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ORGANIZATION ASPECTS OF THE GROUND OBJECTS MONITORING BY UNMANNED AERIAL VEHICLES IN THE VARIABLE OBSERVATION ENVIRONMENT

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ABSTRACT

The work is devoted to the monitoring of ground vehicles by unmanned aerial vehicles (UAV) through the use of on-Board vision systems. The problems related to uncertain variable conditions of observation over the objects of interest (OI) that reduce the monitoring effectiveness are examined. It is shown that the change of observation conditions leads to changes in the visible features of OI and change of their descriptions. The article describes the approach enabling to create descriptions, adaptive to the change of observation conditions. This approach uses interpolation for current conditions according to previously determined reference descriptions, based on the neuro-fuzzy systems. It is shown, that the efficiency of search objects detection on the road depends in a significant extent on the accuracy of descriptions of the respective underlying surfaces and objects in various observation conditions. The presented results of studies confirm the effectiveness of the proposed approach.

Keywords: computer vision, objects recognition, statistical criteria, adaptive descriptions, neuro-fuzzy systems, UAV.

INTRODUCTION

One of the areas of using unmanned aerial vehicles (UAV) is monitoring of moving ground vehicles (Kim and Chervonenkis, 2015; Türmer *et al.* 2011), including traffic monitoring.

The basic monitoring procedures are OI detection – moving and nonmoving vehicles, as well as object tracking (Farnebäck, 2001; Lienhart *et al.* 2002; Zhang *et al.* 2012).

After detecting the objects of interest, determining their position and evaluating motion parameters, the observed situation can be classified in accordance with the predetermined possible classes of traffic situations. It should be noted that in some cases objects can be situated on various underlying surfaces, for example, after an accident.

UAV on-board equipment providing reception of the observed scene status information is observation system or observation equipment set: radar, television, imaging infra-red or multispectral facilities. Small UAV are limited with the allowable load weight (at most 1kg). Therefore, similar UAVs are frequently equipped only with light video cameras.

UAV computer vision systems, including observation equipment and facilities for processing and analyzing the received information, allow solving numerous monitoring tasks automatically (Farnebäck, 2001; Lienhart *et al.* 2002; Zhang *et al.* 2012). Currently development of UAV computer vision system that is able to function in a real-time environment and variable observation conditions is a complicated and generally unsolved scientific and technical task.

LITERATURE REVIEW

Particularly challenging problem in designing vision systems is a selection of image processing algorithms that would operate most efficiently in the definite operating conditions. Karasulu (2010) presents a survey of object detection and tracking (D & T) algorithms, as well as assessment criteria via metrics. Yilmaz *et al.* (2006) provide a survey of object tracking methods, classification of methods according to various categories and determination of new development trends. The survey considers the problems relating to tracking arrangement. In particular these problems may arise due to sharp changes in object motion parameters, camera motion, change in the exterior view of the object model and scene, etc. Detailed descriptions of methods, their advantages and disadvantages are analyzed here. Some important issues of tracking relating to the use of the appropriate image details, selection of motion models and object detection are discussed. A great number of works are devoted to the algorithms of ground object detection and tracking using small UAV, including helicopters. Video observation systems for small unmanned helicopter are considered in (Lin Feng *et al.* 2009; Qadir *et al.* 2011). A two-step information processing algorithm was proposed for automatic detection of ground targets in real time environment (Lin Feng *et al.* 2009). The algorithm uses geometrical features of target, as well as the target motion features. Kalman filter is applied to single out motion features. Visual Tracking System is proposed in (Qadir *et al.* 2011), it is able to operate in real-time environment on board a small unmanned aerial vehicle (UAV). The tracking system is computationally efficient and invariant for changes of the lighting conditions, object or camera rotations. Patch images are used for detection and tracking. It is proposed to use two various methods to create a patch from the initial image. The first method is based on usage of data obtained in previous flights. The second method is based on the object selection by the operator on the ground.

Kalman filter usage in considered in a number of works (Lin Feng *et al.* 2009; Welch and Bishop, 2001; Kelly, 1994). It is shown that Kalman filtration increases considerably the coordinate estimation accuracy of the observed objects and allows compensating the interference effect distorting geometrical features. A system for efficient detection and tracking of moving objects from an airborne platform of unmanned aerial vehicle (UAV) is presented in (Lin *et al.* 2011). It is proposed to detect and track targets in geo-coordinates (longitude and latitude). This requires stitching images acquired by satellite and UAV cameras. Experiments showed that this method can efficiently operate even when targets fall out the field of view.

The issues of discovering objects with abnormal behavior differing from the usual one are discussed in (Yu and Moon, 2009). Motion of objects is defined using the optical flow estimation. The principal component analysis (PCA) method is applied to detect behavior features. The proposed algorithm detects abnormal behavior of the object and re-trains itself in real-time.

One of the main reasons that lead to tracking failures is appearance of the distracting factors in the environment that present similar visual appearances as the tracking objects (target) (Fan *et al.* 2010). An approach is proposed ensuring moving target tracking stability. This approach is based on the two-stage identification of some special regions on the target, called attentional regions (ARs). Identification and usage of these regions enables to increase performance of object tracking.

A new advanced Vicept description intended to improve image semantic understanding is discussed in (Li *et al.* 2012). Vicept allows obtaining hierarchic semantic description of the image. That is the description may be of various level ranging from the local description to the global one. Possibility to use Vicept description is confirmed by the experiments, including a large-scale semantic search for image, image annotation and semantic re-ranking of images. A novel approach was presented in (Yan *et al.* 2012) for multi-target tracking using an ensemble framework that optimally choses target tracking results. The ensemble model is designed to select the best candidate scored by a function integrating detection confidence, appearance affinity, and smoothness constraints imposed using geometry and motion information. To increase detection reliability a second target classifier was introduced. The proposed algorithm robustly tracks a large number of moving objects in complex scenes with occlusions.

Thus, there is a great number of various methods (Forsyth and Ponce, 2003; Jahne, 2005) ensuring possibility to disentangle objects of interest on the observed scenes, including on the basis of stereo vision (Jiri, *et al.* 2004; Lucas and Kanade, 1981), using cluster analysis (Zhong and Ghosh, 2003), etc.

At the same time in the real conditions traffic monitoring may occur in various lighting environment of the observed scenes, objects and underlying surfaces. The analysis of the known works shows that object detection problem in the real variable observation conditions is understudied (Kim and Bodunkov, 2014).

METHODOLOGY

Object detection in variable conditions of observation

Decision-making with regards to the observed object detection or recognition is carried out based on the matching of certain descriptions (or a set of features: brightness distribution, texture, form and so on) of objects on the accepted (current) image (CI) with previously stored reference descriptions of the object. Characteristics of various features can be used as reference descriptions of objects. The most efficient observed features of object detection are color, brightness distribution, texture, form and dimension of the objects.

In particular, a reference image (RI) may be a reference description previously stored and held in the airborne computer memory (Forsyth and Ponce, 2003; Kim and Bodunkov, 2014).

In case of changing observation conditions the previously stored RI (for other conditions) will not match the accepted CI of the object. Thus, changes of observation conditions may lead to increase in object detection errors.

When classifying the traffic state, two groups of situations can be distinguished. The first group includes classes of situations determining changes of traffic capacity of the investigated road section, but excluding accident situations, and the second is related to the classification of accident situations (Kim and Chervonenkis, 2015).

In case of classifying accident situations using UAV based on the analysis of the observed consequences, it is required to detect and identify location of the nonmoving objects that were participants of the traffic accident. In these circumstances, some objects may be outside the road on various underlying surfaces.

Effectiveness of accident damage control significantly depends on the classification validity. Coordinates of the objects of interest with respect to the road, relative location of objects and their angular position will be considered as classification features. To evaluate these features it is necessary to solve the detection problem for all the objects OI. In its turn classification accuracy is determined by the accuracy of estimating object coordinates and position.

Object can be detected on various underlying surfaces on the basis of various approaches. The most general approach is to employ statistical methods of detection and recognition.

It should be noted that OI detection features and situation classification features are different.

Let us consider the recognition problem for the objects of interest (Forsyth and Ponce, 2003; Kim and Bodunkov, 2014).

Alphabet of classes of the recognized objects (landmarks) is designated as

$$X = (x_1, x_2, \ldots, x_m, \ldots, x_M),$$

and feature vector as

$$Y = (y_1, y_2, \ldots, y_n, \ldots, y_N),$$

where M is quantity of the recognized classes, N is quantity of the analyzed features, the detection problem is solved with 2 recognized classes available.

Decision on certain class membership of the object (or an image fragment) is made based on the determination of region covering the values of object features, obtained CI. Assume that statistical connection between the obtained values of features and classes is defined by the conventional probability density functions (PDF) $p(Y|x_m)$, which are reference descriptions of the objects.

Let two classes are the recognized ones: object - x_2 and background - x_1.

The following values are specified: R_{21}, R_{12} – losses due to wrong detection (occurrence of the I type error - α and occurrence of the II type error - β, respectively); $P(x_1)$, $P(x_2)$ – a priori probabilities of presence of objects x_1, x_2. In this regard it is required to satisfy the conditions: $R_{21}+R_{12} = 1$ and $P(x_1)+P(x_2) = 1$.
Based on these data threshold value of the likelihood factor is calculated:

$$\lambda_0 = \frac{R_{21}\,P(x_1)}{R_{12}\,P(x_2)}. \tag{1}$$

Let in the process of observing a certain section of the search region some video information is received that contains values of feature vector Y. Then having descriptions of objects x_1 and x_2, it is possible to detect current values of PDF $p(Y|x_1)$, $p(Y|x_2)$.

It is known that decision on object x_2 detection is made if the following condition is fulfilled:

$$\lambda_0 \le \frac{p(Y\,|\,x_2)}{p(Y\,|\,x_1)}. \tag{2}$$

If PDF $p(Y|x_m)$ parameters are unknown, sound decision making (about a definite class membership of the object) is impossible.

If loss tolerance values of R_{21}, R_{12}, as well as a priori probabilities $P(x_1)$, $P(x_2)$ are known, decision on object detection or non-detection is made based on *Minimum Bayes Risk* criterion.

If losses are unknown, a hypothesis can be accepted that $R_{21} = R_{12} = 0.5$.

Similarly, if a priori probabilities are unknown, it is accepted that $(x_1) = P(x_2) = 0.5$.

With unknown losses and a priori probabilities threshold likelihood factor takes on a value of $\lambda_0 = 1$ and matches Fisher ratio test. Selection of loss tolerance values and estimation of a priori probabilities significantly influences the detection results. In real conditions Fisher ratio test may happen to be redundantly pessimistic or optimistic. That is why it is desirable to define some rules which will help, at least roughly, determine values of loss tolerance and priori probabilities.

According to the scenario described in (Kim and Chervonenkis, 2015) to specify detection decisions additional flights are implemented for more detailed examination of possible location of the objects of search.

In case of frequent occurrence of errors of the first type ('false alarm' or 'false positive') similar flights may significantly increase the time of search. Thus, if it is required to reduce the time of search, R_{21} value should be increased. Concurrently, probability of false alarm will be decreased respectively; however the second type error ('skipping target' or 'false negative') will also increase.

If both detection errors (α and β) should be constrained, Wald sequential probability ratio test (SPRT) may be applied.

Presetting probabilities $P(x_1)$, $P(x_2)$ may reduce time of the object search.

Designate $P_{ij}(x_2)$ – a priori probability of object x_2 presence in the point of the search region with coordinates i, j . Let the supposed place of accident has coordinates i_0, j_0 in the center of the region S of the probable object presence. Then we can assign values of a priori probabilities $P_0(x_2), P_n(x_2)$

$$\textbf{if}\;\; i_0 - 0{,}5\Delta i_0 \le i \le i_0 + 0{,}5\Delta i_0, j_0 - 0{,}5\Delta j_0 \le j \le j_0 + 0{,}5\Delta j_{0_{ij}},\; \textbf{then}\; P_{ij}(x_2) = P_0(x_2)$$
$$\textbf{else}\; P_{ij}(x_2) = P_n(x_2),$$

where $\Delta i_0, \Delta j_0$ are dimensions of the region S of the probable object presence, $P_0(x_2) > P_n(x_2)$.

In real conditions of object description, including parameters $p(Y|x_m)$, depend on the observation conditions and will differ from the reference values.

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Thus, when solving object detection or recognition problem, a need arises to determine PDF, considering current observation conditions - $p(Y|x_m, Q_v)$, where $Q_v = (q_{v1}, q_{v2}, ..., q_{vr}, ..., q_{vR})$ is a vector of observation conditions in the state with index v. Various factors may be understood as observation conditions designated by index $r \in R$, for example, lighting characteristics of the observed scene, time of day, season of the year, region, etc. Assuming that observation conditions discretized with some quantization interval, definite current observation conditions are designated by index v.

This means that after UAV observation system receives feature vector Y for conditions Q_v, it is required to determine PDF values $p(Y|x_m, Q_v)$ and verify fulfilment of the condition:

$$\lambda_0 \leq \frac{p(Y \mid x_2, Q_v)}{p(Y \mid x_1, Q_v)}.$$

However, implementation of similar approach requires PDF of object description for all v of possible conditions to be stored in the UAV vision system memory.

Solution of this problem may be implemented by means of using reference descriptions, adapted to variation of the current observation conditions, in particular:

- By using previously prepared RI set or dictionary of features for all v possible observation conditions. However this approach is complicated to implement as it requires a very large-scale preparation (even for the advanced computational means) of numerous multi-angle images of the OI on various underlying surfaces and in variable lighting conditions;
- Another option is an approach focused on modeling possible reference descriptions of the searched objects on the basis of known physical laws. Complexity of implementing this approach is in the necessity to form visualization model of the objects in the observed scene (on the basis of known physical laws) with regard to numerous factors which are difficult to formalize connected with the properties of various textures, lighting conditions and so on.

It is proposed here to use the approach to the formation of adaptive reference descriptions based on interpolation of the available descriptions obtained for other conditions. Neuro-fuzzy approach is used to interpolate descriptions. The advantages of the approach include possibility to obtain descriptions in a wide range of changing current conditions, considerable reduction of the number of the required reference descriptions as compared to the first approach and simplification of the technique to form current descriptions as compared to the second approach.

The proposed approach to construction of the adaptive PDF $p(Y|x_m, Q_v)$ based on using neuro-fuzzy systems allows reducing the set of the required typical PDF by applying expert rules and properties of fuzzy systems, and also enables to correct them by applying limited sample-based training mechanisms.

The following steps of proposed fuzzy system construction procedure can be distinguished:

1. To determine general requirements (for example, determination of class dictionary and accuracy recognition requirements);
2. To identify a range of possible observation conditions (for example, observation may be conducted in the period "Summer" – "Autumn");
3. To determine requirements for the training sample in terms of volume and quality (sample volume depends on the accuracy requirements, and quality depends on the observation conditions range – training sample should be covered by the range);
4. To obtain a sample (obtaining reference images for each class of objects and conditions). Sample be obtained by means of modeling or as a result of real surveying;
5. To build conventional PDF p(Y|x_m,Q_v) according to the obtained samples (for example, based on Parzen-window method (Parzen, 1962) or k-nearest neighbors algorithm (k-NN);
6. To match the set of fuzzy rules (in addition to the direct formulation of rules this step includes formation of linguistic variables and their membership functions).

Construction of conventional PDF p(Y|x_m,Q_v) according to the obtained samples (for example, based on Parzen-window method (Parzen, 1962) or k-nearest neighbors algorithm (k-NN);

RESULTS

In the fuzzy rule a specific PDF is assigned to a certain set of conditions. In this regard conditions are written in the form of fuzzy values, for example: season of the year – "Summer", "Winter", etc., time of day – "Morning", "Noon", "Evening", weather conditions – "Rain", "Sunny", etc.

Fuzzy values are connected with specific numerical (physical) values of the parameter q (for example, current time) via membership functions $\mu(q)$. The membership function is determined in the range of [0, 1]. The higher value, the greater extent in which specific values of the conditions match a definite fuzzy value.

During the system operation in the real observation conditions several rules may be deployed simultaneously and finally, resultant PDF and averaging PDF will be formed as assigned in the rules.

One of the crucial peculiarities of the proposed approach is the possibility to train an already formed system. During training a certain test image is selected. For this image conditions are described and a resultant PDF is formed. Based on this PDF recognition is carried

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out. If recognition accuracy is unsatisfactory, correction of fuzzy rules occurs.

Let us consider three scenes “Day” (Figure-1), “Evening 01” (Figure-2), “Evening 02” (Figure-3), where underlying surfaces of the following types are present: forest, field (a clearing in the woods), road. There are 3objects of search on the road: from left to right a truck (O_1), dark vehicle (O_2), light vehicle (O_3).

Here all underlying surfaces and objects of search are *objects of interest.*

Figure-1. Scene “Day”.

Figure-2. Scene “Evening 01”.

Figure-3. Scene “Evening 02”.

Variable observation conditions were simulated by computer modeling.

Assume that it is required to:

1. identify (recognize) types of underlying surfaces;
2. disentangle (determine) objects of search on the road;
3. determine impact of brightness changes on underlying surface type recognition errors and search object detection errors.

Assume that

- recognition (detection) of objects is performed by statistical methods;
- the principal detection feature is mathematical expectation (arithmetic mean) of brightness $Y = y_1 = E$;
- PDF are obtained by histogram method based on the initial images and approximated by Gaussian distribution law;
- range of brightness variation 0÷255.

Assume that image references for scenes “Day” (Figure-1) and “Evening 01” (Figure-2) were obtained earlier. Later on image “Evening 02” is considered as a current image.

Figure-4 shows approximated PDF brightness probabilities for the objects of interest in the scene “Day”. The vertical axis values are PDF $p(Y|x_m, Q_n)$, the horizontal axis gives brightness values.

PDF are designated as:

1 – forest;

2 – field;

3 – road;

O_{11} – van roof;

O_2 – dark vehicle;

O_3 – light vehicle.

Brightness PDF parameters of truck cockpit match PDF designated as O_3.

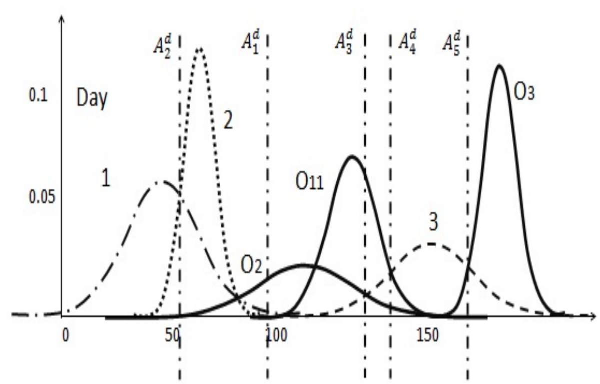

Figure-4. PDF brightness of objects of interest in the scene “Day”.

Surface type recognition. Surface type recognition when monitoring vehicles may be implemented for:

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- determination of UAV location (visual navigation) in case of unreliable operation of the satellite navigation system;
- situation analysis to evaluate possible places of presence of the search objects;
- search of moving and nonmoving objects.

Let us consider underlying surface type recognition applying statistical methods.

As seen from the presented curves, for example, in Figure-4 (Day), road brightness PDF (3) practically does not cross PDF of forest (1) and field (2).

Let $R_{21} = R_{12} = 0{,}5$ and $P(x_1) = P(x_2) = 0.5$.

Therefore, in these observation conditions the *road recognition* (with respect to forest and field) may be implemented loss-free, for example, according to Fisher criterion.

Vertical line A_1^d in fig. 4 (in the intercept with horizontal axis) corresponds to the threshold value of the likelihood factor $\lambda_0 = 1.$

When examining the observed scene brightness values to the right of the threshold should be referred to the surface of "road" type, and those to the left – to the other types of surfaces.

In this point brightness for objects 1, 2, 3 $p(Y|x_m, Q_u) \to 0$, therefore recognition errors small to negligible

Recognition of forest and field in this observed scene (Day) is impeded. PDF of forest and field brightness values are crossed, that is why application of Fisher test results in appearance of recognition errors.

In Figure-4 vertical line A_2^d designates the threshold. Points, in which brightness values are to the right (above) the threshold, are assumed as belonging to the field. Otherwise it is assumed that the point belongs to the forest.

Recognition errors are calculated by the known formulas (Forsyth and Ponce, 2003).

In the example under consideration error probability $P_{21} \approx 0.33$, where 21 is index designating that a decision had been made on the presence of object 2 and object 1 (forest) is a true one.

Error probability $P_{12} \approx 0.15$ corresponds to the cases when decision "forest" is made instead of the decision "field".

Similarly, during recognition of surfaces in the scene "Evening 01" (Figure-5), if the respective PDF are known, threshold values can be determined and recognition error probabilities can be obtained (Table-1).

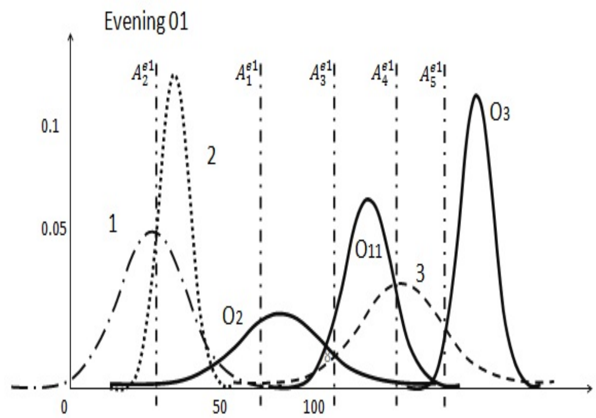

Figure-5. Probability density function for brightness of objects of interest on scene "Evening 01".

Thus, in the considered scenes considerable values of error probabilities will be present during recognition of surface types "forest" and "field". Error probabilities may be decreased using additional features, for example, root-mean-square deviation of brightness.

Let us consider the situation when scene "Evening 02" is presented for analysis (Figure-3). In this case brightness PDF for this scene are unknown.

If for recognition we use thresholds obtained for other scenes ("Day" and "Evening 01"), recognition errors may become unacceptable (Table-1). So, when using threshold from the scene "Day" to recognize the pair "forest – field" probability of the first type errors (false positive) approaches practically to unity. And when using threshold obtained for scene "Evening 01", probability of the second type errors (false negative) exceeds value 0.6. Thus, it is *impossible* to use thresholds obtained for reference descriptions "Day", "Evening 01", for recognition of objects in the scenes with changed observation conditions (scene "Evening 02").

Since according to the conditions of the considered problem scene "Evening 02" is presented only for obtaining the current information and decision-making, this information cannot be used for estimation of the PDF parameters sought for.
At the same time PDF corresponding to reference descriptions "Day", "Evening 01" are known.

Consider the technology of obtaining sought descriptions according to the procedure described earlier.

To calculate new thresholds it is necessary to form PDF for the conditions of scene "Evening 02". Let us consider the problem of forming adaptive PDF "Forest", "Field", "Road" in the variable observation conditions. Since in this case PDF are parametrized, adaptation will be made by means of adjustment M (mathematical expectation) and STD (root-mean-square deviation).

Since 2 reference scenes "Day" and "Evening 01" are predetermined, therefore, time of day will be considered as observation conditions, and knowledge database of fuzzy system will consist of 2 rules:

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It has been shown in the experimental studies that ФП $\mu_{day}(q)$ and $\mu_{evening}(q)$ take values:

- for 12:00 - $\mu_{day} = 1$, $\mu_{evening} = 0$,
- for 14:00 - $\mu_{day} = 0.6$, $\mu_{evening} = 0.4$,
- for 16:00 - $\mu_{day} = 0.7$, $\mu_{evening} = 0.3$,
- for 18:00 - $\mu_{day} = 0$, $\mu_{evening} = 1$.

Scene "Evening 02" was conventionally obtained at 16:00, respectively condition membership function time = "Day" will take value $\mu_{day} = 0.3$, and condition membership function time = «Evening» will take value $\mu_{evening} = 0.7$.

Parameters of adapted PDF will be calculated by the following formulas:

$$M = M_{day} * \mu_{day} + M_{evening} * \mu_{evening}$$

$$STD = STD_{day} * \mu_{day} + STD_{evening} * \mu_{evening}$$

Figure-6 shows true (1, 2, 3) and adapted (1_a, 2_a, 3_a) object brightness PDFs for "Forest", "Field", "Road".

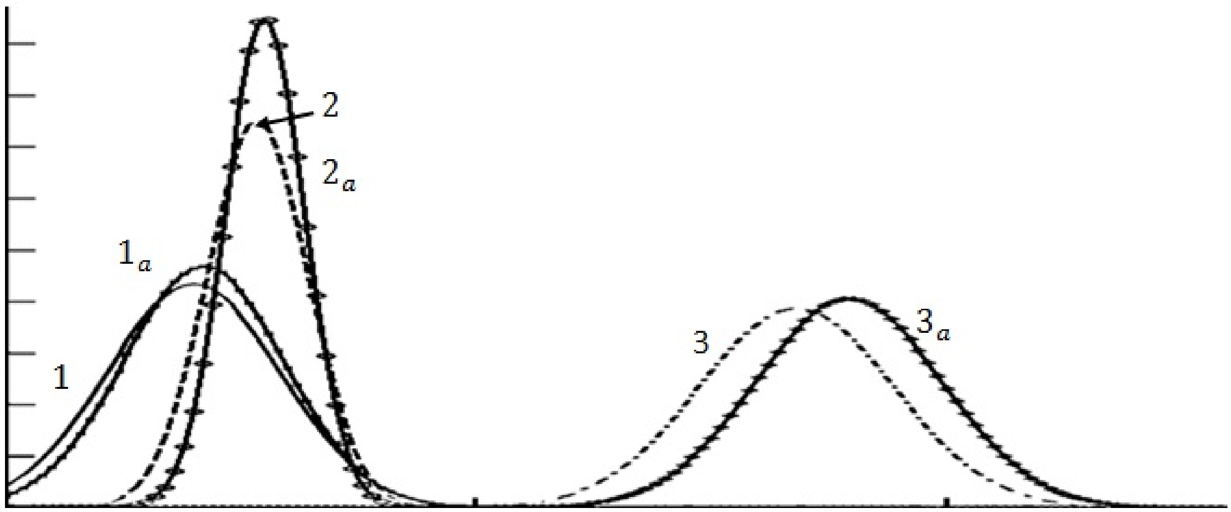

Figure-6. Brightness probability density functions of the underlying surfaces for scene "Evening 02".

True PDF were obtained directly from the simulated image (Figure-3). Approximated PDF were obtained as a result of calculation using parameters of the reference descriptions.

It is seen from the figures that the adapted and true PDF similar, their thresholds differ inessentially and will not result in essential errors in detection of objects "Forest", "Field", "Road". Table-1 gives error probabilities of surface recognition in scenes "Day", "Evening 01", "Evening 02".

In this case in scene "Evening 02" recognition was carried out with three groups of thresholds.

Two options of recognitions (italicized lines of Table-1) are implemented using thresholds obtained from the reference descriptions.

The last line of Table-1 given in bold type indicates recognition errors obtained using the proposed procedure for determination of brightness PDF parameters.

Table-1. Error probabilities for surface recognition.

	Target acquisition failure (false negative)			False alarm (false positive)		
	Forest-Field	Field-Road	Road-Forest	Forest-Field	Field-Road	Road-Forest
"Day"	0.33	0	0.0023	0.15	0	0
"Evening 01"	0.426	0	0.0048	0.218	0	0
"Evening 02" (as "Day")	*0.028*	*0*	*2.56E-07*	*0.978*	*0.037*	*0.042*
"Evening 02" (as "Evening 01")	*0.602*	*0.093*	*0.0575*	*0.041*	*0*	*0*
"Evening 02" (as "Evening 02")	**0.456**	**0**	**0.0002**	**0.136**	**0.0007**	**0.0009**

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The analysis of the results demonstrates that application of the proposed technique enables to reduce considerably recognition errors obtained using reference thresholds. Large error values, for example, target acquisition failure in the pair of surfaces "forest – field" are determined by the initial distribution of brightness for the respective surfaces and are similar to the errors obtained in scenes "Day" and "Evening 01".

Detection of the search objects on the road

The procedure for statistical recognition of the search objects corresponds to the procedure for recognition of the underlying surfaces.

In Figure-4, 5 road brightness PDF is designated by index 3. As seen from the curves, this PDF intersects all PDF of the search objects O_{11}, O_2 and O_3. Therefore, loss-free detection of the search objects is impossible.

For detection of objects 3 thresholds were determined for each scene: threshold A_3^{d} (for scene "Day") and to detect object O_{11}, and threshold A_3^{d} and A_3^{r1} to detect object O_3.

To estimate effectiveness of the proposed technique assume that observation conditions change and search for objects is carried out when observing scene "Evening 02" (Figure-3).

In these circumstances there is information available in the form of reference images and brightness PDF obtained on the images of scenes "Day" and "Evening 01".

Let us consider 2 options of detection arrangement.

In the first case thresholds calculated during detection of objects in scenes "Day" or "Evening 01" are used.

In the second case thresholds are calculated using brightness PDF obtained according to the proposed procedure.

In this case thresholds for detection of objects in scene "Evening 02"are calculated in the same way as for scene "Day" or "Evening 01".

Results of the detection process modeling are given in Table-2.

Table-2. Object detection error probabilities.

	Target acquisition failure (false negative)			False alarm (false positive)		
	O11-Road	**O2-Road**	**O3-Road**	**O11-Road**	**O2-Road**	**O3-Road**
"Day"	0.09	0.054	0.047	0.14	0.052	0.214
"Evening 01"	0.16	0.076	0.033	0.056	0.0005	0.398
"Evening 02" (as "Day")	*0*	*0.00017*	*0.999*	*0.972*	*0.885*	*0*
"Evening 02" (as "Evening 1")	*0.95*	*0.628*	*0*	*0.027*	*0.0004*	*0.659*
"Evening 02" (as "Evening 2")	**0.193**	**0.154**	**0.028**	**0.430**	**0.0386**	**0.150**

DISCUSSION

The given results show that if we use previously obtained reference threshold values to detect objects of search on the current image "Evening 02", detection errors will increase essentially as compared to the detection errors in scenes "Day" or "Evening 01" .

Application of the proposed approach increases the object detection effectiveness (error probabilities are given in bold type) and can be recommended for use in variable observation conditions.

CONCLUSIONS

Uncertain and variable observation conditions can be considered the problems reducing effectiveness of applying UAV computer vision systems when monitoring ground moving objects.

To solve the problems of changing observation conditions an approach to formation of adaptive descriptions of objects based on neuro-fuzzy systems was proposed.

This approach interpolates descriptions for intermediate conditions with previously specified reference descriptions for some supportive conditions. Thus, adaptation of descriptions is provided with a small number of references. Ease of calculation and ability of additional learning can be also referred to the advantages.

In the course of studies simulation experiments were carried out for recognition of underlying surfaces "forest", "field", "road", and for detection of vehicles on the road, as well.

The presented experimental results confirm effectiveness of application of the proposed technique during analysis of current images in the variable observation environment.

It should be noted that the results above were obtained for two reference conditions and show only the efficiency and feasibility of the proposed approach. Thus, as future research it is expected to expand the fuzzy system to a larger number of different observation conditions (e.g., seasons or weather conditions) and increasing the number of recognized objects of interest and surface types.

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REFERENCES

[1] Fan J., Y. Wu and Sh. Dai. 2010. Discriminative Spatial Attention for Robust Tracking. European Conference on Computer Vision (ECCV), 6311, pp. 480-493.

[2] Farnebäck G. 2001. Very high accuracy velocity estimation using orientation tensors, parametric motion, and simultaneous segmentation of the motion field. Proceedings of the Eighth IEEE International Conference on Computer Vision, Vancouver, Canada, Vol. 1, pp. 171-177.

[3] Forsyth D.A. and J. Ponce. 2003. Computer Vision: a Modern Approach. New Jersey: Prentice Hall.

[4] Jahne B. 2005. Digital Image Processing. Springer. ISBN 3-540-24035-7.

[5] Karasulu B. 2010. Review and Evaluation of well-known Methods for Moving Object Detection and Tracking in videos. Journal of Aeronautics and Space Technologies, Vol. 4, No. 4, pp. 11-22.

[6] Kelly A. 1994. A 3D state space formulation of a navigation Kalman filter for autonomous vehicles. DTIC Document: 13. Carnegie Mellon University.

[7] Kim N., and M. Chervonenkis. 2015. Situational control unmanned aerial vehicles for traffic monitoring. Modern Applied Science, 9 (5), Special Issue. Canadian Center of Science and Education. ISSN (printed): 1913-1844. ISSN (electronic): pp.1913-1852.

[8] Kim N. and N. Bodunkov. 2014. Computer Vision in Advanced Control Systems: Innovations in Practice, 2, / M. Favorskaya, Lakhmi C. Jain (Eds.), Springer, 295 p. ISBN-10: 3319114298.

[9] Li L., Sh. Jiang and Q. Huang. 2012. Learning Hierarchical Semantic Description Via Mixed-Norm Regularization for Image Understanding. Multimedia, IEEE Transactions. 14:5, pp.1401 – 1413.

[10] Lienhart R. and J. Maydt. 2002. An extended set of haar-like features for rapid object detection." Proceedings of 2002 International Conference on Image Processing. IEEE ISIP, 1, pp. 900-903.

[11] Lin F., K.-Y. Lum B.M. Chen and T.H. Lee. 2009. Development of avision-based ground target detection and tracking system for a small unmanned helicopter. Science in China, Series F: Information Sciences, Springer, Vol. 52, No. 11, pp. 2201-2215.

[12] Lin Y., Q. Yu and G. Medioni. 2011. Efficient detection and tracking of moving objects in geo-coordinates.” Machine Vision and Applications, Springer-Verlag, Vol. 22, No. 3, pp. 505-520.

[13] Lucas B. D. and T. Kanade. 1981. An iterative image registration technique with an application to stereo vision. Proceedings of Imaging Understanding Workshop, pp.121-130.

[14] Matas J., O. Chum M. Urban and T. Pajdla. 2004. Robust wide-baseline stereo from maximally stable extremal regions. Image and Vision Computing, Vol. 22, No. 10, pp. 761-767.

[15] Parzen E. 1962. On the estimation of a probability density function and the mode. Annals of Mathematical Statistics, Vol. 33, No. 3, pp.1065-1076.

[16] Qadir A., W. Semke and J. Neubert. 2011. Implementation of an Onboard Visual Tracking System with Small Unmanned Aerial Vehicle (UAV). International Journal of Innovative Technology & Creative Engineering (ISSN: 2045-8711), Vol. 1, No. 10, pp. 17-25.

[17] Türmer S., J. Leitloff P. Reinartz and U. Stilla. 2011. Evaluation of selected features for car detection in aerial images. ISPRS Hannover Workshop 2011, 14.-17. Jun., Hannover.

[18] Welch G. and G. Bishop. 2001. An Introduction to the Kalman Filter, Tutorial of SIGGRAPH, pp.1-81.

[19] Yan X., X. Wu I.A. Kakadiaris and Sh.K. Shah. 2012. To Track or To Detect? An Ensemble Framework for Optimal Selection, Buchkapitel Computer Vision, ECCV, 7576 (5), Proceedings of 12th European Conference on Computer Vision, Florence, Italy, pp. 594-607.

[20] Yilmaz A., O. Javed and M. Shah. 2006. Object tracking: A survey. ACM Comput. Surv. 38 (4), Article 13, 45 pages. http://doi.acm.org/10.1145/1177352.1177355.

[21] Yu T.-H. and Y.-S. Moon. 2009. Unsupervised Abnormal Behavior Detection for Real-time Surveillance Using Observed History. MVA2009

IAPR, Conference on Machine Vision Applications, Yokohama, Japan, pp. 166-169.

[22] Zhang J., L. Liu B. Wang X. Chen Q. Wang and T. Zheng. 2012. High speed automatic power line detection and tracking for a UAV-based inspection. International Conference on Industrial Control and Electronics Engineering (ICICEE), pp. 266-269.

[23] Zhong S. and J. Ghosh. 2003. A Unified Framework for Model-based Clustering. Journal of Machine Learning Research, Vol. 4, pp. 1001-1037.