Optimization of Drone Quantity Based on Empirical Analysis in Bushfire Extinguishment

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Abstract. With the deterioration in the environment, extreme weather is more likely to occur. The wildfire is becoming severer in turns of frequency and magnitude, causing disastrous damage to our fragile ecosystem. In this paper, we purpose a model to identify the optimal number of drones in case of any potential threat posed by bushfire in Victoria, Australia. In this paper, we use satellite data from space agencies such as NASA and the European Space Agency to determine the initial conditions and parameters of the model. including land cover, topography, traffic development, potential reinforcements nearby, distance to water and historical wildfires. We extract the data of several modes and determine the coefficients that affect the forest-mass. According to our simulation results, the optimal expected number of SSA UAV and relay UAV is 53 and 85 respectively.

Keywords: UAV, wildfire protection, relay communication, optimization.

1. Introduction
In Australia’s hot, dry season, wild fires are common [1]. High temperatures and droughts are the main reasons for the raging wildfires. The occurrence of forest fires often causes negative effects [2]. For example, in Australia, a large area of forest farms will be destroyed by fire every year, and fire will also cause property losses and casualties. In July 2019, a bushfire which lasted for seven months broke out, destroyed about 400 hectares of land and killed one billion wild animals. This fire had a very serious impact on the ecology [3].
With the continuous progress of science and technology, in order to solve the problems caused by forest fires, many advanced technologies and instruments have been used in fire monitoring and extinguishing activities. SSA (Surveillance and Situational Awareness) drones can carry cameras, sensors, and other instruments to monitor the data that front-line firefighters carry with their instruments, while repeater drones can extend the communication distance between front-line firefighters and the command center. Both drones help monitor the changing fire situation and reduce information transmission time. They also allow the command center to make decisions about the fire quickly, help prevent further spread of the fire and speed up the extinguishment of the fire.

In this paper, we plan the use of SSA drones and repeaters to make optimal decisions in terms of coverage, security and economy.

2. Experimental data source

2.1. Data Collection
Because we need to consider the impact of terrain, historical fire data, traffic and other factors on the distribution and number of drones. So, we need to collect a lot of data. Then we directly visualize some of the data for display. The data we collected mainly included historical bushfires in Australia, vegetation cover in Australia, topography in Australia, distance from water bodies in Australia and distribution of fire stations in Australia.

After some rudimentary preprocessing, the raw data can be interpreted as images displayed in figure 1.

2.2. Data Collection
All the data we collected are related to Australia. In order to analyze only the Victoria region, we need to process the data and isolate the data that are only relevant to Victoria region.

According to the geographical information of Victoria region, we extracted the longitude and latitude of the boundary part of Victoria region and delineated a roughly polygon to define Victoria region. Then all the data related to Australia were processed by using this polygon, and the relevant data of Victoria region was extracted.
3. Data Extraction
First of all, topographic data and distance data from water bodies should be considered to extract the corresponding images into discrete data. We mainly consider using the digital image processing method to process the image and extract the data.

3.1. Data Collection

In order to extract the discrete data, we should use the gray value information of the digital image. However, the original image is RGB image, that is three-channel image, which cannot be directly mapped to data. Therefore, the three-channel image needs to be converted into a single-channel gray image first.

By determining the coefficients for the three channels, we use the following conversion formula to convert RGB images to grayscale images.

\[
\text{Gray} = R \times 0.299 + G \times 0.587 + B \times 0.114
\]  

(1)

Take the degree of traffic development as an example, the pictures before and after the conversion are shown in figure2.

![RGB image](a) RGB image ![Grayscale image](b) Grayscale image

**Figure. 2** Pictures before and after the conversion

3.2. Extract traffic development degree data

In order to obtain the data of traffic development degree corresponding to each location from the gray image, the following steps are adopted for processing.

**Step 1: The sigmoid activation function is used to map the image gray value to the range of 0 to 1**

We use sigmoid, the activation function, to artificially define the median of traffic development, that is, the symmetric point of the function distribution center, and then map the gray value to the range from 0 to 1. We specifically choose the grayscale value of 128 as the median, and then use the following formula for mapping:

\[
\text{tr}(x, y)' = \frac{1}{1 + e^{-(\text{tr}(x, y) - 128)}}
\]  

(2)

**Step 2: Use a 3*3 median filter template to convolve the image.**

In order to reduce the abrupt change of grayscale value, the median filter is used to convolve the image. Finally, we get the corresponding value of the traffic development degree of each discrete position.

3.3. Extract data from heat map of fire occurrence

In order to obtain the fire heat map data corresponding to each position from the gray image, and then get the fire probability at each position, we use the following steps for processing:

**Step 1: Use a 3*3 median filter template to convolve the image.**

In order to reduce the mutation of the image, we use median filter to convolve the image.
Step 2: The sigmoid activation function is used to map the image gray value to the range of 0 to 1.

We also use sigmoid, the activation function, to map the gray value. The gray value of 128 was selected as the median value, and the following formula is used for mapping:

$$P(x,y)' = \frac{1}{1+e^{-(P(x,y)-128)}}$$ (3)

Finally, we get the corresponding value of the discrete fire frequency at each position.

3.4. Extract data of distance from water body

In order to obtain the data of distance from water body corresponding to each position, we use the following steps for processing [4]:

Step 1: Use a 3*3 median filter template to convolve the image.

Step 2: The sigmoid activation function is used to map the image gray value to the range of 0 to 1.

We also use sigmoid, the activation function, to map the gray value. The gray value of 57 was selected as the median value, and the following formula is used for mapping:

$$w(x,y)' = \frac{1}{1+e^{-(w(x,y)-57)}}$$ (4)

Finally, we get the corresponding value of the discrete fire frequency at each position.

3.5. Extract the heat map data of the fire stations

We use the following steps for processing:

Step 1: Multiply with the traffic information of the corresponding position.

Since the fire station’s influence on fire extinguishing is measured by the time firefighters arrive at the fire site, the influence factor of fire station’s distribution on fire extinguishing cost can be obtained by combining with the traffic distribution specifically.

Step 2: Use a 3*3 median filter template to convolve the image.

The image matrix after multiplication also has the mutation of gray value, and the median filter is used to reduce its influence.

3.6. Extract vegetation cover data

We use the following steps for processing:

Step 1: The boundary of vegetation is made clear by morphological expansion

Because the gray difference at the image boundary is not clear, it is difficult to judge the boundary of vegetation. Morphological expansion method is used to expand the range with high gray value, so that the boundary becomes clear and the separation can be better.

The following is the vegetation cover before and after morphological expansion:

The application for vegetation cover before and after morphological expansion is shown in figure 3.
Figure 3: Pictures before and after the morphological expansion

**Step 2: Use a 3*3 Gaussian filter template to convolve the image.**
Since the coverage range of a single pixel in the image is about 350m, there is a mutation of vegetation species, and Gaussian filter is used to reduce the transition mutation between vegetation.

3.7. **Extract terrain data**

**Step 1: Use a 3*3 median filter template to convolve the image.**
**Step 2: Use Laplace operator to calculate the gradient.**

In topographic map, the change rate of gray value can be used as the basis to measure the height of terrain. We use gradient to determine the maximum change rate of gray value. The method to calculate the gradient is to use Laplace operator to convolve the image, and then square the convolution result, and finally get the terrain height data of each position. We use the following Laplace operator to calculate the gradient:

\[
\begin{pmatrix}
-1 & -1 & -1 \\
-1 & 8 & -1 \\
-1 & -1 & -1
\end{pmatrix}
\]  

(5)

4. **Data Interpretation**
After the process mentioned above, a weight matrix is gained. Suppose, and each of the dimension represents an aspect that will affects the number of the drone. To dig deeper, we apply principal component analysis (PCA) to the data exploited from the satellites.

We discover that the probability of the bushfire to happen, the vegetation cover and the topography have a dominant positive relation, and the transportation, distance to the water body and the number of fire station nearby have a dominant negative relation.

5. **Model simulation results**

5.1. **Normalization**
Due to the difference in the order of magnitude of those coefficients, we first apply normalization to all the data. Let \( S \) be the sorted multi-set of a data to be normalized and \( S_i \) represents the \( i^{th} \) element. To normalized set \( S \), we apply the following equation to each element of \( S \).

\[
S'_i = \frac{s_i - \text{min} S}{\text{max} S - \text{min} S}
\]

(6)

5.2. **The concept of forest-mass**
To further simplify our model, we propose the concept of Forest-mass. In the satellite images, each pixel represents a 350m x 350m square area. Although a 350m x 350m square is not a small area in reality, it
still poses a problem when taking the number of pixels into consideration. The forest-mass, which is derived from the data gained of the NASA’s MODIS satellite using the following algorithm, is block of land and can help us view the problem in a discrete way (As shown in figure 4).

Figure 4 Hexagon shape forest-mass

Note that the result shown above regards the whole Victoria as a forest area, and the ‘forest-mass’ boundary can be gained from the product of the multiplication of the mask of forest and the above result.

5.3. The coefficient of forest-mass

At this point, we simplify the problem to calculate the expectation of the drone in each forest-mass; the emphasis lies on how to derive the risk of a given forest-mass from the area it encompasses. To analysis the risk of each forest-mass, we pose following assumption:

• Each pixel’s contribution to the given forest-mass satisfies the gaussian distribution.

For a given forest-mass, we use the convolution product of the hexagon shape and a given gaussian mask to represent its cost function

$$Coe_j^i = G(\sigma, \mu) \ast Coe_i(x, y)$$

Where $G(\sigma, \mu)$ stands for a gaussian mask whose variance equals to $\sigma$ and expectation equals to. $Coe_i^j(x, y)$ stands for the $i^{th}$ coefficient to be calculated. $Coe_i^j$ stands for the $i^{th}$ coefficient of $j^{th}$ forest-mass. Several example parameters of forest quality are shown in Table 1.

Table 1 Some example parameters of forest-mass

| P        | tr      | w      | f       | v       | tp       |
|----------|---------|--------|---------|---------|----------|
| 0.137254902 | 0.235294118 | 0.996509804 | 0.043572549 | 0.88889 | 0.568627451 |
| 0.135513725 | 0.018300784 | 0.904156863 | 0.003921569 | 0.88889 | 0.610470588 |
| 0.117211765 | 0.130717647 | 0.732901961 | 0.030936863 | 0.88889 | 0.42745098 |
| 0.11067451 | 0.223529412 | 0.729843137 | 0.057952941 | 0.33111 | 0.396078431 |
| 0.09847451 | 0.501960784 | 0.861019608 | 0.132027451 | 0.88889 | 0.436588235 |
| 0.066231373 | 0.501960784 | 0.983019608 | 0.130717647 | 0.88889 | 0.157298039 |
| 0.000435725 | 0.587372549 | 1        | 0.140741176 | 0.88889 | 0.198694118 |
| 0.078431373 | 0.599568627 | 0.969921569 | 0.374729412 | 0.88889 | 0.632666667 |
| 0.108062745 | 0.501960784 | 0.93027451 | 0.294988235 | 0.88889 | 0.369498039 |
5.4. The expectation of the number of the drone

The expectation of the number of the drone is a function of those coefficient, which can be represented as:

\[ E(P, tr, w, f, v, tp) \]  \hspace{1cm} (8)

and possess the following properties:

\[ E(1,1,1,1,1,1) \leq \text{const} \]  \hspace{1cm} (9)

\[ \frac{\partial E}{\partial P} > 0, \frac{\partial E}{\partial tr} < 0, \frac{\partial E}{\partial w} < 0, \frac{\partial E}{\partial f} < 0, \frac{\partial E}{\partial v} > 0, \frac{\partial E}{\partial tp} > 0 \]  \hspace{1cm} (10)

First, the expectation should have a upper bound, which is realistic due to the manpower and resource of a country is always limited. Second, the partial derivative should meet the PCA result and our interpretation towards the data.

\[ E_{SSA} = \sum \sqrt{\frac{tp \times w}{(1-f)(1-tr)(1-P)v'}} \]  \hspace{1cm} (11)

\[ E_{Repeater} = \sum \sqrt{\frac{e^{tp+tr}}{2(1-P)} e^{1-v}} \]  \hspace{1cm} (12)

The expectation number of the SSA drone and repeater drone is 53 and 85 respectively, according to our model.

6. Conclusion

First of all, the fire probability is calculated according to the historical data of hill fire, and the fire hazard function is obtained by using topography and thermal radiation data. Then the data mining algorithm is used to divide the forest farm area. Finally, the number and distribution of SSA UAV and relay are determined by these two functions. According to our simulation results, the expected number of SSA UAV and relay UAV is 53 and 85 respectively.

References

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