Formation and research of UAV safety models and observability of objects when monitoring the fire setting

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Abstract. Fire monitoring with the use of an unmanned aerial vehicle is a two-criterion task, since there is a need to maximize the vehicle protection against the thermal influence of the fire, as well as to increase the observability as much as possible achieved by reducing the flight height. This paper contains empirical models, representing the flight safety of an unmanned aerial vehicle and the observability of the target objects during fire situation monitoring. The proposed models allow to consider the peculiarities of the monitoring conditions, using a car as a sample target. The analysis of the proposed models is carried out, and the relevant quantitative results are provided. The work defines the criteria for the selection of an optimum aerial vehicle flight height over the area under surveillance, and they are generated, using an expert assessment database.

1. Introduction
One of the actual problems nowadays is monitoring fires, covering large areas, such as forest fires, burning steppe, fields. The most efficient solution to fulfil this mission is the use of unmanned aerial vehicles (UAVs). Mostly while monitoring UAVs also perform the task to search for objects under consideration: people, cars, agricultural and other industrial equipment [1].

The complexity of aerial search is determined by the danger of relatively low UAV flyovers above the points of fire outbreaks and variations of area observability levels, caused by the presence of smoke. When the flight height is reduced, the UAV gets exposed to the hazardous impacts of the fire; however, this allows to increase the level of observability, and, therefore, the probability to detect the objects of interest. To take the mentioned above successful monitoring operation criteria into account, the authors proposed the method of selecting the optimum flight height, based on the developed heuristic safety and observability models, which are given below. Conducted by mathematical simulation experiment has confirmed the efficiency and effectiveness of the proposed in this paper approach to determine the altitude of a UAV flight.

2. UAV flight safety model
When flights are conducted at low heights, such as a few meters, the UAV safety is substantially affected by the thermal exposure to flames and smoke, as well as by the objects, located in the UAV flight path (buildings, structures, trees, bushes, etc.).
Let us assume that the relative safety of the UAV is evaluated through the vehicle loss or crash confidence level, which varies in the range from 0 to 1, depending on the height. The authors obtained a heuristic model, defining the UAV safety in accordance with the reasoning provided above, which is presented as equation (1). When \( R_S(h) = 1 \), the UAV suffers an accident, leading to its destruction, and when \( R_S(h) = 0 \), the flight conditions are absolutely safe

\[
R_s(h) = \frac{1}{1 + e^{-k_s(h-h_s)}},
\]

where \( k_S \) is an empirical coefficient, determined, considering the fire intensity, the location and height of ground-based objects, and flight conditions; \( h_S \) is the UAV flight altitude, at which the relative flight safety \( R_S(h) \) under current conditions is equal to 0.5; \( s \) is the UAV flight safety model index.

The \( k_S \) coefficient (with the units of measurement of 1/meter or 1/m) and height values \( h_S \) (with the units of measurement of meter or m) can be determined, using the previously generated knowledge bases, created based on the earlier obtained experience of monitoring during similar abnormal situations. The following are the examples of expert assessment database rules, used to evaluate the UAV flight safety model parameters:

- if the surface is a forest with the object height of \( h_T \), then \( h_S > 0.8h_T \);
- if the forest is sparse, then \( k_S < 0.4 \);
- if the forest is dense, then \( k_S > 0.6 \);
- if the fire is strong with the flame height of \( h_T \), then \( h_S > h_T \);
- if the forest is sparse and the fire intensity is medium, then \( 0.2 < k_S < 0.4 \);
- . . . .

The expert assessment knowledge base can be increased based on the analysis of developing situations.

If the area being monitored is composed of \( F \) sections, where fire characteristics are different, then the UAV flight safety level may be different at various sections and can be calculated for each section separately.

3. Object observability model

The fire situation monitoring takes place in smoke conditions, which reduce the contrast of images, obtained for their processing, search and recognition of objects. This effect is caused by the fact that smoke contains small solid particles in their suspended state [2]. If the area being monitored is composed of \( F \) sections, where the fire characteristics are different, and, therefore, the observation conditions are also different, the object detection results will depend on the smoke density within the specific section and the UAV flight height. In this case, within each \( f \in F \) section, the observation conditions are the same (constant smoke density parameters).

To describe the dependence of the variations in the contrast level of the resulting image on the height, let’s use a sigmoid of the following form

\[
K_f(h) = K_{f_{\text{max}}}[1 - 1/(1 + e^{-k_f(h-h_f)})],
\]

where \( h \) is the UAV flight height, \( k_f \) is an empirical coefficient, depending on the fire conditions, ambient conditions, etc., \( h_f \) is the height, at which the contrast is equal to 0.5 * \( K_{f_{\text{max}}} \), \( f \in F \) is the fire section index, \( F \) is the number of fire area sections with constant smoke parameters, and \( K_{f_{\text{max}}} \)—is the maximum contrast level.

Figure 1 shows an object, a car, the contrast of which is reduced by 15% from its maximum level, i.e. the reference contrast against the current terrain at a height of \( h = 0 \) m.
Figure 1. Simulated reduction of image contrast level by 0.15.

Figure 2. Experimental reduction of image contrast by 0.15.

The following input data were taken for this experiment: $k_f = 0.43$, $K_{f_{\text{max}}} = 3$, flight height $h = 4$ m, $h_f = 8$ m; in this case, $K_f(4) = 2.54$. These conditions also ensure a contrast decrease by 0.15, which indicates the feasibility of the applied contrast reduction model (2) (see figure 2).

Based on the contrast variation impact described above, the authors have derived a heuristic model for the deterioration of the observability of target objects (3) during fire situation monitoring.

When $R_a(h) = 1$, the monitoring was conducted with an error, leading either to an omission of the target, or to an issue of a “false alarm” (wrong object recognition), and when $R_a(h) = 0$, the observation condition is perfect. This covers the case, when the observation conditions do not allow to detect an object, which is present

$$R_a(h) \left[ \frac{1}{1 + e^{-k_a(h-h_a)}} \right] \left[ \frac{1}{1 + e^{-\beta}} \right],$$

(3)

where $k_a$ is an empirical coefficient, which depends on the fire conditions, meteorological conditions, day or nighttime, etc.; $h_a$—is the UAV flight height, at which the image contrast, obtained within the $f \in F$ section, is equal to 0.5; $\beta$ is a value that takes into account the impact of random factors, calculated, using equation (4)

$$\beta = \frac{\sigma_n^2}{\sigma_f^2},$$

(4)
where $\sigma_s$ is root-mean-square deviation of the signal, $\sigma_n$ is root-mean-square deviation of the additive white Gaussian noise with zero mathematical expectation.

The following are the examples of rules, supporting the evaluation of the parameters, included in the observability models:

- if the surface is a forest, the fire is strong, and the humidity is high, then $0.7 < k_a < 0.9$;
- if the surface is a forest, the fire is weak, the forest is sparse, and the humidity is low, then $h_a > 0.7 h_f$, $0.4 < k_a < 0.6$;
- if the surface is a field, the fire is strong, and the humidity is low, then $h_a > 3$ m;
- if the surface is a field, the fire is strong, and the humidity is high, then $h_a > 5$ m;
- ...

Both for the observability model and the UAV flight safety model, the compiled database of coefficients can be refined and expanded with the application of expert knowledge.

4. Analysis of the results

Thus, when calculating the height of the UAV flight over a specific fire area section $f$, using the proposed UAV flight safety (1) and desired objects observability (3) models, it is possible to derive the following model of overall losses during the fire situation monitoring (5), which covers both the UAV losses and the omissions or false recognitions of the desired objects:

$$R_P(h) = a_a \left[ 1 - \frac{1}{1 + e^{-k_f(h-h_f)}} \right] + a_s \frac{1}{1 + e^{-k_s(h-h_s)}},$$

where $a_a$ and $a_s$ are ranking coefficients, allowing to consider the priority of the operation goal.

Model (5) allows selecting the UAV flight height, at which the total losses will be minimized.

Figure 3 shows the outputs of the model of losses, associated with the UAV flight safety (dotted line), as well as the outputs of the model of losses, associated with the desired object observability (solid line).

![Figure 3. Graphs of observability and safety models.](image.png)

In the case being considered, the optimum flight height, selected from the point of view of minimizing the total losses, will be 10.7 meters, and the minimum total losses will be 0.48, provided that the ranking coefficients are equal.
To assess the effectiveness of the proposed algorithm for selecting the optimum UAV flight height while searching for objects, the search processes were simulated.

The results of calculations are given below, conducted to estimate the losses exploring two target areas. The parameters of the models are provided in table 1.

Table 1. Parameters of fire situation models.

| Fire outbreak point No. | 1       | 2       |
|------------------------|---------|---------|
| $h_a$ coefficient      | 11      | 7       |
| $k_a$ coefficient       | 0.8     | 0.5     |
| $h_s$ coefficient      | 9       | 3       |
| $k_s$ coefficient       | 0.7     | 0.8     |

When ranking coefficients are equal, meaning $a_a = a_s$, for the fire outbreak point 1 (figure 4(a)), the lowest losses will occur at the flight height of $h_{opt,1} = 9.82 \, h_{opt}$ m, and for the point 2 (figure 4(b)), $h_{opt,2} = 5.17 \, h_{opt}$ m; for these cases, the correct object detection probability, crash probability, and average losses are provided in table 2.

Table 2. Fire monitoring simulation results for various UAV flight heights with equal ranking coefficients.

|          | $R_a(h_1)$ | $R_a(h_2)$ | $R_s(h_1)$ | $R_s(h_2)$ | $R_{avg}$ |
|----------|------------|------------|------------|------------|-----------|
| $h_{opt}$ | 0.72       | 0.71       | 0.64       | 0.85       | 1.6       |
| $h = 10 \, m$ | 0.69       | 0.18       | 0.66       | 0.99       | 2.2       |
| $h = 7 \, m$ | 0.96       | 0.5        | 0.19       | 0.96       | 2.1       |

Figure 4. Losses during fire monitoring for the following fire outbreak points: (a) point 1; (b) point 2.

If the correlation between ranking coefficients is modified, for example, by increasing the significance of observation losses relative to the safety losses twice, the results will be as follows: $a_a = 2 \cdot a_s$, the optimum flight height for the fire outbreak point 1 will be $h_{opt,1} = 8.52 \, h_{opt}$ m, and for the point 2, $h_{opt,2} = 4.21 \, h_{opt}$ m; in this case, the average losses will be $R_{avg}(h_{opt}) = 1.5$; $R_{avg}(h = 10 \, m) = 2.6$; $R_{avg}(h = 7 \, m) = 1.9$. 

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5. Conclusion
A computer simulation of the algorithm, designed for the selection of the optimum height for flying over fire outbreak points, was carried out. When the simulation results were compared, the proposed approach resulted in a 27% decrease in average losses, compared to the flight at a constant altitude of $h = 10$ m, and a 23% decrease in losses for the flight height of $h = 7$ m with equal ranking coefficients.

With a twofold increase in the significance of the observability characteristic, the decrease in average losses for the height of $h = 10$ m was 34%, and for the height of $h = 7$ m, the reduction in losses was 21%.

The obtained results indicate an enhancement in the performance of fire situation monitoring using UAVs, achieved by the application of the presented algorithm.

The UAV flight safety and target object observability models, presented in this paper, provide the possibility to consider the peculiarities of the flight conditions over each fire outbreak point and select the optimum flight height, enabling to ensure the fulfillment of the assigned object search and recognition tasks with the specified reliability and safety of search resources.

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