UDC 621.396.969.3:004.932
DOI: 10.15587/1729-4061.2025.330905

DEVISING A METHOD TO FORM REFERENCE IMAGES TO PROVIDE HIGH-PRECISION NAVIGATION FOR UNMANNED AERIAL VEHICLES WHEN CHANGING GEOMETRIC VIEWING CONDITIONS

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The object of this study is the process of forming a minimally sufficient set of reference images for use in correlation-extreme navigation systems when changing the navigation parameters of unmanned aerial vehicles. The paper reports the results related to solving the task to form a set of reference images taking into account changes in the navigation parameters of high-speed unmanned aerial vehicles and their impact on the information features of images. The effect of changing the viewing angles and altitude on the formation of segmented images by energy characteristics has been studied. The discrete steps for navigation parameters were established, at which the correlation between image fragments is maintained at the level of 0.9. These values are from 90 to 120 meters in height and from 15° to 25° in angular parameters. The effect of the structure of segmented images on the selection of the reference object has been studied. It is shown that the feature of the selection of the reference object in the segmented image is the value of the fractal dimension 2.998…2.999.

The study was conducted in the MATLAB software environment using the source image selected from Google Earth Pro. The application of the selected sequence of constructing fragments of reference images has made it possible to identify objects that have the best characteristics in terms of signal-to-noise ratio and structure with increasing discreteness of navigation parameters. The method differs from known ones in using the image structure as information features along with the brightness and contrast of objects. This would reduce the number of fragments of reference images while maintaining the accuracy indicator. The results could be implemented in secondary processing systems of correlation-extreme navigation systems used on high-speed unmanned aerial vehicles

Keywords: reference images, navigation parameters, discrete in viewing angles and altitudes, information features, decision function

Received 27.02.2025
Received in revised form 28.04.2025
Accepted date 20.05.2025
Published date 25.06.2025

How to Cite: *Sotnikov, A., Sydorenko, R., Zakirov S., Mykus, S., Vlasov, I., Shkvarskyi, O., Samsonov, Y., Petik, A., Nechaus, A., Rikunov, O. (2025). Devising a method to form reference images to provide high-precision navigation for unmanned aerial vehicles when changing geometric viewing conditions. Eastern-European Journal of Enterprise Technologies, 3 (9 (135)), 79–92. https://doi.org/10.15587/1729-4061.2025.330905*

1. Introduction

The use of correlation-extreme systems for autonomous navigation of unmanned aerial vehicles (UAVs) is one of the possible ways to obtain important information about the state of various objects under difficult access conditions and at significant distances. They play an important role in monitoring various viewing surfaces (VSs), performing complex search and rescue operations [1, 2]. The effectiveness of solving these and similar tasks depends not only on the current information received but also on the corresponding reference information support prepared in advance. Without this, the functioning of correlation-extreme navigation systems (CENSs) is not possible [1, 2]. It is the correspondence of the reference and current information that leads to the formation of a unimodal decision function (DF), which determines the accuracy indicator of CENS binding or the state of the monitored objects. That is, the formation of reference images (RIs) for UAV CES is an important aspect of ensuring navigation accuracy, primarily under conditions where satellite navigation systems have limited use or are impossible at all [2, 3].

The basis for the formation of reference information, which is provided in the form of reference images (RIs), are aerial photographs, digital maps of the terrain and space photographs. Catalogs of informative features (I) of sighting objects and surrounding backgrounds are also used [1, 2]. In this case, the synthesis of RIs must be necessarily connected with algorithms for processing and comparing images and forming DF. Current images (CIs), which are formed by CENS sensors, depend on the conditions of sighting, information features that are measured, weather conditions, and interference conditions. Therefore, DF must also be formed taking into account these factors [2, 3]. But, in addition, it is still necessary to take into account the speed characteristics of UAV, which impose their time restrictions on the formation of DF. These restrictions become even more significant given the fact that the UAV flight trajectory is unstable and, under the influence of a number of factors, significant changes in navigation parameters and orientation parameters occur. Based on this, the synthesis and formation of a set of RIs for the functioning of CENS is an important and rather difficult task.

At present, much attention is paid to devising the methods to form DFs [1, 3]. Improvement of these methods is proposed by taking into account the influence of large-scale and perspective distortions on CENS depending on the geometry of the sighting [1], the search and application of various informative features for the formation of DFs. Many papers report devising the methods for highlighting key points and objects in images that are relevant to image segmentation algorithms [2–8]. Methods and algorithms for the formation of CIs and DFs are proposed to increase the speed of CENSs [7–10]. Methods for increasing the speed of selecting a fragment of RI from the existing set in the secondary processing system of CENS are considered [11]. However, in works that consider UAV navigation using CENS, at present, insufficient attention has been paid to the formation of DFs as a set of information features for describing the sighting scene. They do not take into account possible changes in the viewing conditions, the speed characteristics of UAV, and the impact of changes in navigation parameters on information features. Therefore, devising a method for forming RIs that could allow for high-precision navigation of a high-speed UAV when changing geometric viewing conditions is an urgent task.

2. Literature review and problem statement

In [1], the results of studies on the features of correlation-extreme visual navigation are reported. It is shown how to select characteristic image points. The use of a normalized correlation function based on the properties of the multiplication of descriptor matrices is proposed. However, the issue of minimizing the number of false matches compared to the Euclidean distance in the descriptor space and reducing the calculation time remains unresolved. The reason for this may be the failure to take into account reference information and methods of its formation for the operation of the navigation system. This is the approach used in [2]. A method for approximately determining the location of consecutive UAV images on satellite reference images is proposed, namely the SuperPoint feature extraction method. However, the method demonstrated low stability in areas with weaker textures. All this gives grounds for conducting a study aimed at determining information features for image formation, including reference ones, taking into account the influence of sighting conditions. This would make it possible to ensure the high accuracy of UAV location and ensure the required speed of the secondary processing system of CENS.

In [3], a method of UAV localization using georeferenced aerial photographs based on a reusable algorithm is presented. The advantage is the reduction of sensitivity to scene changes due to the use of mutual information that is resistant to local and global scene changes. However, the algorithm demonstrated insufficient reliability, which remains an unresolved issue. The reason for this is the lack of consideration of the conditions of sighting to informative scene features.

In paper [4], the first study of UAV localization using the features of the oriented gradient (HOG) in a non-GPS environment by registering aerial photographs and Google Map is reported. It is proposed to use a histogram (HOG) for UAV navigation. The advantage of this approach is a small error in UAV localization. However, the issue of localization taking into account the effects of wind and vibration, as well as night conditions, remains unresolved. The reason for this may be the failure to take into account the conditions of RI viewing.

In [5], a method for improving the localization accuracy of UAV images using satellite images is proposed. The advantage of the method is the possibility of significantly increasing the localization accuracy, especially in environments where GNSS is prohibited. The issue of taking into account the influence of external and internal factors on the result remains unresolved, which can also be associated with information support for RI.

In [6], the results of research on monitoring marine and coastal processes, georeferencing and mosaic modeling in the absence of fixed reference points are reported. The results of georeferencing for creating a georeferenced orthophoto plate that integrates several UAV images were presented. The advantage is the possibility of monitoring marine and coastal processes, eliminating the main limitation faced by UAV technology in remote observation of local-scale phenomena over water surfaces. But the unresolved issues include the narrow focus of the research, which is due to the insignificant attention to the secondary information processing system, namely, the standards.

In [7], attention is paid to the cleaning of feature points to increase the accuracy of the estimation of the homography matrix between images, thereby improving the accuracy of image registration using the RANSAC algorithm. The advantage is the possibility of using such an approach to improve the joint positioning and navigation of several UAVs during GNSS deviation. But the disadvantages include the failure to take into account the sighting conditions for image formation, which is associated with the limitation of the study by the defined framework.

In [8], visual cooperative positioning of several UAVs based on geographic information about invariant features of ground objects was investigated. The group drift of UAVs was eliminated by comparing pre-compiled geographic information data and adjusting for observations from several angles. The advantage is the use of visual odometry for observation in the case of rapid maneuvering with geographic information, which increased the cumulative accuracy of measurements and the reliability of visual odometry. The issue of not taking into account the features of the construction and use of reference information for the functioning of a UAV swarm, which is due to the conditions of the functioning of a UAV swarm, remains unresolved.

In paper [9], works that consider UAV navigation in environments without satellite navigation systems using computer vision systems (optical rangefinders) are analyzed. Various algorithms and methods of DF formation are considered. The advantage is a detailed analysis of various approaches to practical use and types of algorithms are determined. Their use for global positioning over sufficiently large areas allows one to estimate only the coordinates of UAV. But during navigation in local areas, all parameters of the object's motion remain unresolved. The issue of assessing the accuracy of location determination remains unresolved, which is due to the lack of reference information for UAV positioning.

In [10], alternative techniques for obtaining UAV positioning information in real time to ensure mission continuity are investigated. An algorithm is proposed that takes into account the need for online implementation, supporting access to terrain with multiple resolutions, thus capable of generating a direct path with high accuracy within the permissible time. The advantage is the consideration of the height threshold based on a multi-partition representation, as well as the construction of a network based on a terrain model, which allows using this network for routing a fleet of vehicles. The issue of taking into account the stability of templates covering the positioning area remains unresolved.

In [11], attention is paid to finding a new approach to selecting RIs from the set to determine the spatial position of a UAV with CENS. The advantage of the method is the reduction of the computational complexity in the formation of DF. The disadvantage is a significant number of RI fragments, which is due to the use of only the brightness of objects for the formation of RIs to ensure the correlation between neighboring fragments.

In [12], in order to increase the efficiency of the onboard CENS in the presence of isomorphic transformations of the software, as well as obstacles of various origins, it is proposed to form an adaptive RI based on the use of a multi-hypothesis brightness meter. The advantage of the method is the ability to achieve values of the transmission coefficient of 0.94...0.98, which is 1.36...5.64 times greater than for the frame-by-frame change method. Compared to the exponential smoothing method, it is more than 1.18...1.42 times. The issue of using other ISs along with the brightness remains unresolved, which is due to the lack of research on the issue of determining the dependence of these features on the viewing conditions.

In [13], it is proposed to use local features extracted by a deep neural network to find the corresponding features on the reference RGB satellite image and infrared image in real time. The advantage of the method is to improve the performance of the CENS by (4...6)% in accuracy for infrared aerial images and satellite reference images. The issue of taking into account the speed and trajectory changes depending on the efficiency of functioning remains unresolved. The reason for this may be the lack of information about RI and the technique of their formation.

In [14], a method is considered that combines segmentation and classification methods with connected component analysis to determine the road class from orthophoto images. The advantage is the efficiency of separating different road components in the images and the ability to filter non-road parts and noise. The issue of classifying roads into two classes: road and non-road remains unresolved. This may be due to the lack of information about the morphological processing of the image.

In [15], the results of the study on a two-stage procedure for selecting a link object on the software generated by the UAV CENS are reported. Segmentation of the generated images and subsequent selection of the object in the presence of various objects that differ in bright and planar characteristics are carried out according to the brightness parameters and area sizes using the established thresholds. The advantage is that the influence of noise on the quality of the generated software is taken into account. However, changes in the viewing conditions on the images used for the formation of DF are not taken into account. The reason for this may be the limitation of the study to constant viewing conditions.

In [16], a new semantic segmentation processing platform is proposed, which evaluates various methods of merging and combines visible and thermal infrared images. The advantage is the high accuracy of semantic segmentation of merged images. The issue of taking into account the viewing conditions on the accuracy remains unresolved, which may be due to the lack of information about the standards.

In [17], an algorithm for extracting ISs in an image using SIFT, Forstner, Harris, and Moravec operators is investigated. The advantage is the ability to choose a specific algorithm based on speed and accuracy. The issue of selecting an algorithm for specific viewing conditions that change rapidly, which can significantly affect the final result, remains unresolved. The reason for this is the lack of information about the change of ISs depending on the viewing geometry.

In [18], an algorithm for semantic segmentation of UAV remote sensing images is proposed. The algorithm is based on the combination of edge features and multi-level upsampling integrated with Deeplabv3+ (EMNet). The advantage is the use of multi-level upsampling to preserve high-level semantic information (for example, target location and boundary information). The unsolved problems include the failure to take into account the application conditions, which is limited by the segmentation algorithm and the failure to use different ISs.

In [19], the efficiency and effectiveness of SegFormer, a semantic segmentation system for UAV images, were investigated. The advantage is improved object resolution and flexibility. The issue of applying this system under different viewing conditions remains unresolved, which is associated with the lack of VS standards.

In [20], hierarchical multi-scale IS extraction was proposed. The results of this study highlight the effectiveness of the proposed method in solving the problems of semantic drone segmentation, which is its advantage for accurate and efficient segmentation of aerial images. The unresolved issues include the issue of real-time application on large-scale, diverse, and complex datasets specific to drone images, which is associated with the limited information on the standards.

In [21], an image segmentation method was investigated for fast extraction of fruit tree crowns from UAV images under natural lighting conditions. It was implemented using the shadow region brightness compensation method (SRLCM), which is proposed to reduce the interference of shadow regions. The advantage is the improvement of the segmentation quality compared to the K-means and GMM algorithms. The issue of using other ISs remains unresolved, which is associated with the complexity of forming ES for different observation conditions.

In [22], an algorithm for improving images under low-light conditions based on the camera response model and Retinex theory was investigated. The advantage compared to the illumination improvement algorithm based on the fusion of infrared and visible images is the improvement of illumination without the introduction of additional airborne sensors. The issue of taking into account the impact of changing viewing conditions on image quality and the need to ensure high information processing speed remains unresolved. This is due to the lack of reference information in different frequency ranges and the need to use a large amount of reference information.

In [23], an unsupervised semantic segmentation method was investigated for fast and accurate detection of flooded areas using color images obtained from UAVs. The method is based on nonparametric computed masks and unsupervised image analysis methods. Flood detection is performed by applying segmentation with hysteresis and threshold. The advantage is the possibility of using data on board and making decisions during UAV flights. The issue of applying the method when using other types of sensors remains unresolved, which is associated with the need to build and use different types of RI.

In [24], an innovative unsupervised learning framework based on convolutional neural networks (CNNs) is presented. A hybrid attention module is introduced, which is added to each CNN module. This improvement ensures the integrity of the segmentation results and the consistency of the boundaries. The advantage is the possibility of achieving an accuracy of 98.15%, an F1-score of 97.01%, and an mIoU of 95.58%. The disadvantage is the lack of consideration of the conditions of sighting and the representation of reference information.

In [25], a lightweight asymmetric network is proposed, which uses an asymmetric architecture of the encoder-decoder. The encoder uses an asymmetric bottleneck module to jointly extract local and contextual information. The advantage of the network is to achieve an optimal compromise between segmentation accuracy, inference speed, and model size. However, the accuracy is 73.6% at 95.8 frames per second, which is a disadvantage of the network.

In [26], a two-way cascade network is proposed to merge the functions of preserving information about the target and providing segmentation capabilities for multi-scale targets due to the requirements for lightweight models. The advantage is the ability to reduce redundant information and balance segmentation accuracy and processing speed for ground robots. The issue of applying the method to objects moving at high speed, namely aircraft, remains unresolved. The reason for this is the difficulty of taking into account the geometric conditions of sighting and the formation of RIs.

In paper [27], the formation of CENS DFs is studied when reducing the signal-to-noise ratio of the software by using a set of ISs for selecting the reference object, namely: brightness, contrast, and its area. The advantage is that the signal-to-noise ratio of the software is taken into account, which provides the necessary probability of selecting the object. The issue of forming a set of RIs for different viewing conditions remains unresolved. This is due to the need to conduct relevant research.

In [28], the method of forming a set of RIs is improved. The approach to forming a set of selective images of critical infrastructure objects using invariants obtained on the basis of correlation analysis of scenes and the sufficiency of maintaining the correlation coefficient from 0.6 to 0.7 is substantiated. The advantage is the high efficiency of object control due to optimization of the number of RIs. The issue of establishing the dependence of RI quality on changes in the geometric viewing conditions and minimizing the number of RI fragments remains unresolved. This is due to the need for further research into the formation of RIs.

In [29], the possibility of selecting objects in an image formed by CENS using structural and geometric features was investigated. The advantage is that the selection of the reference object is carried out on images with heterogeneous object composition, which significantly reduced the computational complexity of object selection compared to using the classical correlation algorithm. The issue of determining the exact value of the fractal dimension remained unresolved. This is due to the use of an approach that is associated with the need to know the exact value of the noise level.

In [30], a method using the U-net deep learning architecture was proposed. The advantage of this method is good separation of buildings in images with high population density. The issue of expansion in different areas of the terrain remained unresolved. This is due to the need to form a large base of standards and dependence on different viewing conditions.

Thus, despite the great attention to studies that report the results of investigating CENSs, they take into account only individual, certainly important factors that affect the efficiency of the system. At the same time, some factors are not given enough attention. This concerns, as our review has shown, such an element of the CENS secondary processing system as reference information support. It is perceived, as a rule, as a given. Such an approach somewhat narrows the scope of research and requires further development, taking into account both the flight and technical characteristics of the carrier, the features of the flight trajectory, and the features of the selection of ISs. This could provide the necessary characteristics of UAV location in real time.

Therefore, the task to form RIs, taking into account the changes in the navigation parameters of high-speed UAVs and their impact on the ISs of images, needs to be solved.

3. The aim and objectives of the study

The purpose of our study is to reduce the number of fragments in the reference image for the formation of a decisive function when ensuring the navigation of an unmanned aerial vehicle while maintaining the accuracy indicator.

To achieve the goal, it is necessary to solve the following tasks:

– to state the problem of forming a minimum set of RIs based on the search and use of ISs of objects of VS with reduced dependence on the geometric conditions of sighting;

– to conduct a study on the influence of changing navigation parameters on the formation of RIs while maintaining CCC between neighboring fragments and evaluate the effectiveness of RI formation according to the specified segmentation procedure.

4. The study materials and methods

The object of our study is the process of forming a minimally sufficient set of reference images for use in CENSs when changing the navigation parameters of UAV. The principal hypothesis of the study assumed that the use of a certain sequence of image segmentation by selected ISs could ensure a reduction in the number of RI fragments in the set. It is proposed to carry out segmentation in parallel by brightness and structure, as well as by the contrast of objects and their structure. Segmentation by brightness and contrast should be carried out while maintaining the correlation between RI fragments. Next, segmentation is carried out by the structure of already segmented images. Due to this, an increase in discrete values by navigation parameters will be carried out.

The following research methods were used in the study: methods of correlation-spectral analysis, methods of image segmentation, fractal analysis, methods of numerical modeling, MATLAB software environment.

The following limitations and assumptions were accepted in the study:

– CENS sensor – optoelectronic;

– UAV altitude range is from 500 m to 1500 m;

– CENS sighting angle range is from 30° to 60°;

– UAV heading is 51°;

– VS image is object-saturated, with the presence of three-dimensional objects, randomly selected from Google Earth;

– brightness and contrast of VS objects are not less than the sensitivity of the CENS sensor;

– signal-to-noise ratio of the CENS sensor is sufficient for receiving signals;

– image fragment comparison algorithm is classical correlation;

– cross-correlation coefficient (CCC) between RI fragments is 0.9.

Limitations and assumptions adopted in the description of VS:

– changes in ISs under the influence of weather, daily and seasonal conditions are absent or minimal;

– the software is undistorted; no masking tools are used;

– IS measured by the CENS sensor are functionally related to the electrophysical characteristics of objects and backgrounds.

Segmentation is understood as the assignment of image pixels by a certain information attribute to the corresponding segments by determining the threshold to preserve the correlation relationship.

5. Results of the study on the formation of reference images when changing the geometric conditions of sighting

5. 1. Setting the task for the formation of a minimum set of reference images

In accordance with the principle of operation of CENS, regardless of the type of sensor, the determination of the coordinates of the reference object is carried out by forming DF. For this purpose, taking into account the selected algorithm of secondary processing of CENS, the comparison of RI with CI is carried out. Based on this, the DF in the general case is represented as follows [15, 27]

$$\mathbf{R}(\mathbf{r},t)=\mathbf{F}_{SP}\left(\mathbf{S}_{RI}\left(\mathbf{r},t_k\right),\ \mathbf{S}_{CI}\left(2\theta_{0,5},h_g,\alpha_l,\beta_f,t_\rho\right)\right), \qquad (1)$$

where $\mathbf{F}_{SP}$ is the image comparison operator;

$\mathbf{S}_{RI}(\mathbf{r}, t_k)$ is the RI;

$\mathbf{S}_{CI}(2\theta_{0,5}, h_g, \alpha_l, \beta_f, t_\rho)$ is the CI;

h_g, α_l, β_f are navigation parameters: altitude, latitude, and longitude;

$2\theta_{0,5}$ is the resolution of the CENS sensor;

$t_\rho = t_0 + \Delta t_\rho$; t_0, t_ρ are the time points of formation of the CI frames ψ_0, ψ_ρ;

$r(t) = (x(t), y(t))$ is the vector characterizing the displacement in the image coordinate system;

Δt_ρ is the time interval between the frames ψ_0 and ψ_ρ.

In fact, CENS generates several frames that depend on the flight dynamics of the UAV, each of which corresponds to its own values of the navigation parameters h_g, α_l, β_f. That is, the CIs generated by CENS is a set of elements

$$\mathbf{S}_{CI}\left(\mathbf{r},t_k\right)=\left\| S_{CI_{i,j}} \right\|_{\substack{i=\overline{1\ldots M_1}\\ j=\overline{1\ldots N_1}}}, \qquad (2)$$

where M_1, N_1 – dimensions of CI;

t_k – k-th moment of time of formation of CI;

i, j – coordinates of the PF image element.

Accordingly, the on-board computer stores reference information, which can be either in the form of a single RI or in the form of a set of images. The option of representing reference information depends on the selected DF formation algorithm. To ensure high accuracy rates and simplify the DF formation algorithm by eliminating affine transformations, a set of DF fragments is used as reference information, which we shall represent as follows

$$\mathbf{S}_{RI}=\left\| S_{RI_{i,j}} \right\|_{\substack{i=\overline{1\ldots M_2}\\ j=\overline{1\ldots N_2}}}, \qquad (3)$$

where M_2, N_2 are the dimensions of RI.

Let us consider that the formation of images occurs using the ISs measured by the CENS sensor and used in the implementation of image segmentation. In optoelectronic CENSs, as a rule, the brightness B_b or contrast ΔB_b of the objects of sighting are used as such features. Based on this, let us represent the RI and CI formed at some time t through the parameters of the informative features in the following form:

$$\mathbf{S}_{\tilde{N}I}\left(i,j\right)=f\left(B_b,\Delta B_b,t\right), \qquad (4)$$

$$\mathbf{S}_{RI}\left(i,j\right)=f\left(B_b,\Delta B_b,t\right). \qquad (5)$$

Let us take into account that the brightness, and, accordingly, the contrast, from the VS element are parameters that vary depending on the lighting and observation conditions.

According to [31], the brightness received by the CENS sensor from the VS element can be written as

$$B_b\left(i,j,t,\varepsilon,\mu,\varpi\right)=\begin{pmatrix} E\left(i,j,t,\varepsilon,\mu,\varpi\right)\times \\ \times r_b\left(i,j,t,\varepsilon,\mu,\varpi\right)\end{pmatrix}, \qquad (6)$$

where E $(i, j, t, \varepsilon, \mu, \varpi)$ is the spectral field of illumination of the image element;

ε, μ– dielectric and magnetic permeability of objects and backgrounds of VS;

$r_b(i, j, t, \varepsilon, \mu, \varpi)$ is the spectral brightness coefficient;

ϖ is the vector of observation conditions

$$\varpi = \left\| \alpha \;\; \beta \;\; \omega \;\; \psi \; E_a / E_r \right\|, \tag{7}$$

ω and ψ are the illumination angles of the VS element;

E_a and E_r are random illumination fields created by direct and scattered radiation.

Thus, based on relations (4) to (7), the influence of lighting and observation conditions will lead to the formation of image fragments that will differ from each other. This difference, depending on the difference in navigation parameters, will also occur in their sets. This circumstance will lead to a decrease in the coincidence (correlation) between the compared images. As a result, the accuracy of determining the coordinates of the reference object will deteriorate

$$\mathbf{R}(\mathbf{r},t) = \mathbf{F}_{SP}\left(\mathbf{S}_{CI}(\mathbf{r},t_k),\ \mathbf{S}_{RI}\left(2\theta_{0,5},h,\alpha,\beta,t_\rho\right)\right) \to \min. \tag{8}$$

In order to eliminate the possibility of deterioration of the accuracy of CENS, it is possible to increase the number of fragments of RI N_{RI} with a reduced sampling step in height and angles of sighting. This will allow us to provide the required value of CCC between the images that are compared in the process of forming DF [28]. But such an approach will lead to an increase in the number of operations when forming the DF. This is especially necessary to take into account under the conditions of navigation of high-speed UAVs. In fact, a contradiction arises between the accuracy and speed of CENS.

Problem statement. For the selected conditions and initial data, it is necessary to devise a method for forming a minimum set of RIs based on the search and use of the ISs of objects of VS with reduced dependence on the geometric conditions of sighting.

Thus, it is necessary to solve the problem of forming a minimally sufficient set of RIs N_{RI} with ensuring maximum DF $\mathbf{R}(\mathbf{r}, t)$

$$N_{RI} \to \min, \;\; \mathbf{R}(\mathbf{r},t) \to \max. \tag{9}$$

Solution to the problem. To solve this contradiction, another information feature was used, which only indirectly has an energy character in relation to the CENS sensor but is a characteristic of the segmented image. As such an IS for the numerical description of the texture of images segmented by energy features, the fractal dimension was chosen [32]. In relation to the description of the image, it can be considered non-energetic. This approach provides a reduction in the number N_{RI} of fragments of the set of RIs independent of navigation parameters. In this case, the accuracy indicators of CENS were determined using partial DFs.

Thus, a four-stage procedure for forming a segmented RI was actually proposed.

At the first stage, the original image was converted into a binary one by quantizing the background brightness relative to the average value. Errors of the first and second types were taken into account in the conversion process. In this case, the minimum signal-to-noise ratio of the image q_{min} is determined from the formula given in [27]

$$q_{\min} = \Phi^{-1}\left(1-l-p_{01}\right) + \Phi^{-1}\left(1-l-p_{02}\right), \tag{10}$$

where $\Phi(x)$ – Laplace integral;

l – quantization threshold.

The second stage occurs simultaneously in parallel. It involves segmenting the binary image $S_{BI}(m,n)$ by brightness and by contrast. At this stage, the condition of preserving the correlation of the segmented image $S_{SI}(m, n)$ with the binary one at the level of 0.8…0.9 is chosen. This is necessary so that the formed partial DFs do not lose their unimodality in the future. The determination of CCC for the informative features of brightness $K_b(k, l)$ and contrast $K_K(k, l)$ is carried out using the following formulas [27]:

$$K_b(k,l) = \\ = \frac{1}{M_2 N_2} \sum_{m=1}^{M_2} \sum_{n=1}^{N_2} S_{SI}(m,n) \cdot S_{BI}(m+k-1, n+l-1), \tag{11}$$

$$K_K(k,l) = \frac{1}{M_2 N_2} \times \\ \times \sum_{m=1}^{M_2} \sum_{n=1}^{N_2} \left[S_{SI}(m,n) - \bar{S}_{SI} \right] \cdot \left[S_{BI}\begin{pmatrix} m+k-1, \\ n+l-1 \end{pmatrix} - \bar{S}_{BI_{kl}} \right], \tag{12}$$

where $i = 1 \ldots M_1 - M_2, \;\; j = 1 \ldots N_1 - N_2;$

$$\bar{S}_{SI} = \frac{1}{M_2 N_2} \sum_{m=1}^{M_2} \sum_{n=1}^{N_2} S_{SI}(m,n);$$

$$\bar{S}_{BI_{kl}} = \frac{1}{M_1 N_1} \sum_{i=1}^{M_1} \sum_{j=1}^{N_1} S_{BI}(m+k-1, n+l-1).$$

At the next stage, the segmentation of the images formed at the second stage was carried out using the structure of the images obtained at the first stage.

For this purpose, the fractal dimensionality D, according to the covering method, is determined according to the following relation [29]

$$D = \left[\lg C - \lg N(\chi) \right] / \lg \chi, \tag{13}$$

where C is a constant;

χ is the size of the sliding window;

$N(\chi)$ is the number of elements required to cover the image.

According to [29], the selection of the anchor object in images involves setting the values of D at which the largest difference between the structural composition of the image and the background occurs.

Thus, a method is proposed that combines the threshold selection of objects in the image by brightness and contrast and segmentation by image structure.

To quantitatively assess the quality of image segmentation, an approach was used applied for solving most similar problems by determining the similarity measure of two images: the segmented image and the original image [33]. In most practical tasks, the quality of segmentation is perceived as a measure of the similarity of two images: an image segmented by an expert and an image segmented by a certain algorithm.

Based on this, at the fourth and fifth stages, the quality of the segmented image was assessed. Considering the principle of operation of CENS, the classical correlation algorithm was chosen as a measure of image similarity and the partial and final DF $\mathbf{R}(\mathbf{r}, t)$ were constructed according to the expression

$$\mathbf{R}(\mathbf{r},t)=\mathbf{R}_b^D\mathbf{R}_K^D=\left\|R_b^D(i,j)\cdot R_K^D(i,j)\right\|, \qquad (14)$$

where $\mathbf{R}_b^D$ – partial DF, constructed using brightness;
$\mathbf{R}_K^D$ – partial DF, constructed using contrast.

The main stages of forming an image fragment, segmented using energy and non-energy ISs, are shown in Fig. 1.

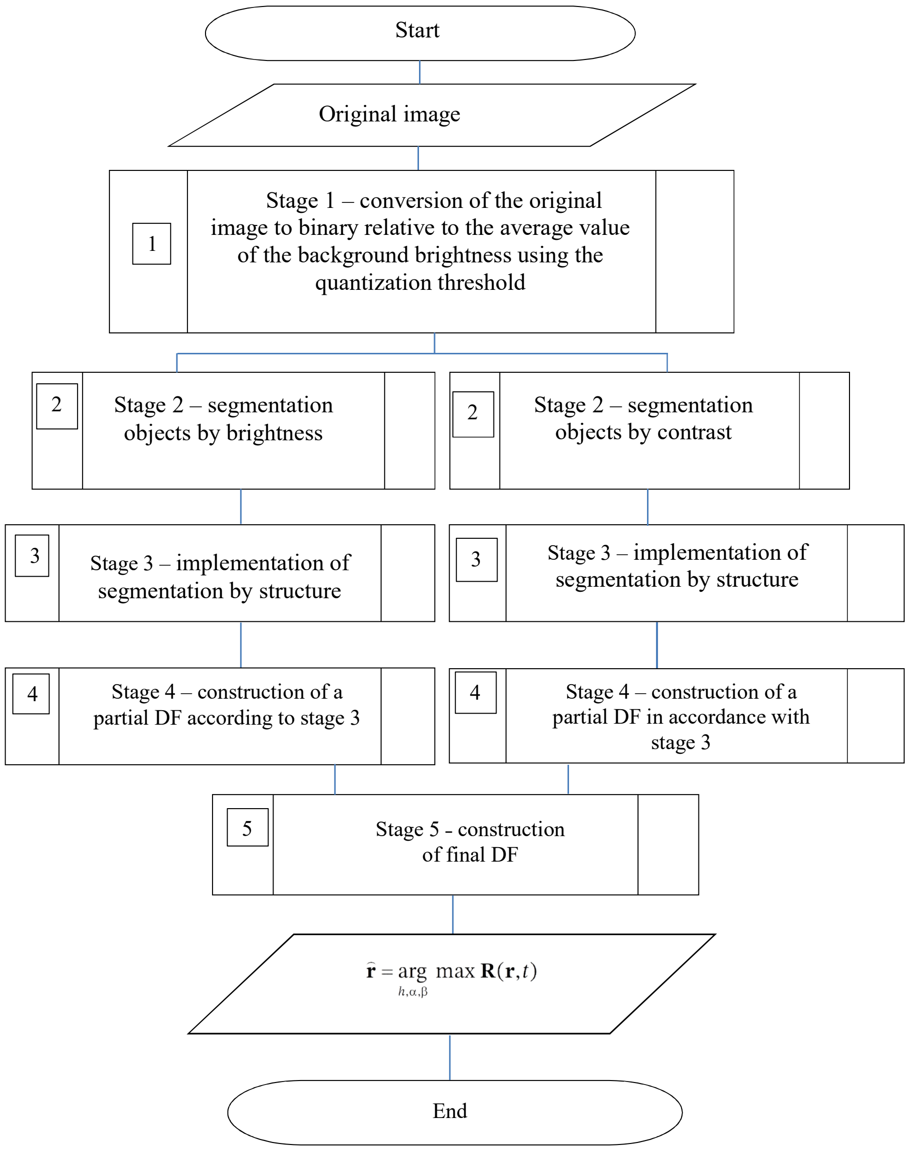


Fig. 1. Main stages of the method to form an image fragment segmented using energy and non-energy information features

Expression (13) allows us to assess the quality of the formed set of RIs for use in CENS for different geometric conditions of sighting using energy and non-energy ISs.

But the application of the devised method for forming a set of RIs in practice requires determining the maximum permissible steps of discretization by navigation parameters. In other words, solving this problem requires conducting research into the impact of changing the geometric conditions of sighting on the formation of RIs with preservation of CCC between neighboring fragments.

5. 2. Results of investigating the influence of changing geometric conditions on the formation of reference images

The formation of RIs requires taking into account both stochastic viewing conditions and the stochastic dependence of ISs on these conditions. Therefore, solving the problem of studying the influence of changing geometric viewing conditions on the formation of RIs with the preservation of CCC between neighboring fragments in a generalized analytical form is not possible. In addition, each area of the possible location of UAV has its own object features in terms of ISs, number, and structure, which also complicates the solution to this problem. Therefore, the problem was solved by numerical modeling. To this end, in accordance with the stages of forming an image fragment shown in Fig. 1, a study of different object composition of VS images was conducted. The images were selected from Google Earth Pro and for different viewing conditions corresponding to the operating range of UAV application.

Modeling conditions:

– discretization steps at a height of 30 meters with a further increase to 100 m;

– discretization steps at viewing angles of 5° with an increase to 30°;

– the noise component is not taken into account.

During numerical modeling under the specified conditions for each individual case of the study, 480 fragments of segmented images were obtained.

As a result of the modeling, the values of the required discretization steps for the geometric parameters of the viewing were found, at which the correlation between neighboring image fragments is preserved. It was established that the preservation of CCC between image fragments does not depend on the number of objects in the images. But it varies depending on the discretization threshold, the value of which will affect the structural properties of the segmented images obtained at the third stage.

It was determined that the numerical values of the discretization steps, at which CCC is equal to 0.9, are:

– for the height parameter from 90 to 120 meters;

– for the angular parameters from 15° to 25°.

The numerical values of the discretization steps, at which CCC is equal to 0.8, are:

– for the height parameter from 120 to 150 meters;

– for the angular parameters from 25° to 35°.

As an example, the results of modeling the process of forming an RI fragment using an object-saturated image of VS from Google Earth Pro are given. A fragment of the image is shown in Fig. 2. The VS image was obtained for the following viewing conditions – height 500 m, viewing angles $\alpha = 30°$, $\alpha = 45°$, $\alpha = 60°$, $\beta = -51°$.

a *b* *c*

Fig. 2. Original images of the sighting surface from Google Earth Pro (1732 × 1080 pixels): $a - \alpha = 30°$; $b - \alpha = 45°$; $c - \alpha = 60°$

Using the images shown in Fig. 2, we shall construct binary images with a CCC of 0.9. The results of binarization are shown in Fig. 3.

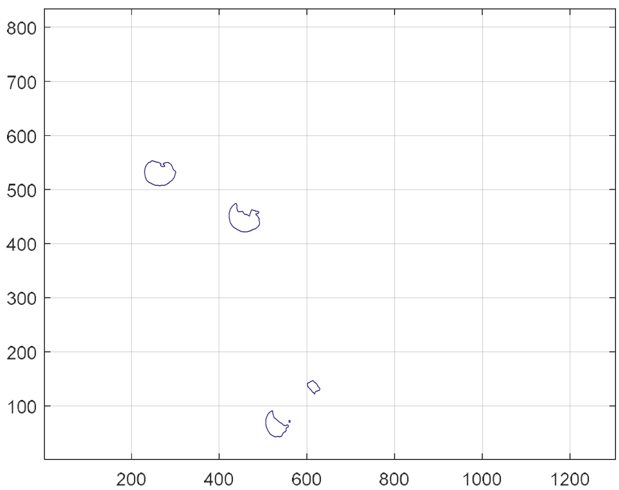
At the second stage, using the generated binary images, segmented images were constructed using brightness and contrast for a CCC of 0.9. The results of constructing segmented images are shown in Fig. 4, 5.

a *b* *c*

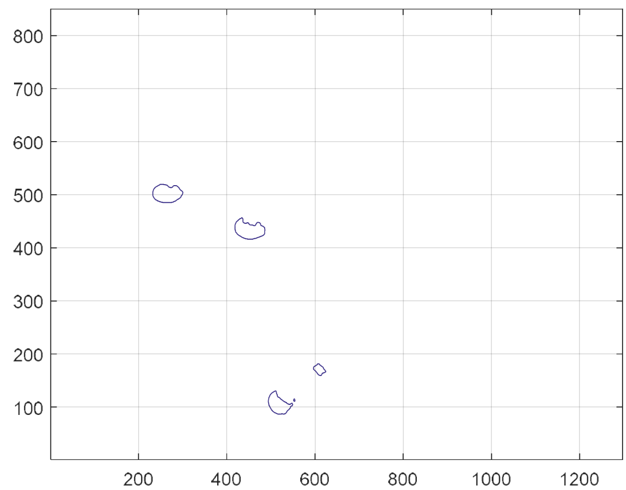
Fig. 3. Binary images of the sighting surface: $a - \alpha = 30°$; $b - \alpha = 45°$; $c - \alpha = 60°$

According to the third stage, segmented images by structure and corresponding FD histograms were constructed. The segmentation results are shown in Fig. 6, 7. FD histograms are shown in Fig. 8, 9.

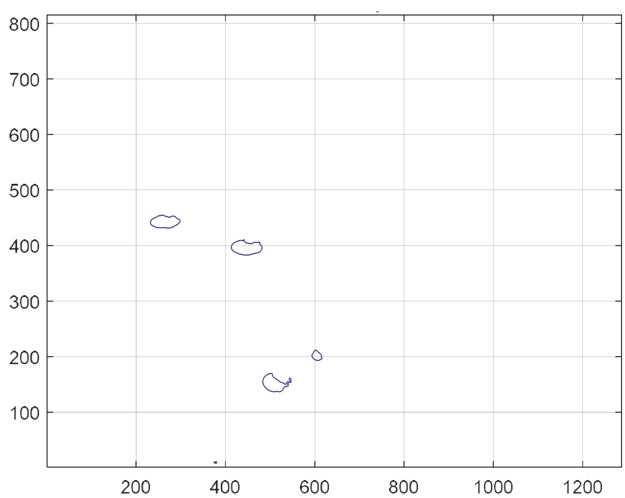
The segmented images of VS shown in Fig. 6, 7 represent fragments of RIs, which are constructed in accordance with the proposed approach using the original images shown in Fig. 2.



a



b



c

Fig. 4. Segmented images of the sighting surface by brightness: $a - \alpha = 30°$; $b - \alpha = 45°$; $c - \alpha = 60°$

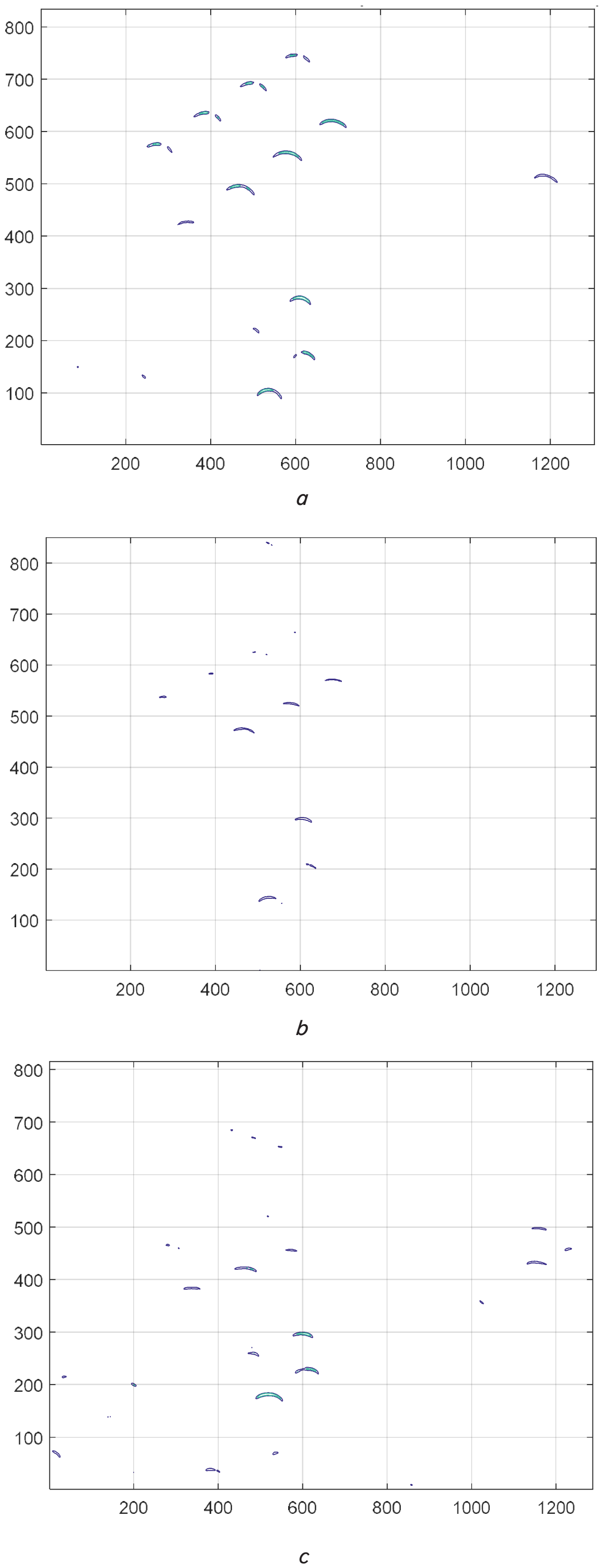


Fig. 5. Contrast-segmented images of the sighting surface: $a - \alpha = 30°$; $b - \alpha = 45°$; $c - \alpha = 60°$

The efficiency of the formation of the RI fragment was assessed. For this purpose, partial and final DFs were constructed, which correspond to the fourth and fifth stages. The results of the formation of partial DFs for a height of 500 m and sighting angles $\alpha = 30°$, $\beta = -51°$ are shown in Fig. 10.

According to the modeling results obtained at the fourth stage, the final DF was formed, represented in Fig. 11.

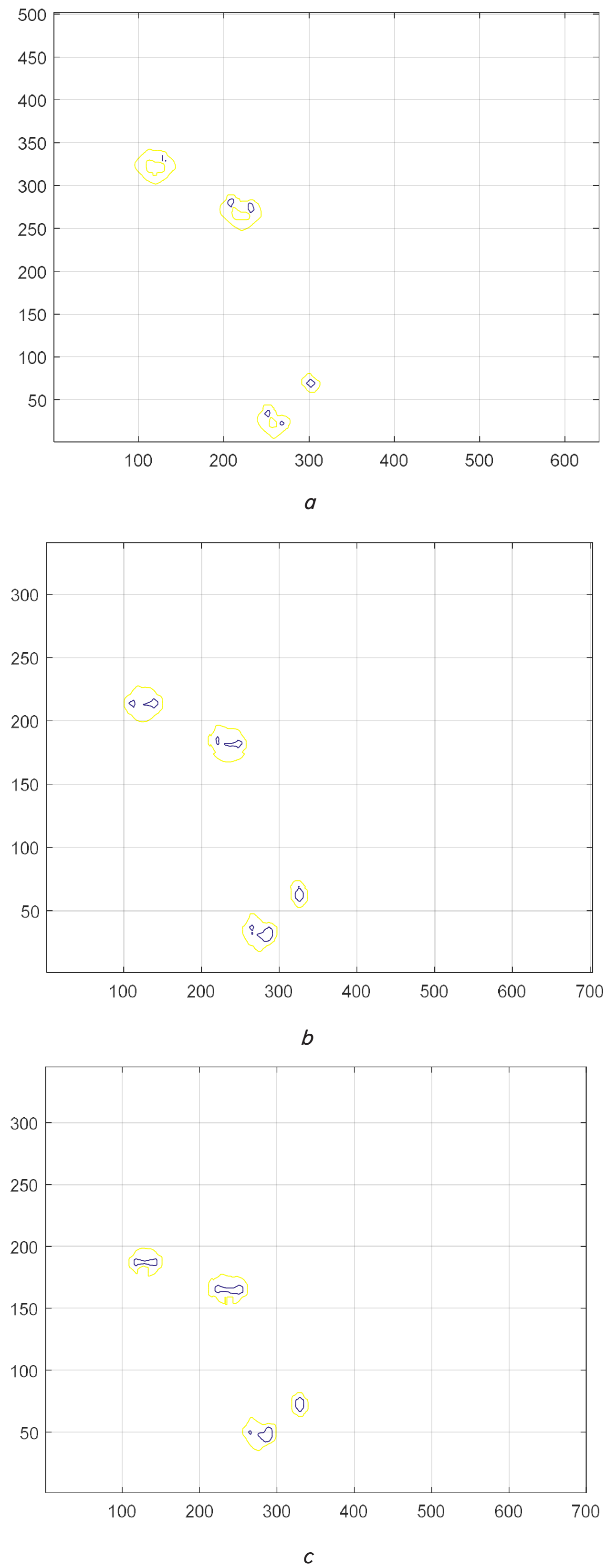


Fig. 6. Segmented images by structure: $a - \alpha = 30°$; $b - \alpha = 45°$; $c - \alpha = 60°$

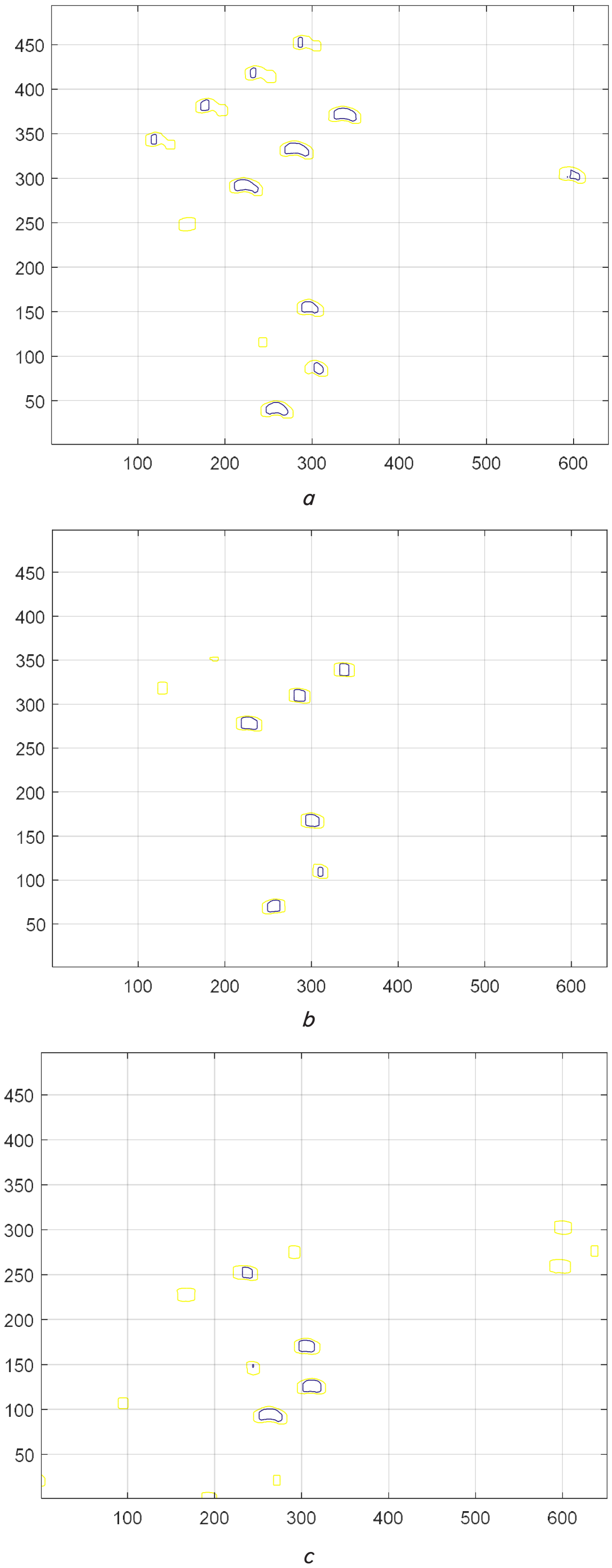


Fig. 7. Segmented images by structure: $a-\alpha=30°$; $b-\alpha=45°$; $c-\alpha=60°$

It is quite clear that from the simulation results shown in Fig. 6, 7, *b*, *c* partial and final DFs for the sighting angles of 45° and 60° will be similar.

As an example, the number of fragments of RIs N_{RI}, which constitute a minimum, but sufficient for high-precision navigation of UAV, was calculated. The calculation was carried out for the conditions selected for modeling and determined as a result of modeling for CCC 0.9.

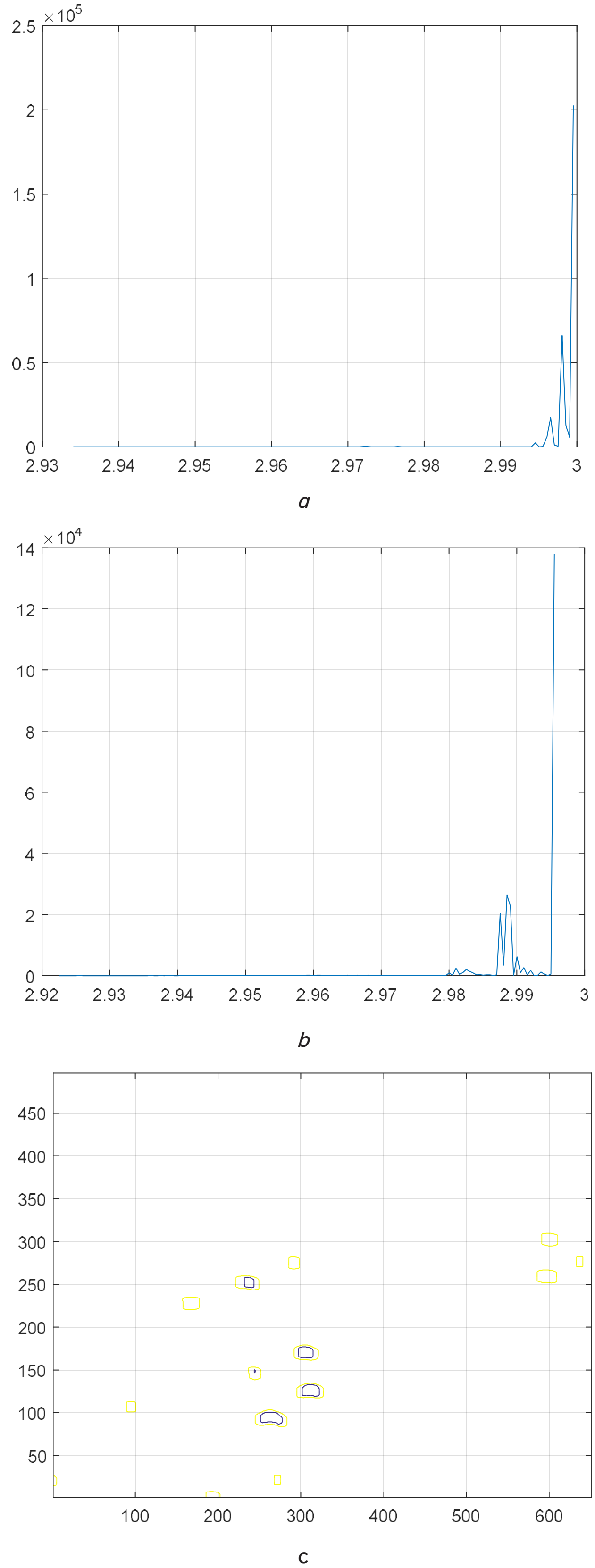


Fig. 8. Histograms of fractal dimensionality: $a-\alpha=30°$; $b-\alpha=45°$; $c-\alpha=60°$

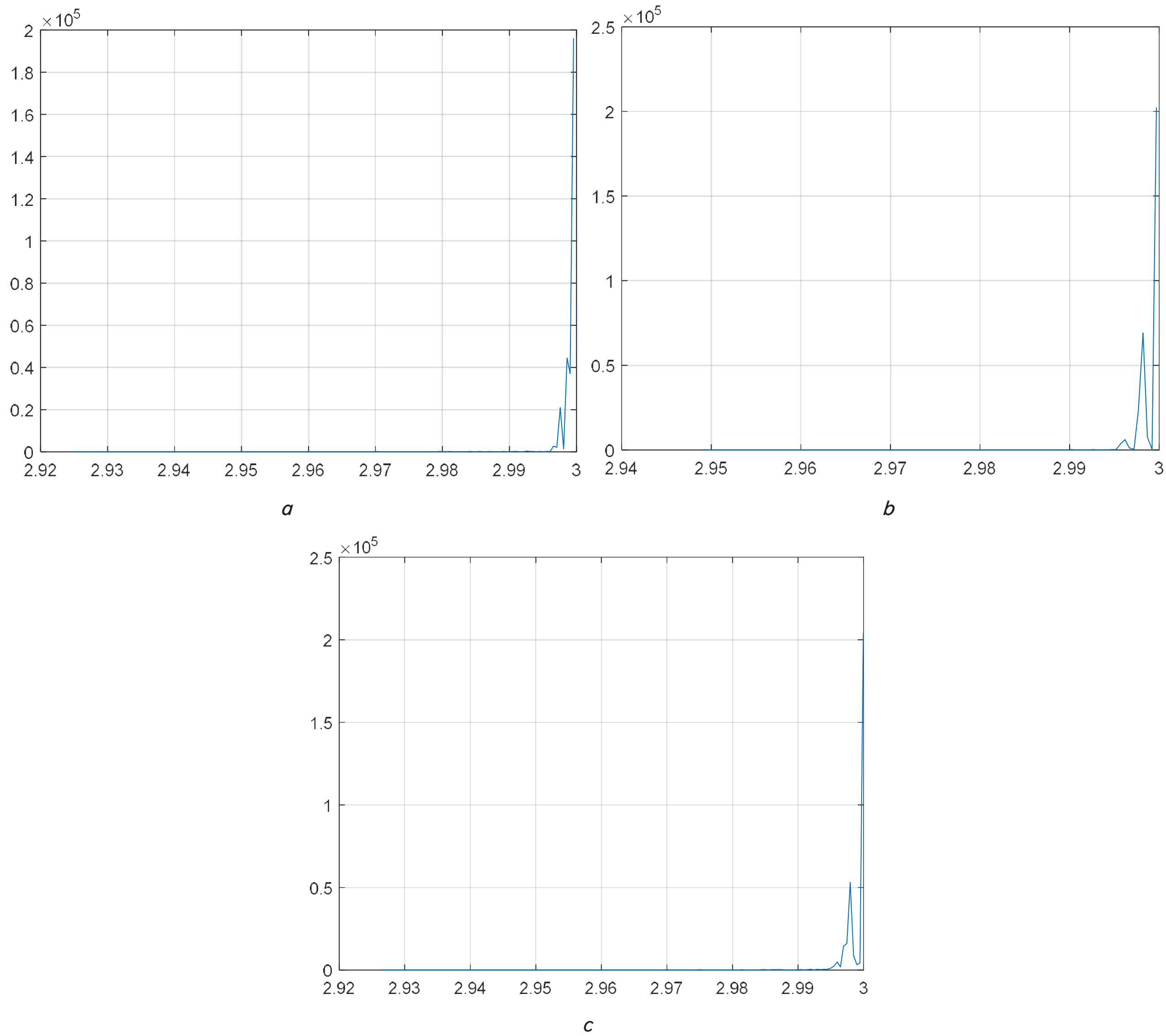


Fig. 9. Histograms of fractal dimensionality: *a* – $\alpha = 30°$; *b* – $\alpha = 45°$; *c* – $\alpha = 60°$

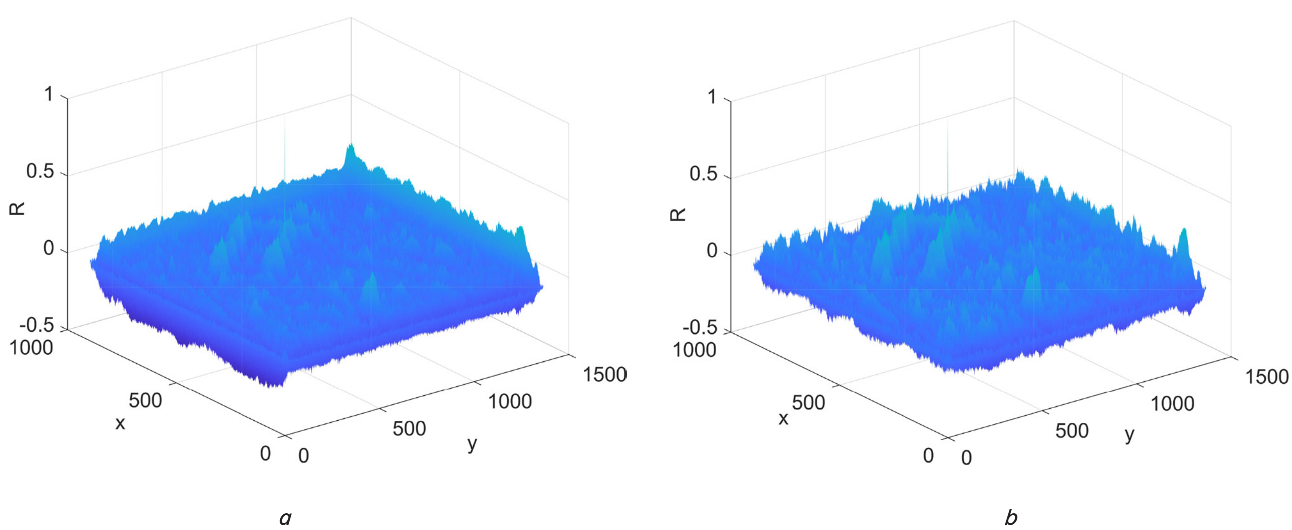


Fig. 10. Partial decision functions for a height of 500 m and viewing angles $\alpha = 30°$, $\beta = -51°$:
a – using the contrast of objects and image structure; *b* – using the brightness of objects and image structure

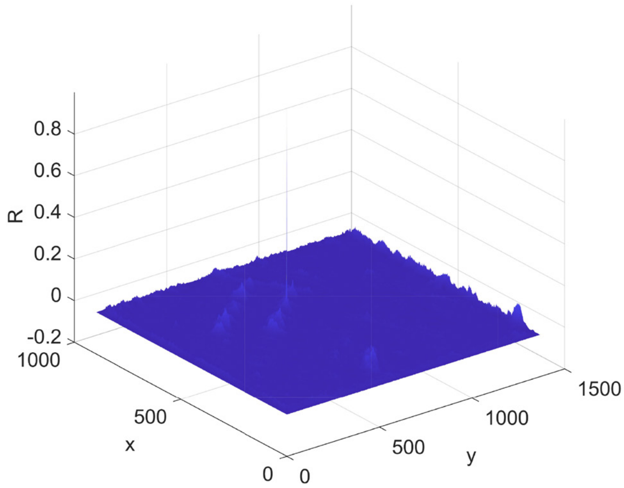


Fig. 11. The final decision function, which is formed based on the use of partial decision functions shown in Fig. 10

In fact, the set of RIs will be a three-dimensional matrix for three navigation parameters. The columns represent the change in height h_i, the terms of the change in the sighting angles α_i, β_i. It is clear that for the selected calculation conditions taking into account the smallest values of discretization, for example, for three values of the angle β, the matrix of the set of RIs will have dimensions 12*4*3. That is, the number of fragments of RIs in the set will be $N_{RI} = 144$.

If we conduct a full search of images when comparing them with one CI, the number of operations will be 144. In comparison with the results reported in [11], where the matrix size is 10*10*10, the gain in reducing the number of fragments is almost 7 times. This confirms the effectiveness of the method in terms of reducing computational complexity.

Thus, the results of modeling the process of forming an RI fragment and evaluating the effectiveness of the proposed approach have confirmed the possibility of its use for forming a set of RIs. At the same time, a reduction in the number of RI fragments is ensured while maintaining correlations between them. The formation of a unimodal DF, as shown in Fig. 11, is ensured with discretization parameters for height up to 120 meters, and for viewing angles up to 25° at a CCC of 0.9.

6. Discussion of results of investigating the formation of a set of reference images

Our paper reports the results of devising a method for forming a set of RIs for describing a sighting scene, the use of which provides the possibility of reducing the number of fragments in the set. This is achieved due to the lower dependence of segmented energy and non-energy ISs on changes in geometric sighting conditions. This paper is a continuation of our development of methods and algorithms for representing reference and current information used in UAV CENSs. Our work proposes a new statement and solution to the problem of forming a minimally sufficient set of RIs for CENSs of high-speed UAVs with the provision of unimodal DF when changing geometric sighting conditions.

Solving the problem in the proposed statement allows for high-precision navigation of high-speed UAVs when the UAV flight trajectory is affected by both external factors and a planned change in the trajectory.

The method devised, unlike [11], in which only the brightness of objects is used as IS, allows us to significantly reduce the number of RI fragments. This is achieved by using the brightness and contrast of objects for segmentation, as well as the structure of images segmented by energy parameters. In addition, unlike [28], the proposed method allows us to ensure the connection between image fragments at the level of 0.9. At the same time, unlike [11], the number of RI fragments is 7 times and does not lead to a decrease in the accuracy of CENS binding and the appearance of multi-extreme DFs.

The method consists of five stages of forming the segmentation of the original images. At the first stage, depending on the sensitivity of the sensors and their resolution, the original image is converted into a binary one. These parameters are determined by the electrophysical characteristics of the objects and their placement on VS (4) to (7). They are used by the primary processing sensors and are the signals that are received. That is, at this stage, processing is carried out taking into account errors of the first and second kind by choosing the appropriate quantization threshold (10). The second stage is based on the use of energy parameters as ISs. At this stage, segmented images are simultaneously formed by the brightness (11) and contrast (12) of the objects. The last stage consists of further processing of the segmented images in accordance with the segmented images formed at the second stage using a non-energy parameter – the structure of the image itself (13). A feature of the method is the verification of its effectiveness by using the similarity measure of two neighboring image fragments. For this purpose, partial and final DFs are used (Fig. 10, 11), which will determine the accuracy characteristics of CENS when using the set of RIs formed in this way.

As a disadvantage of the method, it is worth pointing out the dependence of the formation of segmented RIs and their number on the geometric dimensions of objects on VS and their possible distortion. This limits the application of the method in the presence of small-sized objects on VS and a decrease in the signal-to-noise ratio below the minimum permissible (10).

In the course of solving the second problem, an experimental study of the influence of changing the geometric conditions of sighting on the formation of RIs with the preservation of CCC between neighboring fragments and an assessment of the effectiveness of RI formation was carried out. The first stage of the formation of binary images is shown in Fig. 3. The results of image segmentation by brightness and contrast for three values of the sighting angles are shown in Fig. 4, 5, and by the structure of the images in Fig. 6, 7. From the analysis of the numerical modeling results shown in these figures, it follows that the application of the proposed approach allows the formation of individual fragments of RIs with the provision of a certain correlation relationship. In this case, the discretization steps for the navigation parameters are relatively large (for the height parameter from 90 to 120 meters; for the angular parameters from 15° to 25° at CCC 0.9). At the same time, according to the results shown in Fig. 7, high accuracy rates are provided (Fig. 11). The process of forming a set of RIs requires significant time, which limits the possibility of its application for operational preparation of a flight task.

The results of solving the stated problems show that the use of a certain sequence of image segmentation using selected ISs ensures the formation of a minimum set of RIs. At the same time, changes in navigation parameters do not lead to a significant impact on ISs, and, accordingly, on the accuracy indicator. Thus, the obtained results resolve the identified problem of forming a set of RIs taking into account changes in navigation parameters of high-speed unmanned aerial vehicles and their impact on the information features of images.

The results of our study might prove useful in preparing information support for CENS of UAVs in the form of RIs, as well as for forming CIs when using optoelectronic sensors to obtain primary information.

Potential areas of research are to improve the method for use in CENSs of UAVs with radar and infrared sensors. In addition, it is advisable to pay attention to the development of algorithms and software using the proposed procedure for forming RIs and its use in forming CIs.

7. Conclusions

1. A new problem statement has been proposed and a method for forming a minimum set of RIs with reduced dependence on the geometric conditions of sighting has been devised. The method, unlike known ones, is based on the formation of fragments of segmented RIs by energy and non-energy ISs, which ensures a reduction in the number of fragments in the set.

The formation of RI fragments and the assessment of efficiency are proposed to be carried out in five stages. In this case, the process of forming RIs is closely related to both the electrophysical characteristics of VS of objects and takes into account the navigation and technical parameters of CENSs. A quality indicator is proposed to assess the efficiency of the method, which takes into account the features of all stages of the formation of RI fragments.

2. The influence of changing the geometric conditions of sighting on the formation of individual RI fragments was investigated by numerical modeling. It was established that segmentation of VS images using the brightness and contrast of objects allows the formation of individual RI fragments with a CCC of 0.9. In this case, the size of the discretization steps is from 90 to 120 meters in height and from 15° to 25° in angular parameters. For CCC 0.8, the size of the discretization steps is from 120 to 150 meters in height and from 25° to 35° in angular parameters. The effectiveness of the method has been assessed by using the similarity measure of two neighboring image fragments. It is shown that the formation of DF fragments is carried out with high accuracy, which is confirmed by the formation of a narrow unimodal final DF.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Funding

The study was conducted without financial support.

Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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