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Investigation of Dependence of Brightness-Structural Features of Images Generated by the Vision System on Navigation Parameters of Unmanned Aerial Vehicles and their Use for Selection the Object of Reference

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Abstract. The aim of the article is to substantiate the use of brightness-structural features of images to select a reference object. This goal is achieved by studying the dependence of brightness-structural features of images on the sighting geometry. The solution to the first problem is based on the study of the brightness properties of images for their subsequent segmentation. The study was performed in the MATLAB software environment. The influence of sighting geometry on the distribution of image brightness was determined for sighting angles from -30˚ to -60 ˚ and altitudes from 500 to 1500 meters. The solution to the second problem is based on the study of the structural properties of images segmented by brightness. The solution to the third problem is to assess the efficiency of selecting a reference object on a segmented image using structural-brightness features. The most significant result is the substantiation of the use of brightness-structural features of images and the definition of the conditions for their use to select a reference object. The significance of the results lies in the analysis of brightness-structural features of images with different object content from the sighting geometry. The novelty of the work lies in the development of the procedure for forming current images and the decision function using the brightness-structural features of images. The difference from known works is the use of a new set of informative features in the formation of a segmented image, which is necessary for making a decision on the selection of a reference object.

Keywords: brightness-structural features of images, unmanned aerial vehicle, navigation parameters, reference object.

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Studiul dependenței caracteristicilor luminozității-structurale ale imaginilor generate de un sistem de viziune artificială de parametrii de navigație ai vehiculelor aeriene fără pilot și utilizarea acestora pentru identificarea unui obiect de referință

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Rezumat. Scopul articolului este justificarea posibilității utilizării caracteristicilor structurale-luminozitate ale imaginilor pentru a selecta un obiect de referință. Scopul declarat este atins pe baza unui studiu al dependenței caracteristicilor luminozitate-structurale ale imaginilor de geometria vizualizării. Soluția primei probleme se bazează pe studiul proprietăților de luminozitate ale imaginilor pentru segmentarea lor ulterioară. Studiul a fost realizat în mediul software MATLAB. Este determinată influența înălțimii și a unghiurilor de vedere asupra distribuției luminozității imaginii. Studiile au fost efectuate pentru unghiuri de vizualizare de la -30˚ la -60˚ și altitudini de la 500 la 1500 de metri. Soluția celei de-a doua probleme se bazează pe studiul proprietăților structurale ale imaginilor segmentate după luminozitate. Rezolvarea celei de-a treia problemă este evaluarea eficienței selectării unui obiect de referință pe o imagine segmentată folosind caracteristici de luminozitate structurală. Rezultatul cel mai semnificativ este justificarea utilizării caracteristicilor structurale de luminozitate ale imaginilor și determinarea condițiilor de utilizare a acestora pentru identificarea obiectului de referință. Semnificația rezultatelor obținute constă în analiza caracteristicilor de luminozitate-structură ale diferitelor zone de teren cu conținut diferit de obiect în funcție de înălțimea și parametrii unghiulari ai observării. Noutatea lucrării constă în elaborarea procedurii de formare a imaginilor curente și a funcției de decizie folosind caracteristicile structurale de luminozitate ale imaginilor formate. Diferența față de lucrările cunoscute este utilizarea unui nou set de caracteristici informative în formarea unei imagini segmentate, care este necesară pentru a lua o decizie privind selecția unui obiect de referință.

Cuvinte-cheie: luminozitate-trăsături structurale ale imaginilor, vehicul aerian fără pilot, parametri de navigație, obiect de referință.

Исследование зависимости яркостно-структурных признаков изображений, формируемых системой технического зрения, от навигационных параметров беспилотных летательных аппаратов и их использования для выделения объекта привязки

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Аннотация. Целью статьи является обоснование возможности применения яркостно-структурных признаков изображений, формируемых системой технического зрения беспилотных летательных аппаратов, для поиска и выделения объекта привязки. Поставленная цель достигается на основе исследования зависимости яркостно-структурных признаков различных по объектовому наполнению изображений от навигационных параметров и поиска условий, при которых исключается неоднозначность принятия решения о выделении объекта привязки. Решение первой задачи основано на исследовании яркостных свойств изображений для последующей их сегментации с учетом минимально допустимого коэффициента взаимной корреляции с исходным изображением. Исследование выполнено в программной среде MATLAB с использованием фрагмента местности, выбранного из Google Earth Pro. Определено влияние высоты и углов визирований на распределение яркости изображения. Исследования выполнены для углов визирования от -30˚ до -60˚ и высот от 500 до 1500 метров. Решение второй задачи основано на исследовании структурных свойств полученных изображений и выявлении по фрактальной размерности признаков для выделения объекта привязки. Решение третьей задачи заключается в оценке эффективности выделения объекта привязки на сегментированном изображении с использованием структурно-яркостных признаков. Наиболее существенным результатом является обоснование применения яркостно-структурных признаков изображений и определение условий их использования для выделения объекта привязки. Значимость полученных результатов состоит в анализе яркостно-структурных признаков различных по объектовому наполнению участков местности от высоты и угловых параметров визирования. Новизна работы заключается в развитии процедуры формирования текущих изображений и решающей функции с использованием яркостно-структурным признаков формируемых изображений. Отличие от известных работ заключается в использовании новой совокупности информативных признаков при формировании селективного изображения, необходимого для принятия решения о выделение объекта привязки.

Ключевые слова: яркостно-структурные признаки изображений, беспилотный летательный аппарат, навигационные параметры, объект привязки.

INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become an integral part of numerous processes, particularly in military, reconnaissance, and civilian operations. Their use is primarily driven by the ability to perform tasks in complex and hard-to-reach environments that may be hazardous or prohibitively expensive for manned aviation. A critical role in UAV navigation is played by Technical Vision Systems (TVS), one of whose tasks during navigation is to identify objects or areas of interest in images to facilitatelocalization or visual monitoring of infrastructure objects [1-3].

The composition of onboard UAV equipment can vary significantly depending on factors such as range, navigation accuracy, weather conditions, seasonal changes, characteristics of the observed surface objects (e.g., size, brightness, reflective properties, presence of similar objects, object density), and the UAV control method (autonomous or operator-controlled). TVS employed in UAVs utilize optoelectronic, radar, and radiometric sensors, which can operate independently or in combination. These sensors generate images of areas used for localization or visual monitoring, the quality of which generally depends on the following factors [1-3]:

- noise interference from various generating systems;
- imperfections in sensors measuring informative parameters, shooting conditions, dependence on lighting, etc.;
- heterogeneity and complexity of the background against which measurements are performed;
- occlusion of some objects by others;
- distortive effects such as defocusing, lens distortions, perspective distortions, etc.;
- variations in lighting conditions, glares, shadows, especially in dynamically changing scenes;
- diversity of objects on the observed surface and temporal changes in their shapes;
- vegetation cycles for plant cover;
- changes in the medium between sensors and surface objects, such as smoke, precipitation, dust, artificial interference, etc.

These external factors contribute to the instability of informative features, which can lead to partial or complete discrepancies between the current image (CI) generated by the TVS and the pre-established reference image (RI) [4, 5].

Equally important are the navigation parameters of the UAV, such as altitude and angular parameters, which directly affect the TVS and the CI. Accounting for these factors necessitates, on one hand, the study of informative image features under various observation conditions and their subsequent segmentation, and, on the other hand, the expansion of the range of invariants used to describe observed surfaces. Typically, brightness and related contrast characteristics are used as informative image features [1-3], which may be supplemented, for example, by the area characteristics of objects. Proposals also exist for using structural properties of images [6], which may change with variations in altitude and perspective of the TVS. However, brightness and structural features of images change at different rates. For instance, when observation angles change while altitude remains constant, the brightness of objects remains largely unchanged. Conversely, when altitude increases while observation angles remain constant, brightness decreases, but the image structure remains nearly unchanged as long as the TVS sensor sensitivity allows brightness measurements.

Based on these considerations, one approach to improving the CI formation procedure is the combined use of brightness-structural image features. This approach can mitigate the impact of internal and certain external factors on the formation of the TVS decision-making function required to identify the localization object.

Research Objective: To substantiate the use of brightness-structural image features generated by the UAV’s TVS for detecting and identifying localization objects. This approach aims to reduce ambiguity in the TVS’s decision-making process for identifying localization objects or relevant objects for monitoring and analyzing their condition, depending on observation conditions determined by UAV navigation parameters and the object composition of the observed scene.

Literature review.

In the process of image processing aimed at identifying a target object, image segmentation is performed as a preliminary step. Methods for object detection in images are described in numerous studies, particularly in [1-5]. Let us consider some of the most suitable image segmentation methods for Technical Vision Systems (TVS). Since TVS typically rely on brightness and/or contrast of objects, measured by sensors and determined by their electrophysical properties, single- or multi-threshold segmentation is commonly used in practice. Additionally, object contours are employed for detection, based on separating the image into objects and background according to pixel brightness levels. These segmentation methods are characterized by simplicity, fast implementation, and low computational costs. However, they are sensitive to changes in lighting, weather, and seasonal conditions and are unsuitable for complex scenes with heterogeneous backgrounds. The watershed method is considered a potential alternative, where the image is analyzed as a topographic map, with pixel brightness corresponding to height. Watershed lines are drawn along maximum gradient lines, separating different image regions. This method is suitable for segmenting images with clearly defined boundaries but has drawbacks, including a tendency toward over-segmentation and sensitivity to noise.

Several studies [6, 7] propose segmentation methods based on machine learning. One such method is K-means, which assigns image pixels to k clusters based on their color characteristics, grouping pixels with similar properties into a single cluster. This method is simple to implement but requires color images, which are not always suitable for TVS in UAVs. Deep learning methods [8, 9], such as Convolutional Neural Networks (CNNs), are also part of machine learning-based approaches. CNNs can automatically extract hierarchical features from data, with architectures like U-Net, SegNet, and Fully Convolutional Networks (FCNs) as examples. These methods offer high accuracy and generalization capabilities but require large volumes of training data and have high computational costs, making real-time implementation on UAVs challenging.

Image segmentation methods that incorporate structural properties of images as an additional characteristic are discussed in [10-15].

In [10], an approach is proposed to enhance the efficiency of image recognition systems for objects in monitoring and sensing complexes and unmanned systems by using the fractal dimension (fractal signature) of object contour images as an additional characteristic. Experimental results validating the proposed methods and algorithms are presented. However, these results are not directly applicable to object detection in images and are limited to simple cases of object composition.

In [11], an overview of the core concepts of “fractalization” and the mathematical foundations of modern fractal methods for describing and studying the surrounding world is provided. Key concepts, definitions, and relationships of modern fractal theory, as well as the classification and analysis of existing numerical fractal characteristics, are outlined. The study’s limitation is the lack of practical applications.

In [12], a method of image preprocessing for various shooting conditions for machine vision systems was developed. The study of the method showed that when preprocessing images of the same scene based on entropy analysis, obtained under different conditions, have a more stable correlation coefficient than the original images, which is an advantage. The disadvantage of the method is the implementation of processing without determining the type of IF.

Paper [13] proposed the use of a normalized section for automatic road detection. The advantage of the method is the effective selection of road segments using progressive image texture analysis and the graph method in emergency situations. The disadvantage is the low efficiency of application for the selection of small, non-extending objects.

The authors of [14] proposed a lightweight asymmetric network that uses an asymmetric encoder-decoder architecture. The encoder uses an asymmetric bottleneck module for joint extraction of local and contextual information. The decoder uses an advanced pyramid merging module and an upsampling module, which are used to aggregate multi-scale contextual information and combine functions from different levels, respectively. The advantage of the network is to achieve an optimal compromise between segmentation accuracy, inference speed, and model size. But the accuracy is 73.6 % at 95.8 frames per second, which is a disadvantage of the network.

In [15], a two-way cascading network is proposed for the fusion of the functions of preserving information about the target and providing the possibility of segmentation for multi-scale targets due to the requirements for the light weight of the model. In particular, a feature enhancement module is presented at the stage of feature extraction, including two-dimensional attention in the convolutional layer. This module effectively reduces redundant information and greatly improves network feature extraction capabilities. In addition, the network output uses cross-aggregation to fuse the output characteristics of different branches to solve the problem of missing pixels during the fusion process. The advantage of the method is the balance of segmentation accuracy and processing speed for ground robots. The disadvantage of the method is the impossibility of application on objects moving at high speed, namely on aircraft.

In [16-33], approaches to using fractal dimension for generating images of various media and materials with differing structures are explored. The primary focus was on improving image quality, while the issue of detecting objects of interest in images was not investigated.

Each image segmentation method has its advantages and disadvantages, and the choice of an appropriate method depends on specific application conditions and TVS requirements.

Thus, the analysis indicates that directly applying these methods to solve object observation tasks using TVS is not always feasible, as they do not account for the specific operational features of TVS related to UAV localization or object condition assessment. Furthermore, the review of existing studies shows that research on applying fractal theory to detect objects or areas of interest in images, as well as developing segmentation methods and algorithms using structural properties of objects for UAV navigation, has not yet been sufficiently advanced.

To achieve the stated objective, the following tasks were addressed.

1. Investigate the impact of changes in UAV navigation parameters on brightness features used for image segmentation.
2. Investigate the impact of changes in UAV navigation parameters on the structural properties of images.
3. Evaluate the effectiveness of detecting a localization object in a segmented image using brightness-structural features.

METHODS, RESULTS AND DISCUSSION

In accordance with the results of the studies [1, 2, 4, 19, 21], the regularization function, which compares the reference image (RI) with the current image (CI) generated by the TVS, can be represented as follows:

$$\mathbf{R}(\mathbf{r},t)=\mathbf{F}_{SP}\begin{pmatrix}\mathbf{S}_{CI}(\mathbf{r},t),\\ \mathbf{S}_{RI}=\left\|S_{RI}(i,j)\right\|_{\substack{i=\overline{1...M}\\ j=\overline{1...N}}}\end{pmatrix}, \tag{1}$$

where:

- F_{SP} – localization reference operator;
- $\mathbf{S}_{CI}(\mathbf{r},t)$ – CI;
- $\mathbf{r}$ – spatial position vector of the UAV;
- h,α,β – altitude and angular parameters of the TVS;
- $\mathbf{S}_{RI}$ – RI of size $\mathrm{M}\times\mathrm{N}$;
- i,j – coordinates of the image surface element (ISE).

The CI, accounting for the UAV navigation parameters at time t_z, can be expressed as:

$$\mathbf{S}_{RI}=\mathbf{S}_{RI}(h_k,\alpha_g,\beta_y,t_z)\,. \tag{2}$$

When using sensors operating in the visible range (television (TV) cameras), the image is represented as brightness values of the image elements. If a TV sensor is used, the brightness is expressed as [34]:

$$L(i,j,t,\varepsilon,\mu,\varpi)=\begin{pmatrix}E(i,j,t,\varepsilon,\mu,\varpi)\times\\ \times r_{\text{Я}}(i,j,t,\varepsilon,\mu,\varpi)\end{pmatrix}, \tag{3}$$

where:

$E(i,j,t,\varepsilon,\mu,\varpi)$ - spectral flux density of the image element (ISE);

ε,μ - dielectric and magnetic permeability of the observed surface medium and object propagation;

$r_{\text{Я}}(i,j,t,\varepsilon,\mu,\varpi)$ - spectral brightness coefficient;

v – vector of operating conditions.

$$\varpi=\left\|\alpha\quad\beta\quad\omega\quad\psi\quad E_{\text{пр}}/E_{\text{отр}}\right\|; \tag{4}$$

ω and ψ – incidence and scattering angles of the ISE;

$E_{\text{пр}}$ and $E_{\text{отр}}$ – random flux density components caused by direct and scattered radiation.

Thus, the need arises to solve the problem of generating the CI while accounting for both the UAV navigation parameters and the brightness parameters of objects and background ISE, as measured by the TVS sensor. This may involve morphological changes in the images, describing the structure of the image for specific observation conditions. Accounting for these parameters in accordance with (1) should ensure the formation of a decision-making function:

$$\mathbf{R}(\mathbf{r},t)=F_{SP}\left(S_{CI}(\mathbf{r},t),S_{RI}(h_k,\alpha_g,\beta_y,L,D,t_z)\right)\rightarrow max, \tag{5}$$

where D – parameter characterizing the structure of the image.

Solving this problem necessitates investigating the changes in brightness features used for image segmentation, as well as the structure of the image, resulting from variations in the UAV navigation parameters.

Problem solution.

Analytically investigating the dependence of brightness features, used for segmenting ISE images, on changes in UAV navigation parameters is not feasible. This is primarily due to the significant diversity of object and background ISE types, as well as the lack of results from analyzing and generalizing the vast amount of statistical data on brightness changes, as an informative feature, across the range of UAV navigation parameter variations. Therefore, the stated problem will be addressed by modeling the process of generating selective CIs for the observation conditions of the TVS, determined by the UAV navigation parameters.

Input data for modeling.

1. The image of the terrain area was randomly selected from Google Earth.
2. The range of observation angles is from 30° to 60°.

3. The range of altitudes is from 500 m to 1500 m.

Modeling will be conducted under the assumption that external random factors are absent. The generation of selective images based on brightness is performed for binary images with a correlation coefficient between the original image and the resulting selective image of 0.6. The choice of the cross-correlation coefficient (CCC) equal to 0.6 is driven by the need to account for the impact of geometric distortions on the generated selective image.

The original image for an altitude of 500 m is shown in Figs. 1. The selective brightness images, obtained through modeling in the MATLAB software environment for an altitude of 500 m and observation angles of 30°, 45°, and 60°, are presented in Figs 2, 3, and 4, respectively.

Fig.1. Original image (height 500m).

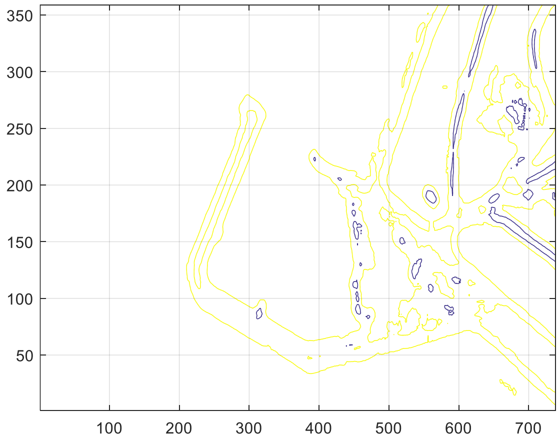

Fig.2. Brightness selective images (30° viewing angle).

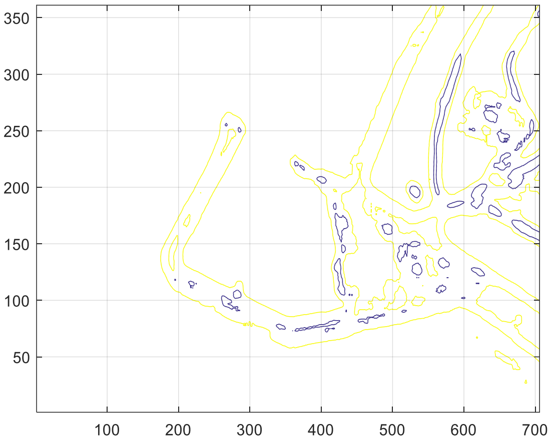

Fig.3. Brightness selective images (45° viewing angle).

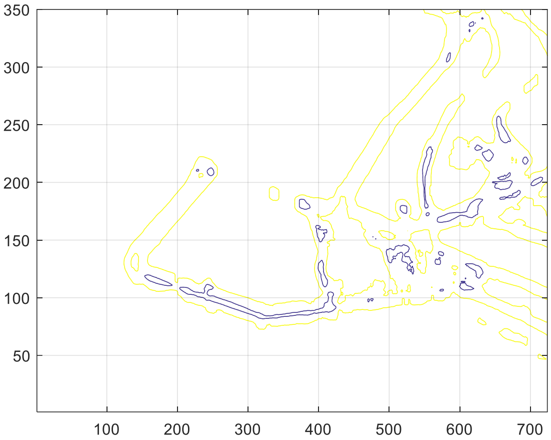

Fig.4. Brightness selective images (60° viewing angle).

Selective brightness images for an altitude of 1000 m and observation angles of 30°, 45°, and 60° are presented in Figures 5, 6, and 7, respectively.

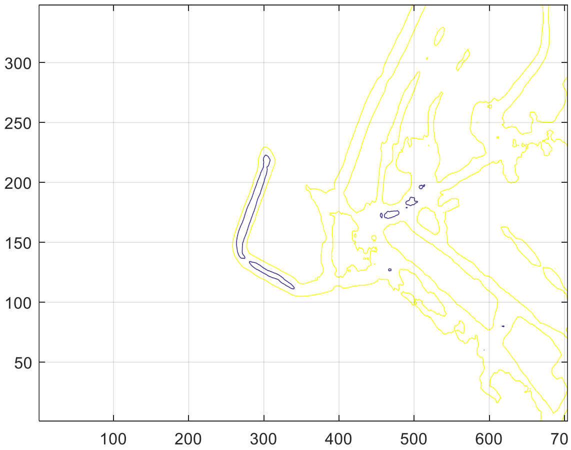

Fig.5. Brightness selective images (30° viewing angle).

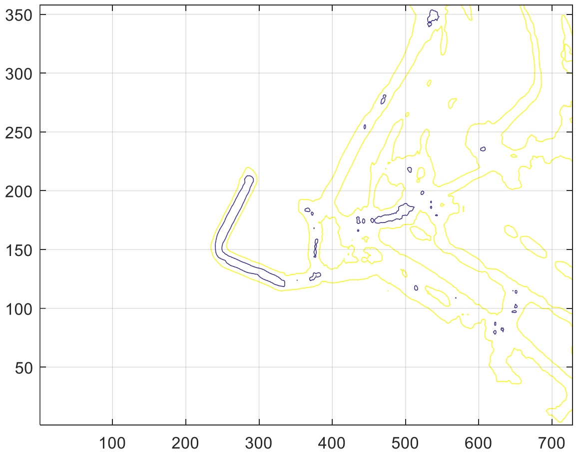

Fig.6. Brightness selective images (45° viewing angle).

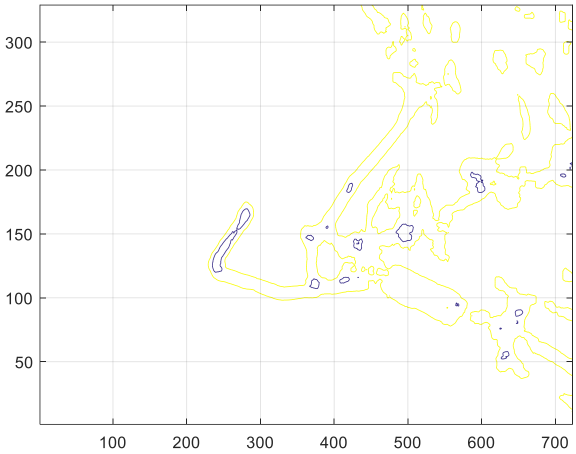

Fig.7. Brightness selective images (60° viewing angle).

Selective brightness images for an altitude of 1500 m and observation angles of 30°, 45°, and 60° are presented in Figures 8, 9, and 10, respectively.

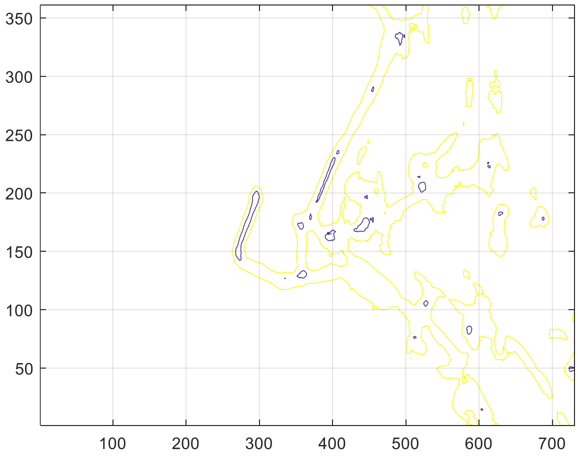

Fig.8. Brightness selective images (30° viewing angle).

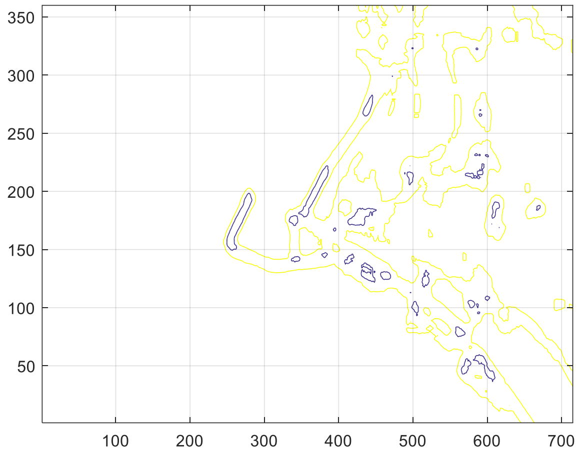

Fig.9. Brightness selective images (45° viewing angle).

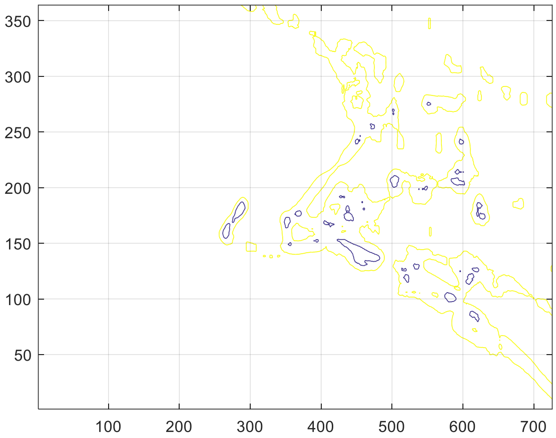

Fig.10. Brightness selective images (60° viewing angle).

The analysis of the modeling results presented in Figures 2–10 indicates that changes in the geometric observation conditions significantly impact the generated selective image. Specifically, as altitude increases, the expansion of the observation area leads to the appearance of additional objects. At the same time, some objects become unobservable due to their small size, resulting in spatial smoothing, as well as their brightness characteristics, which become undetectable with increasing distance from the sensor due to insufficient sensor sensitivity. A similar pattern is observed with changes in observation angles. The most significant impact arises from perspective distortions, which reduce the correlation based on geometric features. It is evident that similar changes in the generated selective images will also occur when using other original images. These changes must be accounted for in the process of solving the problem of localization object detection. It should also be noted that changes in geometric observation conditions lead to some alterations in the image structure due to the appearance or disappearance of certain objects. However, as can be inferred from Figures 2–10, to a first approximation, the structure of selective images does not change significantly, which may allow the structural feature of the selective image to be used as an invariant for localization object detection in further steps.

2. Investigation of structural properties of selective images depending on changes in UAV navigation parameters.

Problem Statement for localization object detection on a selective image using structural features.

A brightness-selective image of an area with developed infrastructure, obtained by the TVS, is available. The task is to detect the target object in the image based on its structural properties. According to [35], the identification of image regions most suitable for TVS localization involves determining fractal dimension (FD) values that significantly differ from the background and lie within a specified FD range.

The fractal dimension will be determined using the covering method as follows [35]:

$$D = \left[lgC - lgN(\chi)\right] / lg\chi \, , \qquad (6)$$

where:

- C – constant;
- χ – size of the covering window;
- $N(\chi)$ – number of elements required to cover the analyzed image.

The parameters lgC and D can be determined from the following system of equations:

$$D = \sum_{J=1}^{n}\left[\left(x_J - \bar{x}\right)\times y_J\right] \Big/ \sum_{J=1}^{n}\left(x_J - \bar{x}\right)^2 \, , \qquad (7)$$

$$lg\,C = \bar{y} - D\times\bar{x}, \qquad (8)$$

wher:

$\bar{x} = \frac{1}{n}\sum_{J=1}^{n} x_J$, $\bar{y} = \frac{1}{n}\sum_{J=1}^{n} y_J$ mean values of the parameters;

n – number of points obtained using the least squares method.

By changing the size of the covering window with coordinates (i,j), we initially determine the coordinates of the selective ISE segment and calculate the FD values $D(i,j)$. The combination of these values represents the intrinsic fractal dimension field (IFDF) of the image:

$$\boldsymbol{D} = \left\| D(i,j) \right\| , \qquad (9)$$

where $i = 1 \ldots M_1 - \chi, j = 1 \ldots M_2 - \chi$.

The obtained IFDF enables the construction of corresponding histograms, based on which the highest FD values, corresponding to the most suitable localization object, will be determined.

Following this approach, in the MATLAB software environment, using the selective images obtained from solving the first task (Figs. 2–10), the following results for modeling IFDF histograms were achieved.

The corresponding normalized IFDF histograms, constructed using brightness-selective images for an altitude of 500 m and observation angles of 30°, 45°, and 60°, as presented in Figs. 2, 3, and 4, are shown in Figs. 11, 12, and 13, respectively.

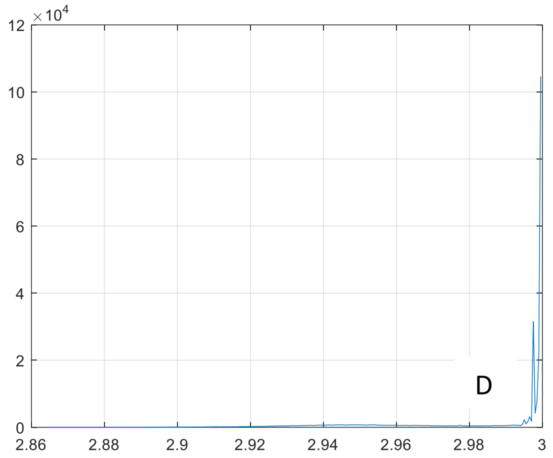

Fig.11. Histogram of the FDF (height 500 m, viewing angle 30°).

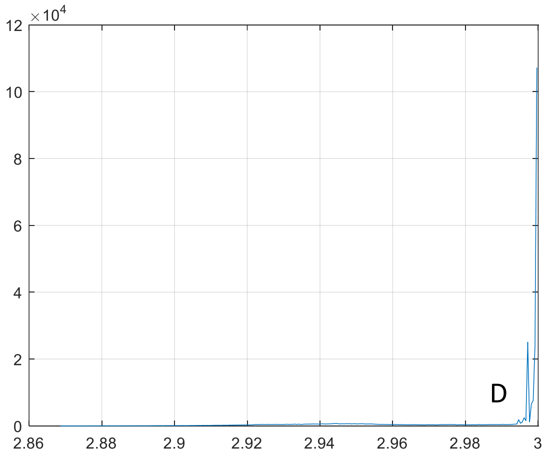

Fig.12. Histogram of the FDF (height 500 m, viewing angle 45°).

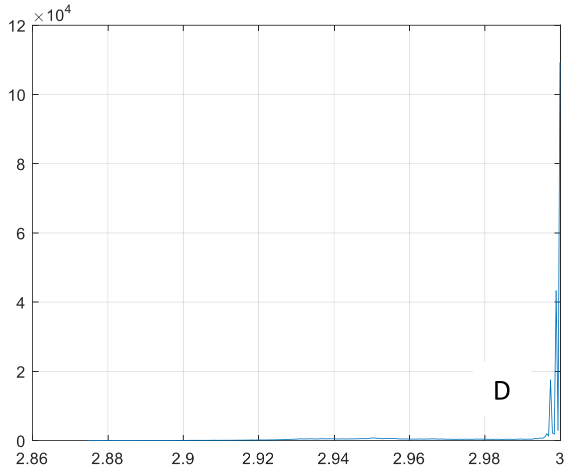

Fig.13. Histogram of the FDF (height 500 m, viewing angle 60˚).

Histograms of the FDF for an altitude of 1000 m and observation angles of 30°, 45°, and 60° are presented in Figs. 14, 15, and 16.

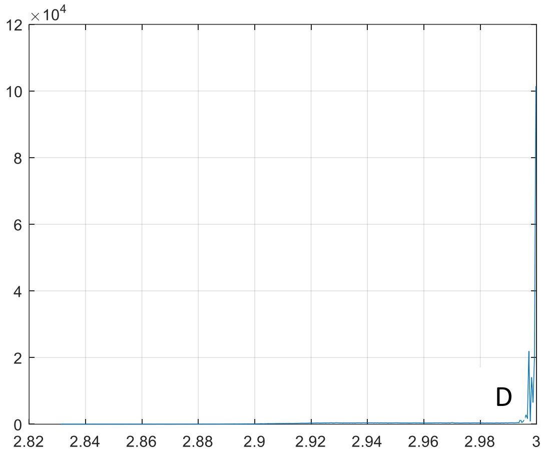

Fig.14. Histogram of the FDF (height 1000 m, viewing angle 30˚).

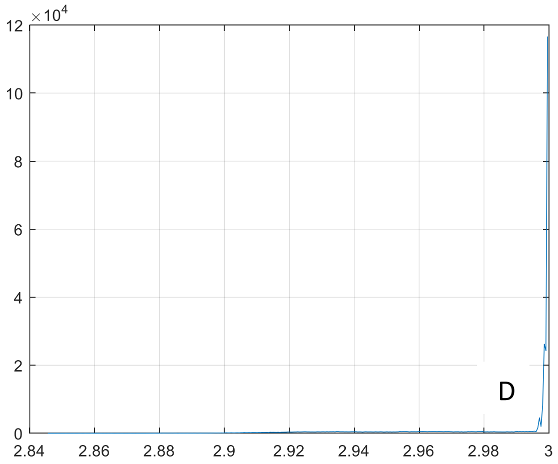

Fig.15. Histogram of the FDF (height 1000 m, viewing angle 45˚).

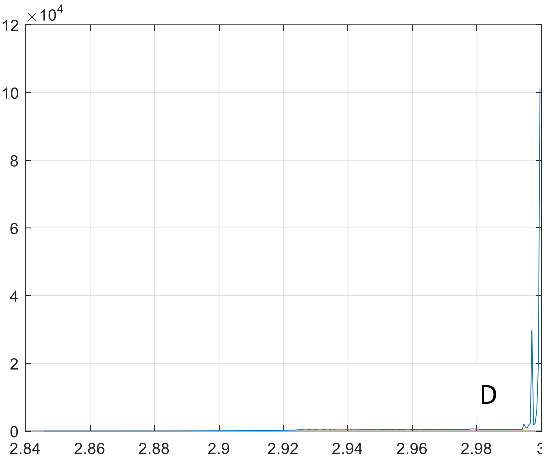

Fig.16. Histogram of the FDF (height 1000 m, viewing angle 60˚).

Histograms of the FDF for an altitude of 1500 m and observation angles of 30°, 45°, and 60° are presented in Figs. 17, 18, and 19.

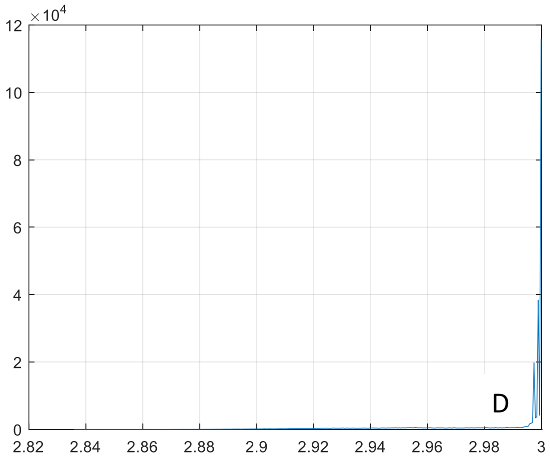

Fig.17. Histogram of the FDF (height 1500 m, viewing angle 30˚).

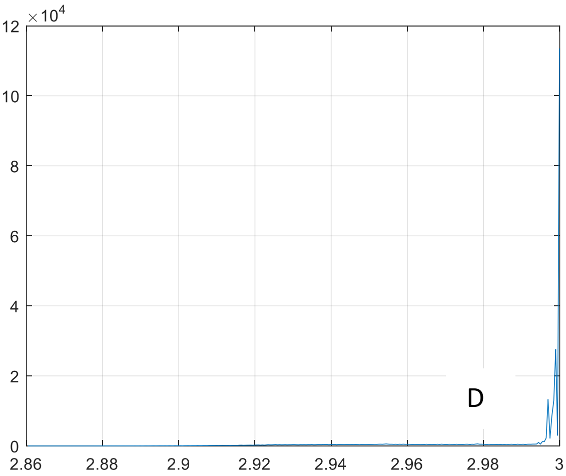

Fig.18. Histogram of the FDF (height 1500 m, viewing angle 45˚).

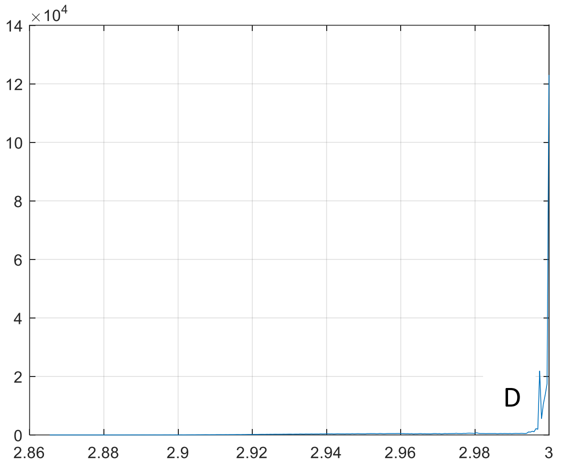

Fig.19. Histogram of the FDF (height 1500 m, viewing angle 60˚).

The analysis of normalized IFDF histograms, constructed through modeling using brightness-selective images for altitudes ranging from 500 m to 1500 m and observation angles of 30°, 45°, and 60°, as presented in Figs. 11–19, shows that the fractal dimension values range from 2.99 to 3 across all geometric observation conditions. There is practically no variation in the fractal dimension values. This supports the validity of the approach to localization object detection using brightness-structural features. In other words, this approach enables solving the task of object detection without introducing ambiguity in the decision-making process.

3. Evaluation of the effectiveness of localization object detection on a selective image using brightness-structural features.

The procedure for localization object detection on the original image is two-stage. Therefore, to evaluate the effectiveness, the probability of object detection on the image can be used, considering the ratio:

$$P_c = 1-(1-P_{cL})(1-P_{cD}), \tag{10}$$

where:

P_{cL} – probability of object detection based on brightness features;

P_{cD} – probability of object detection based on structural features.

However, such an approach requires accounting for errors of the first and second kinds. Therefore, considering (1), it is preferable to use the proposed combined informative features for effective localization object detection on the image based on the path of the intrinsic FD field for each stage:

$$\boldsymbol{R(r,t) = R_L \times R_D}, \tag{11}$$

where:

$\boldsymbol{R_L}$ – part of the regularization function (IRF) obtained at the object detection stage based on brightness features;

$\boldsymbol{R_D}$ – part of the regularization function obtained at the object detection stage based on structural features.

This approach is appropriate when using a combination of both reference and current images. Assuming that at each stage only one image is compared, the final result will effectively be determined by the decision-making function obtained at the stage of object selection based on structural features.

Using a classical correlation algorithm, we obtain the PDF for the case of forming the final IRF for a UAV altitude of 500 m and an observation angle of 30°.

To do this, we will use the modeling results obtained from solving the first two tasks.

The PDF based on brightness features is shown in Fig. 20.

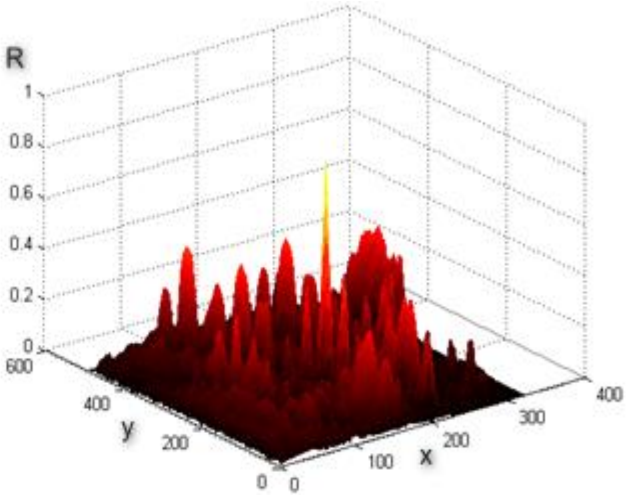

Fig. 20. PDF based on brightness feature.

The PDF obtained at the stage of object selection based on structural features is presented in Figure 21.

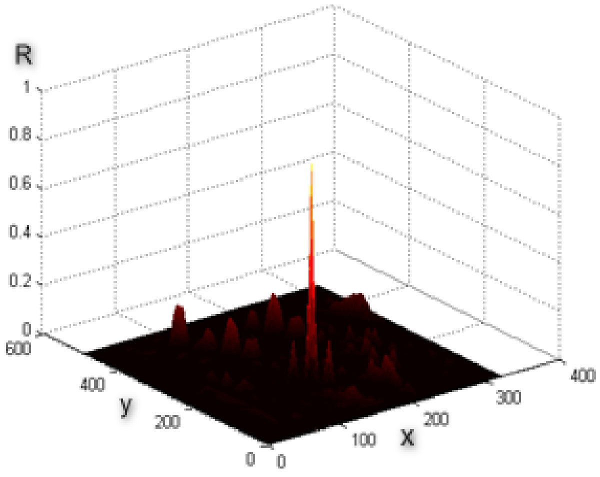

Fig. 21. PDF by structural feature.

Thus, the procedure for localization object detection on the image using brightness-structural features enables the formation of a unimodal IRF. This ensures its maximum value is achieved, and no ambiguity arises in the decision-making process. Moreover, the nearly absent variation in fractal dimension values allows for a significant reduction in the number of operations performed during the formation of the IRF.

CONCLUSIONS

As a result of the conducted studies, the feasibility of using brightness-structural features of images generated by the UAV's TVS for the search and detection of a localization object has been substantiated.

The application of the proposed two-stage CI formation procedure will help avoid ambiguity in the TVS decision-making process regarding the detection of a localization object or a corresponding object for monitoring and analyzing its condition, depending on the observation conditions determined by the UAV navigation parameters and the object composition of the observed scene.

Through modeling in the MATLAB software environment, the effectiveness of the proposed approach has been confirmed. It has been demonstrated that the procedure for localization object detection on the image using brightness-structural features enables the formation of a unimodal IRF.

An important practical advantage of this approach is the increased efficiency of the TVS, achieved through the ability to use a small sample of generated CIs. This is facilitated by the absence of variation in the FD parameter, which characterizes the structural properties of the brightness-selective image.

References

[1] Antyufeev V. Matrix radiometric correlation-extreme navigation systems for aircraft: monograph Ukraine, Kharkov: KhNU V.N. Karazin, 372 p.

[2] Kadem R.K. Komponentnyy analiz bezpilotnykh lital′nykh aparativ. // Elektronika ta systemy upravlinnya. - 2010. - № 2 (24). - pp. 45-51. (In Russian).

[3] Sergiyenko O. Robust Control of Excavation Mobile Robot with Dynamic Triangulation Vision / O. Sergiyenko, A. Gurko, W. Hernandez, V. Tyrsa, J. I. Nieto Hipólito, D. Hernandez Balbuena and P. Mercorelli. // Proceedings of the 9th International Conference on Informatics in Control, Automation and Robotics(ICINCO-2012), Rome, Italy, 28 - 31 July, 2012. – 2012. - Volume 2. - P. 481-485.

[4] Ruban I. V., Shitova O. V. Classification of methods for processing static images for localizing objects (areas of "interest") on them in technical vision systems. Navigation and communication control systems: w. Sci. Ave. / Center science-presled. Navigation and control technology. Kiev, 2009. No. 3 (11). pp. 139–143.

[5] Volkov V. Yu. Adaptive identification of small objects in digital images // Izv. Universities in Russia. Radioelectronics. 2017. № 1. pp. 17–28. (In Russian).

[6] Akkus, Z., Galimzianova, A., Hoogi, A., Rubin, D. L., & Erickson, B. J. (2017). Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions. Journal of Digital Imaging, 30(4), 449-459.

[7] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241). Springer.

[8] Cham, Long, J., Shelhamer, E., & Darrell, T. (2015). Fully Convolutional Networks for Semantic Segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).

[9] Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2017). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834-848.

[10] Forsyth, D. A., & Ponce, J. (2012). Computer Vision: A Modern Approach. Pearson.

[11] Zhu, X., Hu, H., Lin, S., & Dai, J. (2019). Deformable ConvNets v2: More Deformable, Better Results. In Proceedings of the IEEE Conference on Computer Vision and Pattern

Recognition, pp. 9308-9316.

[12] Tsvetkov, O. V., Tananykina, L. V. (2015). A preprocessing method for correlation-extremal systems. Computer Optics, 39(5), 738–743. https://doi.org/10.18287/0134-2452-2015-39-5-738-743.

[13] Senthilnath, J., Rajeshwari, M. and Omkar, S.N. (2009) Automatic Road Extraction Using High Resolution Satellite Image Based on Texture Progressive Analysis and Normalized Cut Method. Journal of the Indian Society of Remote Sensing, 37, 351-361. https://doi.org/10.1007/s12524-009-0043-5.

[14] Singh, P. P., Gard, R. D. (2013). Automatic road extraction from high resolution satellite image using adaptive global thresholding and morphological operations. Journal of the Indian Society of Remote Sensing, 41, 631-640. https://doi.org/10.1007/s12524-012-0241-4.

[15] Pan, Z., Xu, J., Guo, Y., Hu, Y., Wang, G. (2020). Deep Learning Segmentation and Classification for Urban Village Using a Worldview Satellite Image Based on U-Net. Remote Sensing, 12(10), 1574. DOI: https://doi.org/10.3390/rs12101574.

[16] Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). SegNet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(12), 2481-2495.

[17] He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN. In Proceedings of the IEEE international conference on computer vision, pp. 2961-2969.

[18] Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2017). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), pp.834-848.

[19] Esikov O. V., Titov D. V. Application of methods of fractal image analysis in solving problems of assessing the environmental situation and object recognition // Izv. Universities Instrumentation. 2022. T. 65, No. 9. P. 630-639. DOI: 10.17586/0021-3454-2022-65-9-630-639.

[20] Dobrescu R., Popescu D. Image processing applications based on texture and fractal analysis. In: Applied Signal and Image Processing: Multidisciplinary Advancements. IGI Global, 2011. pp. 226-250. DOI: 10.4018/978-1-60960-477-6.ch014.

[21] Kong, X.; Wang, E.; Li, S.; Lin, H.; Xiao, P.; Zhang, K. Fractals and chaos characteristics of acoustic emission energy about gas-bearing coal during loaded failure. Fractals 2019, 27, 1950072.

[22] Huang, J.; Li, W.; Huang, D.; Wang, L.; Chen, E.; Wu, C.; Wang, B.; Deng, H.; Tang, S.; Shi, Y.; et al. Fractal analysis on pore structure and hydration of magnesium oxysulfate cements by first principle, thermodynamic and microstructure-based methods. Fractal Fract. 2021, 5, pp. 164.

[23] Zhang, Z.; Xie, H.; Zhang, R.; Gao, M.; Ai, T.; Zha, E. Size and spatial fractal distributions of coal fracture networks under different mining-induced stress conditions. Int. J. Rock Mech. Min. Sci. 2020, 132, 104364. [CrossRef].

[24] Abeysinghe, W., Wong, M., Hung, C.-C., Bechikh, S. (2019). Multi-Objective Evolutionary Algorithm for Image Segmentation. IEEE Southeast Con. DOI: 10.1109/SoutheastCon42311.2019.9020457.

[25] Grinias I. MRF-based segmentation and unsupervised 16. Grinias I. MRF-based segmentation and unsupervised classification for building and road detection in peri-urban areas of high-resolution satellite images / I.Grinias, C. Panagiotakis, G. Tziritas // ISPRS Journal of Photogrammetry and Remote Sensing. – 2016. – Vol. 122. – pp. 145-166. DOI: https://doi.org/10.1016/j.isprsjprs.2016.10.010.

[26] Bai H. Multi-Branch Adaptive Hard Region Mining Network for Urban Scene Parsing of High-Resolution Remote-Sensing Images / H. Bai, J. Cheng, Y. Su, Q. Wang, H. Han, Y. Zhang //Remote Sensing. – 2022. – Vol. 14. – Is. 21. – 5527. DOI: https://doi.org/10.3390/rs14215527.

[27] Sambaturu B. ScribbleNet: Efficient interactive annotation of urban city scenes for semantic segmentation / B. Sambaturu, A. Gupta, C. V. Jawahar, C. Arora // Pattern Recognition. – 2023. – Vol. 133. – 109011. DOI: https://doi.org/10.1016/j.patcog.2022.109011.

[28] Khudov, H., Makoveichuk, O., Butko, I., et. al. (2022). Devising a method for segmenting camouflaged military equipment on images from space surveillance systems using a genetic algorithm. Eastern-European Journal of Enterprise Technologies, 3(9(117), pp. 6-14. DOI: https://doi.org/10.15587/1729-4061.2022.259759.

[29] Körting, T. S., Fonseca, L. M. G., Dutra, L. V., Silva, F. C. (2010). Image re-segmentation applied to urban imagery. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXVII, B3b, pp.393-398. DOI: https://doi.org/10.13140/2.1.5133.9529.

[30] Yuzefovich, V. V., O. N. Butochnov, and A. V. Mezentsev. "Fractal method for forming reference images in machine vision systems." Data registration, storage and processing (2015).

[31] Murrieta-Rico, F.N. Rational Approximations Principle for Frequency Shifts Measurement in Frequency Domain Sensors. / Murrieta-Rico, F.N.; A. Tchernykh; V. Petranovskii; O. Raymond-Herrera; Sergiyenko, O.; FloresFuentes, W.; Rodriguez-Quiñonez, J.C.; Hernandez-Balbuena, D.; NietoHipolito, J.I.; V.Tyrsa; and V. M. Kartashov. // Proceedings of 41st Annual Conference of IEEE Industrial Electronics (IECON-2015), Yokohama, Japan, November, 9 - 12, 2015, pp. 226-231.

[32] Brynza AA, Korlyakova MO Application of fractal curves for describing images when solving the classification problem in neural networks//International scientific and technical conf. Neuroinformatics-2017.

[33] Fisenko V. T. Fractal methods of texture image segmentation / V. T. Fisenko, T. Yu. Fisenko // Instrument-making, 2013. – V. 56 No. 5. – P. 63–70.

[34] Porev V.A. Television information and measuring systems. — K.: 2015 — 218 p.

[35] Latest image processing methods. // Ed. .A. Potapova - M.: FIZMATLIT, 2008. – 496 p.

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