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Automated Decision Making in Road Traffic Monitoring by On-Board Unmanned Aerial Vehicle System

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Abstract

The study is dedicated to solving the target issues of the ground traffic monitoring aided by the Unmanned Aerial Vehicles (UAV) based on applying the on-board computer vision systems. It has been shown that making decisions on recognizing the occurring traffic situations under the conflicts of functional criteria is a complicated task, affecting considerably the costs associated with elimination of the consequences of such situations. It has been suggested that the classes of the occurring traffic situations should be identified taking into account the necessity to engage the rapid action team of the rescue service. The models have been proposed describing the functional criteria of losses, of the flight safety of the unmanned aerial vehicle and of the class recognition reliability. The issues related to making decisions on recognizing the occurring traffic situations have been considered. The analysis of the strategies to recognize the situation classes have been carried out based on the principles of minimizing the overall losses, on limiting the admissible UAV flight altitude and on ensuring the required class recognition reliability. It has been shown that applying the minimum loss criterion ensures considerable savings of resources under different ratio of the loss quotients.

Keywords: Computer Vision, Functional Criteria, Flight Safety, Losses, Objects Recognition, Recognition Reliability, Road Traffic Monitoring, Situation Classes, Unmanned Aerial Vehicle

1. Introduction

Modern methods of computer vision[1,2] provide automated solutions to many tasks of detecting and recognizing (classifying) the objects, phenomena and different situations. Particularly, the issues of recognizing the objects under complex and alternating surveillance conditions are considered in[2].

The development of such methods allows introducing automation techniques into the areas of activity, where the decisions should be taken by the operator under the conditions of high information workload.

Great attention has been paid presently to automating processes of traffic control and traffic management. In particular, the use of UAVs, equipped with the built-in video cameras, acquired wide application.

In the studies[3–5] and in some others the algorithms of detecting the ground moving objects (transport vehicles) and tracking them applying the small-size UAV, are discussed in detail. The authors[6] and others suggest building the attributes of such objects as cars based on the texture of the image, which is implemented, primarily, by HoG-descriptors (Histogram of Oriented Gradients). In the studies[7,8] the use of the image segmentation in super-pixels with their subsequent unification into the regions was proposed. Describing the object area as a region makes it possible to use the attributes of the object's shape for its classification.

The study in[9] considers the task of detecting transport vehicles in the countryside aerial view pictures. The method, suggested by the authors, consists of two major stages: Fast preliminary detection and the basic classifier.

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At the fast detection stage the images are filtered based on evaluating the density of the attributes, identified with the help of Harris angle detector, then the objects are grouped in clusters as rectangles, and after that they are filtered by color. The basic classification stage also involves identifying the attributes for those rectangular shapes, which passed the first stage filtration. The article investigates two ways of determining the attributes: HoG and Gabor quotient histogram. The attributes are fed to one of four types of classifiers: kNN – k-Nearest Neighbors, DT –Decision Trees, RF – Random Forests, SVM – Support Vector Machine. It has been experimentally shown that the described cascade classifier is suitable for detecting the transport vehicles in the countryside environment on-line. The best results are achieved with the system applying the attributes obtained from Gabor histogram, as well as with the Random Forests classifier.

Another approach to the task of detecting the Transport Vehicles (TV) in the aerial images is illustrated in study[10]. Here also Harris angle detector is used; besides, Canny boundary detector was applied as well. The background subtraction was implemented, and the shadows of the objects were identified. For classification purposes, in addition to the angles and boundaries detection, the color-differentiating characteristics U, V of the color model YUV have been used. The authors maintain that the colors of the vehicles are concentrated in model U, V in considerably smaller regions than they do in other color models. The study deploys SVM method for rejecting the regions where the color setting is obviously not characteristic for a TV. Bayes dynamic networks are used as the final classifier. It has been shown that the results could be considered reassuring, due to, among other factors, sufficiently fast detection speed, approximating to that required for on-line tracking.

Article in[11] investigates the method to detect and to count TVs in video stream, obtained with the help of UAV. The essence of the algorithm consists of the frame-by-frame pixel comparison, subtracting the attributes of the interest points (Moravec operator is used), predicting the conjugate points, calculating mutual correlation and validating the results of comparison. As a result, the sets of points in the neighboring frames are obtained which correspond to one and the same object in the scene of reality. The results of the experiments demonstrate high efficiency of this method in identifying the conjugate points in the frames of a video stream; particularly, the authors maintain that statistical accuracy of determining these points does not exceed several percents.

UAV, equipped with the computer vision systems, Automated Control Systems (ACS) and Navigation Systems (NS), including those with satellite navigation, can perform long-range flights over the road sections under control and transmit the received video information (about the traffic status) to the operator. In study[12] different options of evaluating the position in relation to the road for UAV control purposes are considered. The analysis of the on-board NS accuracy values has been carried out, including that of the one regulated with the assistance of the satellite navigation system. Relevant image processing algorithms have been proposed to evaluate the position of transport vehicles in relation to the roadsides.

To increase the reliability and the efficiency of an operator the investigations are undertaken in order to introduce automation in some separate procedures of video information analysis.

Such basic monitoring procedures are as follows: Detecting the objects of interest, namely, moving and static transport vehicles, tracking the objects, detecting and classifying the occurring special situations. Based on the accident classification, in particular, the operator determines the measures to eliminate the consequences of the accident.

It has been shown in the study[8] that the difficulty in detecting and classifying the occurring special traffic situations is associated with the high information workload of the operator, as well as with the lack of useful information in the received images. In that study the following automation issues are discussed: Detecting special situations, preliminary classification of the special situations, collecting video information, relevant to the preliminary identified class and required for the operator to make informed decisions.

However, the available studies do not consider the issues of classifying the situations, when several tasks need be solved simultaneously, such as, for example, the following:

- Ensuring the required traffic capacity of the road based on the found (detected) traffic impediments, pre-congestion, congestion and in other special, particularly, accident cases, other traffic hindrances; eliminating the consequences of special situations; preventing the road accidents, etc.
- Ensuring the safety of the people by implementing actions (measures) aimed at preserving their life and health,
- Securing the safety of UAV together with its equipment.

The complexity of the decisions increases when the efforts to minimize the potential material damages are undertaken simultaneously to avoid expenses for false alarms in rescue services, technical assistance services, or, expenses related to downtime of transport vehicles, etc.

The mistakes of the operator or delay in making decisions on classifying the special situations can result in considerable material losses and in insufficient safety of the people.

Thus, solving the issue of classifying the occurring special traffic situations is an urgent and practically important problem.

2. Traffic Situation Classification

In[8] it is suggested that the traffic situations should be grouped in 5 classes ($M = 5$).

In this case class x_1 corresponds to the regular traffic situation, when the capacity of the specified road section in the specified season and at the specified time of day is within the predetermined tolerance values.

Occurrence of special situations of classes x_2, x_3, x_4, x_5 is associated with the collision of transport vehicles; and the higher the class of the situation the heavier are the consequences.

Let us interpret the proposed classes according to the tasks solved here.

Assume that class x_2 is a special situation which is not to result in direct material losses, class x_3 is a special situation associated with insignificant material losses. To eliminate the consequences of the situations of these classes no extra assistance from the rescue service is required, i.e., the rapid action team is not to be called for.

Special situation of class x_4 belongs to emergency situations associated with material losses, particularly with serious damages to the transport vehicles. To eliminate the consequences of this situation the assistance from the rescue service, particularly, from the rapid action team of the rescue service is required.

Situation x_5 is a catastrophe and is associated with human casualties.

Assume that an erroneous recognition (classifying) of classes x_1, x_2, x_3, as class x_4 or x_5 results in a false alarm.

The process of classification or recognition, or, in particular case, of detection, is a process of making a decision on the observed traffic situation belonging to a specified class of the situations based on the available video information and relating the identified set of the attributive values to the region, characteristic for the relevant class.

Vectors $Y= (y_1, y_2,\ldots, y_n,\ldots, y_N)$, characterizing different classes of situations in the space of attributes, are called realization vectors, N is the total number of attributes, applied for describing the situation. The full set of the applied attributes is called the dictionary of attributes. The number of attributes can include: Speed of the transport vehicles at collision, character of damages to the car body and to the running gear, location of the transport vehicles after the collision, etc.

To make things easier, assume that the attributes (for example, damages to the car body) of classes x_1, x_2 differ considerably from those of classes x_4, x_5, therefore, classes x_1, x_2 are not considered further.

In making decisions on class x_5 situation, when casualties may be expected, a special approach, taking into account, particularly, ethical principles, has to be applied. The complexity of solving such tasks, associated with the lives of people, is considered, for instance, in[13]. We assume that for such potential situations, neither material losses, nor UAV safety factors together with the relevant decision making strategies are taken into account.

Thus, to analyze the decision making strategies, the identified situation classes x_3, x_4 are selected.

Assume that if class x_3 is classified as class x_4, there is a false alarm error, resulting in false calling for the rapid action team.

Errors in classifying x_4 class as x_3 class, which can result in unreasonable downtime of the transport vehicles, are not considered in this study.

The values of the errors depend, to a large degree, on the accuracy (or reliability) of determining the values of attributes Y.

In general case the maximum possible (from the point of view of reliability) stream of video information about any traffic situation can be obtained if the UAV is moving along the whole surface of the half-sphere, covering the area of the special situation.

Consequently, the potential possibility of the false alarm error becomes lower if the area of the accident is investigated in more detail by means of lowering the altitude of UAV, among other methods. However, when the altitude of UAV becomes lower down to several meters, the risk of damages to UAV increases considerably, i.e., the flight safety becomes insufficient.

Thus, in the process of classification of x_3, x_4 the conflict of interests may occur: On the one hand, to decrease the number of classification errors, and consequently, the expenses, associated with the rapid action team false alarms, the altitude of UAV should be made lower, but, on the other hand, decreasing UAV altitude can lead to the crash and again to the associated expenses. Those expenses will be considered loss criteria in this study.

Consider some versions of the strategies to classify traffic situations, taking into account the effects of different factors.

These factors will include:

- Necessity to call the rapid action team (rescue service) to eliminate the consequences of the accident, when the traffic accidents happen.
- Requirements to ensure UAV flight safety.

Assume that the following versions of the decision making strategies for classifying special situations are implemented, based on the principles as follows:

- Minimizing general losses, including the potential losses, associated with the rapid action team false alarm, and the loses associated with potential damages to UAV.
- Limiting the permissible altitude of UAV flight to ensure the required safety and taking no account of the requirements to the class recognition reliability.
- Ensuring the required class recognition reliability with no account of the required UAV safety.

3. Functional Criteria Models

In order to analyze the specified problem, the criteria models of UAV flight safety and of classes x_3, x_4 recognition reliability should be formulated.

To make the investigation of these criteria simple, the sigmoid curves, which describe the character of the criteria alteration quite plausibly, are selected.

The heuristic models for describing UAV safety and for the class recognition (identification) errors can be represented as follows.

- At low flight altitudes (for example, lower than 50 m) the flight safety is considerably influenced by the objects (the objects of interest), located close to or on the trajectory of UAV flight path. These objects are buildings and structures, trees and bushes, power transmission towers, etc.

Assume that the relative safety of UAV alters depending on the flight altitude in the range of: 0÷1 and it can be calculated according to the formula as follows:

$$W_{su} = \frac{1}{1+e^{-k_{su}(h-h_{su})}}, \quad (1)$$

Where k_{su} is empirical quotient, determined based on the conditions of the flight; h, h_{su} is the altitude of UAV flight and the altitude of the flight at which the safety of the flight equals to 0.5, accordingly; *su* is the index of the flight safety criterion.

At W_{su} = 0 the UAV is crashed and destroyed. At W_{su} = 1 the conditions of the flight are absolutely safe.

- The reliability of classes x_3 и x_4 recognition can depend on the altitude at which the consequences of the accident are investigated (UAV flight altitude). In some cases the character of damages to a TV will be determined reliably only at the altitude of several meters (for example, in investigating the car body through the windows of the car), then the reliability of identification (for such cases) will be calculated as follows:

$$W_a = 1 - \frac{1}{1+e^{-k_a(h-h_a)}}, \quad (2)$$

Where k_a is an empirical quotient, depending on the surveillance conditions and on the location of the objects of interest; h, h_a is the UAV flight altitude and the altitude, at which the reliability of class identification equals to 0.5, *a* is the index of the flight safety criterion.

At W_a = 0 the reliability of identification is minimal. Assuming the equal probability of the outcomes, it can be considered that the probability (reliability) of a false identification is equal to 0.5. At W_a = 1 the reliability is at maximum and the probability of the identification error equals to 0.

Quotients k_{su}, k_a (dimensionality 1/meter or $\frac{1}{m}$) and the values of altitude h_{su}, h_a (dimensionality -*m*) can be determined based on the previous experience of investigating similar special situations.

As an example in Figure 1 the graphs of altering the relative safety W_{su} (dashed line) and of the identification reliability of class x_3 (solid line) are represented. Their values are indicated on the vertical scale; on the horizontal scale the UAV flight altitude in meters is indicated. Here, the following values were assumed:

$$k_{su} = 1\frac{1}{m}, h_{su} = 6m; k_a = 0{,}6\frac{1}{m}, h_a = 11m.$$

From the graph of W_{su} it is clear that at UAV flight altitudes lower than two meters the flight safety is approximating to zero. The safety W_{su} is close to 0.5 at the flight altitude circa 6 meters, and the flight higher than 10 meters is practically safe.

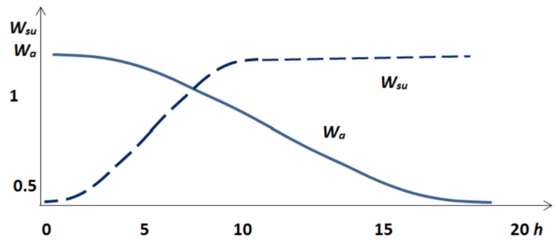

Figure 1. Graphs of the relative safety alteration.

Analysis of graph W_a shows that a sufficiently high reliability of surveillance can be achieved at the flight altitude lower than 4 meters. The reliability close to 0.5 is obtained at the flight altitude of circa 10-12 meters.

Thus, if it is required to improve the reliability of class identification and to ensure UAV safety simultaneously, the corresponding criteria of Equation (1), Equation (2) can come to a conflict.

Basic option for reconciling such conflicts is to minimize the potential general (total) losses (option 1 from section 1), which can be put as follows:

$$R_{\Sigma} = R_{su} + R_a, \tag{3}$$

Where,

$$R_{su} = R^0_{su}(1 - W_{su}) \tag{4}$$

is the loss associated with UAV safety; R^0_{su} is the quotient of losses, depending on UAV price and on its maintenance expenses;

$$R_a = R^0_a(1 - W_a) \tag{5}$$

is the false alarm loss, when the rapid action team of the rescue service is called, which is associated with class identification error; R^0_a is the quotient of losses depending on the expenses for the rapid action team false alarm.

4. Discussion

Assume, for example, R^0_{su} =100 *units*. and R^0_a =15 *units*. , where units identify some conditional units of value. Then, according to the data from the previous example, and also in line with Formulae (3), (4), (5), the graphs of losses will have the representation as shown in Figure 2, where, R_{Σ}, R_{su} ,R_a are shown in dash-dot, dashed and solid lines accordingly.

As is clear from the graphs, the minimal losses R_{Σ} will be achieved at the flight altitude of circa 10-11 meters. The reliability of the situation class identification in this area of the flight altitudes is close to 0.5, but an attempt at increasing this reliability at the expense of decreasing h will result in serious increase in potential losses associated with the UAV crash.

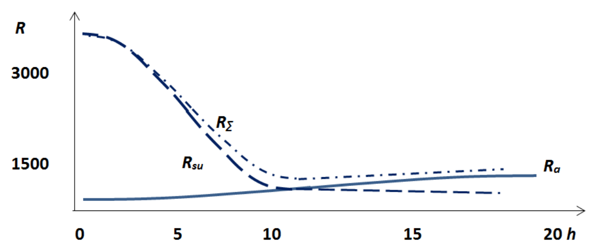

Figure 2. Loss graphs.

The following versions of the decision making strategies (options 2, 3) are realized by limiting the UAV safety and identification reliability in the form of the conditions as follows:

$W_{su} \geq W_{0su}$, $W_a \geq W_{0a}$,

Where, W_{0su}, W_{0a} are the preset limitations.

Table 1 shows the options for calculating the losses and the parameters W_{su}, W_a at different correlations of the loss quotients.

Table 1. Options for calculating losses and parameters W_{su}, W_a

Parameters	Criterion	h	R_{Σ}	R_{su}	R_a	W_{su}	W_a
1.	1.1. *min* R_{Σ}	11	8	1	7	0.99	0.5
Rsu0=100R_	$W_{su} \geq 0.99$						
a0=15	$W_a \geq 0.99$	6	51	50	1	0.5	0.99
2	2.1.*min* R_{Σ}	8	26	13	13	0.87	0.87
Rsu0=100R_	2.2.$W_{su} \geq 0.99$	11	51	1	50	0.99	0.5
a0=1002	2.3.$W_a \geq 0.99$	6	51	50	1	0.5	0.99

Example 1 (Table 1.) considers the case when the loss quotients are substantially different.

Due to the high relative value of R^0_{su} = 100 the losses R_{su} determine the position of *min* R_{Σ} = 8 (criterion 1.1) at altitude $h = 11m$.

This value of altitude is close to the maximum values of criterion 1.2 $W_{su} \geq$ *0.99*, but at a relatively low value of $W_a = 0.5$.

If the precondition $W_a \geq 0.99$ (criterion 1.3) is given, then the minimum of losses is shifted to altitude $h = 6m$. At that, the total losses increase considerably up to $R_\Sigma = 51$, and the UAV safety decreases $W_{su} = 0.5$.

Example 2 (Table 1.) is different in that the loss quotients are equal, which results in shifting the minimum of losses for criterion 2.1 $R_\Sigma = 26$ at the flight altitude of $h{=}8m$.

Limitations $W_{su} \geq 0.99$, $W_a \geq 0.99$ give the same total losses $R_\Sigma = 51$ at the flight altitude values $h = 11m$ and $h = 6m$, accordingly.

In all, according to the calculations, criterion $min\ R_\Sigma$ is the most economically feasible, but, in a number of cases, it does not allow ensuring sufficiently high values of functional criteria W_{su} and W_a.

5. Conclusions

Making decisions on recognizing the classes of the occurring traffic situations under the conflicts of functional criteria is a complex task, affecting considerably the costs associated with eliminating the consequences of these situations.

The models have been proposed describing the functional criteria for evaluating the losses, the UAV safety and the class identification reliability.

The analysis of the situation class identification strategies have been carried out based on the principles of minimizing total losses, limiting the permissible UAV flight altitude and ensuring the required reliability of class identification.

It has been shown that applying the minimum loss criterion ensures considerable savings of resources under different correlation of loss quotients.

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