rating cubed	0.70 hr
Threshold	0.54 hr

Table 6: Mean inspection times of high risk strikes (risk rating ≥ 0.8) for Storm 1. Simulated using forecasting for various prioritisation functions. Prioritisation functions are defined in Table 1.

The primary effect of prioritisation is a significant increase in the mean inspection times. Furthermore, Table 6 demonstrates that prioritisation also increased the mean inspection time of the high risk strikes. By prioritizing the high-risk strikes, the UAVs routes are significantly less efficient as low-risk strikes are ignored until their inspection time is large enough to compete with the prioritization of the higher risk strikes. This increases the inspection time for all strikes as a significantly less efficient route is chosen by the UAVs than when prioritizing on mean inspection time alone.

It is thus suggested that instead of prioritizing the inspection of strikes, to instead select a subset of strikes that can be ignored. This can be achieved by removing strikes with a risk rating below a threshold.

Another potential issue with the model above is that the risk ratings were sampled randomly from a uniform distribution and are thus independent of location. A real world prioritization strategy would likely have clusters of high-risk strikes in dry areas with large fuel load and clusters of lower risk strikes in wet areas. This may instead cause UAVs to swarm towards higher risk areas which may still be beneficial. This could also potentially be implemented as additional "attraction" points in the swarming behaviour to pre-emptively place more UAVs in high risk areas.

3.4 Number of UAVs

Finally, the impact of varying number of UAVs across the initial 100,000 square kilometer region was measured. These tests were run for both storms using swarming and forecasting. The results of this experiment are outlined in Table 7.

Number of UAVs	Mean inspection time (hrs)	
	Storm 1	Storm 2
10	37.59	15.33
20	7.56	2.70
30	4.37	1.08
40	2.37	0.61
50	1.69	0.44
60	1.18	0.37
70	0.89	0.31
80	0.67	0.26
90	0.53	0.23
100	0.45	0.21
200	0.20	0.14
300	0.12	0.11
400	0.11	0.10
500	0.09	0.09

Table 7: Inspection times for varying numbers of UAVs

As expected, the inspection time decreases with increasing numbers of UAVs. As the number of UAVs increase, the mean inspection time also becomes independent of the nature of the storm. Over the 100,000 square kilometres region, a mean inspection time of between 12-30 minutes can be achieved with 100 UAVs and a mean inspection time of 6 minutes can be achieved with 500 UAVs. Note that no modelling was conducted into the infrastructure requirements to support this many UAVs.

4 Future work

There is enormous potential for future work improving the above algorithms and testing the inspection strategy in the field. An important next step is further data collection regarding the time frames of lightning strike ignitions and how rapid a response is required which can help fine tune the algorithms and confirm how many UAVs are required to achieve effective inspection times. This is particularly interesting as the capacity to specify a target maximum inspection time is already implemented in the simulation software. This will prioritise assigning strikes such that the inspection time is kept below the target maximum.

It would also be beneficial to extend the lightning storm data set used for the results in this experiment. The forecasting results demonstrate the importance of the structure of the lightning storm hence a more extensive set of lightning storms could identify other weaknesses, assumptions or opportunities in the simulation. It would also determine how frequent severe storms are and how many UAVs would be required to cover the majority of storm events.

Finally, the simulation software also provides framework to simulate a water bomber fleet to respond to strike ignitions. Coordinating this fleet poses additional challenges including refilling water and lower densities of both ignitions and water bombers. Investigating this further was beyond the scope of this report but would be an interesting concept for future research.

5 Conclusion

The simulations above indicate that with 100 UAVs across the region, mean inspection times of less than 30 minutes can be achieved when utilising swarming drone behaviour. Prioritisation of strikes based on their risk was ineffective at reducing the inspection time of high risk strikes, so it would be preferable to focus research efforts on determining low-risk strikes that could be ignored instead. Assuming that the locality of high-risk storm events can be predicted an hour in advance to allow a pre-emptive increase in UAV density over that region, the inspection time can be reduced further to 12 minutes with 100 UAVs or just 6 minutes with 500 UAVs. This demonstrates the feasibility of a UAV solution for rapid ignition inspection.

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