UDC 004.932
DOI: 10.15587/1729-4061.2022.265775

DEVISING A METHOD FOR SEGMENTING IMAGES ACQUIRED FROM SPACE OPTICAL AND ELECTRONIC OBSERVATION SYSTEMS BASED ON THE SINE-COSINE ALGORITHM

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The object of this study is the process of segmentation of images acquired from space optoelectronic surveillance systems. The method to segment images from space optoelectronic surveillance systems based on the Sine-Cosine algorithm involves determining the threshold level; unlike the known ones, the following is carried out in it:

– preliminary selection of red-green-blue color space brightness channels in the original image;

– calculation of the maximum distance of movement of agents in the image in each brightness channel;

– calculation of the values that determine the movement of agents in the image in each brightness channel;

– determining the position of agents in the image using trigonometric functions of the sine and cosine in each brightness channel.

An experimental study into segmenting images acquired from space optoelectronic surveillance systems based on the Sine-Cosine algorithm was carried out. It was found that the improved method of image segmentation based on the Sine-Cosine algorithm makes it possible to segment the images. In this case, objects of interest, snow-covered objects of interest, background objects, and undefined areas of the image (anomalous areas) are identified.

The quality of image segmentation was assessed using the Sine-Cosine algorithm-based method. It was found that the improved segmentation method based on the Sine-Cosine algorithm reduces the segmentation error of the first kind by an average of 21 % and the segmentation error of the first kind by an average of 17 %.

Methods of image segmentation can be implemented in software and hardware systems that process images acquired from space optoelectronic surveillance systems.

Further studies may involve comparing the quality of segmentation by the method based on the Sine-Cosine algorithm with segmentation methods based on evolutionary algorithms (for example, genetic ones)

Keywords: image segmentation, space optoelectronic surveillance system, Sine-Cosine algorithm

Received date 26.07.2022
Accepted date 05.10.2022
Published date 27.10.2022

How to Cite: *Khudov, H., Makoveichuk, O., Khudov, V., Maliuha, V., Andriienko, A., Tertyshnik, Y., Pashchenko, V., Parashchuk, D., Khizhnyak, I., Kalimulin, T. (2022). Devising a method for segmenting images acquired from space optical and electronic observation systems based on the Sine-Cosine algorithm. Eastern-European Journal of Enterprise Technologies, 5 (9 (119)), 17–24. doi: https://doi.org/10.15587/1729-4061.2022.265775*

1. Introduction

The main source of up-to-date information about heterogeneous areas of the earth's surface in real time are air and space surveillance systems [1]. Owing to the information received from air and space surveillance systems, it is possible to adequately and promptly respond to any changes in the situation [2]. At the same time, one satellite image contains survey information about the earth's surface, which is equal to hundreds of images obtained using air surveillance systems [3]. This fact testifies to the relevance of processing information from space surveillance systems.

Processing and decryption of a significant amount of information completely eliminates manual processing [4]. Therefore, the main way to obtain objective and relevant information for solving heterogeneous problems is automated and automatic processing and decryption of images acquired from space optoelectronic surveillance systems [5]. At the same time, the main attention is paid to the quality of segmentation of images of space optoelectronic surveillance systems [6].

Existing methods of segmentation of images of space optoelectronic surveillance systems have certain disadvantages. They do not meet the requirements for reliability, accuracy, and completeness of image segmentation [7]. Therefore, the development of methods for segmenting images from space optoelectronic surveillance systems is an urgent task.

2. Literature review and problem statement

Paper [8] investigated the main characteristics and principle of operation of the method of global threshold segmentation and the method of adaptive local threshold segmentation. It was found that for images with uneven lighting it is better to use the method of adaptive local threshold segmentation. The advantage of [8] is the ease of implementation of the methods. The disadvantage of [8] is the impossibility of determining the threshold for segmentation on high-contrast and complexly structured images.

Due to the impossibility of segmentation of complexly structured and highly contrast images by the method with the definition of one threshold, in [9], an improved method of multi-threshold image segmentation is proposed. The advantage of the method in [9] is the ability to segment the image into more than two segments. The disadvantage of [9] is the imposed restrictions for input images and obtaining good segmentation results only for reference images.

Paper [10] suggests a method of image segmentation based on random walk using interactive marking. The essence of the method in [10] is representing the image in the form of a fully connected graph and using the approaches of graph theory. The advantage of [10] is to use the probability of transition to a graph. The disadvantage of [10] is the construction and solving a system of equations at each node of the graph to obtain the probability value of such a transition.

Paper [11] proposes an improved method based on simple linear iterative clustering (SLIC)). The advantage of the method in [11] is to reduce the number of initial values for performing the threshold estimate and the total time to perform the image segmentation process. The disadvantage of [11] is the good segmentation results for simple images only.

Paper [12] proposed to use several masks for the same input image to improve the accuracy of segmentation. To obtain one of the best masks, apply a voting rule that takes into consideration the natural geometry and topological properties of masks, for these masks. The advantage of [12] is a better segmentation result compared to a simple arithmetic voting method. The disadvantage of [12] is the high time and computational costs.

Paper [13] proposed image segmentation based on the representation of a minimum spanning tree (MST). The essence of the improved method in [13] is to scan the full structure of the MST image and remove inconsistent edges among a set of adjacent ones, the elements of which are obtained from an MST of a certain length. The advantage of [13] is the low computational complexity of the method and ease of operation. The disadvantage of [13] is a good segmentation result only for simple images.

Methods [8–12] are not suitable for segmentation of high spatial resolution satellite images due to the complexity of image data.

Paper [14] suggested a method of spectral-textural segmentation. The advantage is the use of a single metric for both spectral and textural features in a heterogeneous feature space. The disadvantage of [14] is the segmentation of only multispectral images of high spatial resolution.

Paper [15] proposed the use of the method of morphological segmentation of satellite images based on the graph approach. The advantage of [15] is taking into consideration information about surrounding pixels and eliminating the impact on the results of segmentation of pulsed noise in the image. The disadvantage of [15] is the dependence of the segmentation result on the choice of markers.

Paper [16] suggests using deep learning of neural networks for segmenting satellite images of urban buildings. The advantage of [16] is the high accuracy of segmentation on satellite images of urban objects. The disadvantage of [16] is the impossibility of selecting objects for another purpose in the image.

The authors of [17] proposed segmentation of satellite images using the U-HardNet convolutional neural network with the Hard-Swish activation function. The disadvantage of [17] is working with transformed IHS images (Intensity, Hue, Saturation) to minimize binary cross-entropy losses. The advantage of [17] is highlighting without control over different data sets. The main disadvantages of [17] are the significant time and material costs of obtaining a training sample, which is necessary for a decisive rule.

Paper [18] suggested, for segmentation of aerial photographs, the use of a full-convolutional artificial neural network. The advantage of [18] is the high quality of segmentation results and ease of use due to the lack of need to manually provide a feature description of objects of interest. The main disadvantage of [18] is the high computational costs that will require the additional involvement of a graphics accelerator.

Paper [19] proposes a dataset for semantic segmentation of images acquired from unmanned aerial vehicles (UAVs). With the help of the presented dataset Unmanned Aerial Vehicles (UAV), deep learning methods make it possible to select objects of interest even in motion on high-resolution images of different sizes. The advantage of [19] is the ability to highlight objects in images that were recorded in different projections – both from above and from the side. The disadvantage of [19] is the need for prior training and the use of a limited number of classes for marking.

Study [20] suggest a method for segmenting the sequence of video frames from UAVs by combining the convolutional network FCN (Fully Convolutional Networks) and long-term short-term memory of the Conv-LSTM convolutional (Convolutional-Long Short-Term Memory) network. The advantage of [20] is the ability to perform segmentation in real time. The disadvantage of [20] is the qualitative segmentation of only some defined classes of objects of interest.

The authors of [21] propose a method for detecting floods using images of Red-Green-Blue (RGB) and Hue, Saturation, Intensity (HIS) color models from UAVs. A k-means segmentation method and a region augmentation method are proposed to highlight flooded and non-flooded areas in the image. The advantage of [21] is a good result of image segmentation. The disadvantage of [21] is the separation of the image into only two segments.

Paper [22] suggested a method of multi-scale segmentation of images of remote sensing of the Earth. At the first stage of the method, the method of coherent anisotropic diffuse filtration and the algorithm of the minimum skeleton tree are used. At the second stage, the merging of segments according to the minimum heterogeneity criterion is used. The disadvantage of [22] is the high computational cost.

Work [23] offered a method of automatic segmentation of images of remote sensing of the Earth of ultrahigh resolution based on lines. The essence of the method is applying the lines with the highest entropy value to obtain boundaries and initial values. The advantages of [23] are independence on the knowledge and skills of the expert, segmentation of both multispectral, panchromatic images, and aerial photographs.

Paper [24] suggests an improved method of segmentation of high-resolution Earth remote sensing images based on gradient values – segmentation by watershed. The advantage of [24] is the segmentation of images of RGB, Lab color spaces (the dependence of *L* brightness on tone *a* and saturation *b*) and CIE Luv (dependence of *L* brightness on color *u* and hue *v*; CIE – Commission International Eclairage). The disadvantage of [24] is the need for expert intervention when setting up the parameters of the method.

Study [25] devised an improved method of segmentation of images from onboard optoelectronic observation systems using a genetic algorithm. The advantage of [25] is the good selection of objects of interest, even disguised, in satellite images. The disadvantage of [25] is the high error values of the first and second kind when segmenting images obtained from UAVs.

Paper [26] proposes methods for segmenting images of remote sensing of the Earth based on the *k*-means algorithm and genetic algorithm. It was experimentally established that segmentation methods based on the *k*-means algorithm and based on the genetic algorithm have good segmentation results only for satellite images. For images acquired from UAVs, these algorithms cannot be applied directly. The advantage of the methods [26] is the reduction of segmentation errors of the first and second kind for space images in comparison with known methods. The main disadvantage of the methods in [26] is their limitations in the processing of all types of remote sensing data.

Thus, our review of known methods for segmenting images from space surveillance systems and from UAVs revealed certain disadvantages of those methods. The main disadvantages are related to the peculiarities of images acquired from space optoelectronic surveillance systems. The main feature of such images is their complex structure.

To further study the segmentation of images from space optoelectronic surveillance systems, it is advisable to choose a segmentation method based on the Sine-Cosine algorithm. The main advantages of the Sine-Cosine algorithm are the use of simple functions, avoidance of local optima, convergence to global optima [27].

Therefore, the development of a method for segmenting images from space optoelectronic surveillance systems based on the Sine-Cosine algorithm can solve the problem associated with the limitations of known methods for segmenting images from space optoelectronic surveillance systems.

3. The aim and objectives of the study

The aim of this study is to improve the method of segmentation of images from space optoelectronic surveillance systems through the use of the Sine-Cosine algorithm. This will make it possible to reduce the value of segmentation errors of the first and second kind.

To accomplish the aim, the following tasks have been set:

– to determine the main stages of the method of segmentation of images from space optoelectronic surveillance systems based on the Sine-Cosine algorithm;

– to carry out segmentation of the image from the space optoelectronic observation system by the method based on the Sine-Cosine algorithm;

– to conduct a comparative assessment of the quality of image segmentation from the space optoelectronic observation system by the well-known and developed methods based on the Sine-Cosine algorithm.

4. The study materials and methods

The object of this study is the process of segmentation of images acquired from space optoelectronic surveillance systems.

The main hypothesis of the study assumes that the use of the Sine-Cosine algorithm in improving the method of segmentation of images acquired from space optoelectronic surveillance systems will reduce the value of segmentation errors of the first and second kind.

The following research methods were used during the study: evolutionary methods, methods of image processing theory, methods of probability theory and mathematical statistics, mathematical apparatus of matrix theory, methods of system analysis, iterative methods, methods of mathematical modeling. When validating the proposed solutions, analytical and empirical methods of comparative research were used.

During the study, the following limitations and assumptions were adopted:

– an image from the space system of optoelectronic observation is considered as the initial one;

– the original image is represented in the RGB color space;

– the image shows heterogeneous objects of interest;

– objects of interest are different in spatial structure;

– the size of background objects significantly exceeds the size of objects of interest;

– we do not take into consideration the impact of rotation, scale change, and noise in the original image.

5. Results of the study on image segmentation by the method based on the Sine-Cosine algorithm

5. 1. The main stages of the image segmentation method based on the Sine-Cosine algorithm

Formalization of the problem of segmentation of images acquired from space optoelectronic surveillance systems based on the Sine-Cosine algorithm can be written with expression (1) [25, 26, 28]:

$$f(x,y) \to fs(x,y), \qquad (1)$$

where $f(x, y)$ is the original image from the space optoelectronic surveillance system; $fs(x, y)$ – segmented image.

Segmentation of the original image from the space optoelectronic surveillance system $f(x, y)$ involves the partitioning of $f(x, y)$ into segments B_i according to condition (2) [25, 26, 28]:

$$\begin{cases} \bigcup_{i=1}^{K} B_i = B; \\ B_i \cap B_j = \varnothing, \text{ for } i \neq j; \forall i, j = \overline{1, K}; \\ LP(B_i) = 1; \forall i = \overline{1, K}; \\ LP(B_i \cap B_j) = 0, \text{ for } i \neq j; \forall i, j = \overline{1, K}, \end{cases} \quad (2)$$

where B: $B=\{B_1, B_2,..., B_K\}$ – parsing segments in the segmented image $fs(x, y)$; K is the number of partition segments, LP is the predicate, (i=1, 2, ..., K). The LP predicate is calculated using expression (3) [25, 26, 28]:

$$LP(B_i) = \begin{cases} 1, \text{ if } f(x_1, y_1) = ... = f(x_M, y_M); \\ 0, \text{ others}, \end{cases} \quad (3)$$

where m=1, 2,..., M; $(x_m, y_m) \in B_i$; M is the number of points of segment B_i.

The result of segmentation of the source image from space optoelectronic surveillance systems $f(x, y)$ is its clustering into background objects and heterogeneous objects of interest.

The separation of the original image from the space optoelectronic observation system $f(x, y)$ into background objects and objects of interest involves determining the optimal segmentation threshold.

The main stages of the method of segmentation of images acquired from space optoelectronic surveillance systems based on the Sine-Cosine algorithm are shown in Fig. 1.

The method of segmentation of images acquired from space optoelectronic surveillance systems based on Sine-Cosine involves the following:

1. Input of original data:

– source image from the space optoelectronic surveillance system $f(\boldsymbol{X})$, where $\boldsymbol{X}(x, y)$ – pixel coordinates in the image $f(\boldsymbol{X})$ from the space optoelectronic surveillance system;

– N – the size of the original image $f(\boldsymbol{X})$ from the space optoelectronic surveillance system; N is equal to the number of pixels in the original image $f(\boldsymbol{X})$;

– K is the number of segmented image $fs(\mathbf{X})$;

– the initial values of r_2, r_3, r_4 (the values of these quantities will be given below).

2. Initialization of the initial positions of the agents in the original image $f(\boldsymbol{X})$ randomly.

3. Calculation of the value of r_1 for each agent in the image $f(\boldsymbol{X})$ by expression (4):

$$r_1 = c - i\frac{c}{I_{\max}}, \quad (4)$$

where c is the constant that determines the maximum distance (radius of movement) of agents in the image, i is the number of the current iteration, $I_{\max}$ is the maximum number of iterations.

4. Determining the values r_2, r_3, r_4 as follows [27]. The value of r_2 is determined randomly from the interval [0, 2π], which corresponds to the period of trigonometric functions of the sinus and cosine. The value of r_3 is determined randomly from the interval [0, 2]. The value of r_4 is determined randomly from the interval [0, 1] and defines the function of movement of agents (it will be shown later in the text).

5. Determining the position of agents in the image using expression (5):

$$\mathbf{X}^{i+1} = \begin{cases} \mathbf{X}^i + r_1 \cos(r_2) \left| r_3 \mathbf{X}_{best}^i - \mathbf{X}^i \right|, \text{ if } r_4 \geq 0.5; \\ \mathbf{X}^i + r_1 \sin(r_2) \left| r_3 \mathbf{X}_{best}^i - \mathbf{X}^i \right|, \text{ if } r_4 < 0.5, \end{cases} \quad (5)$$

where $\mathbf{X}_{best}^i$ is the best position of agents on the i-th iteration.

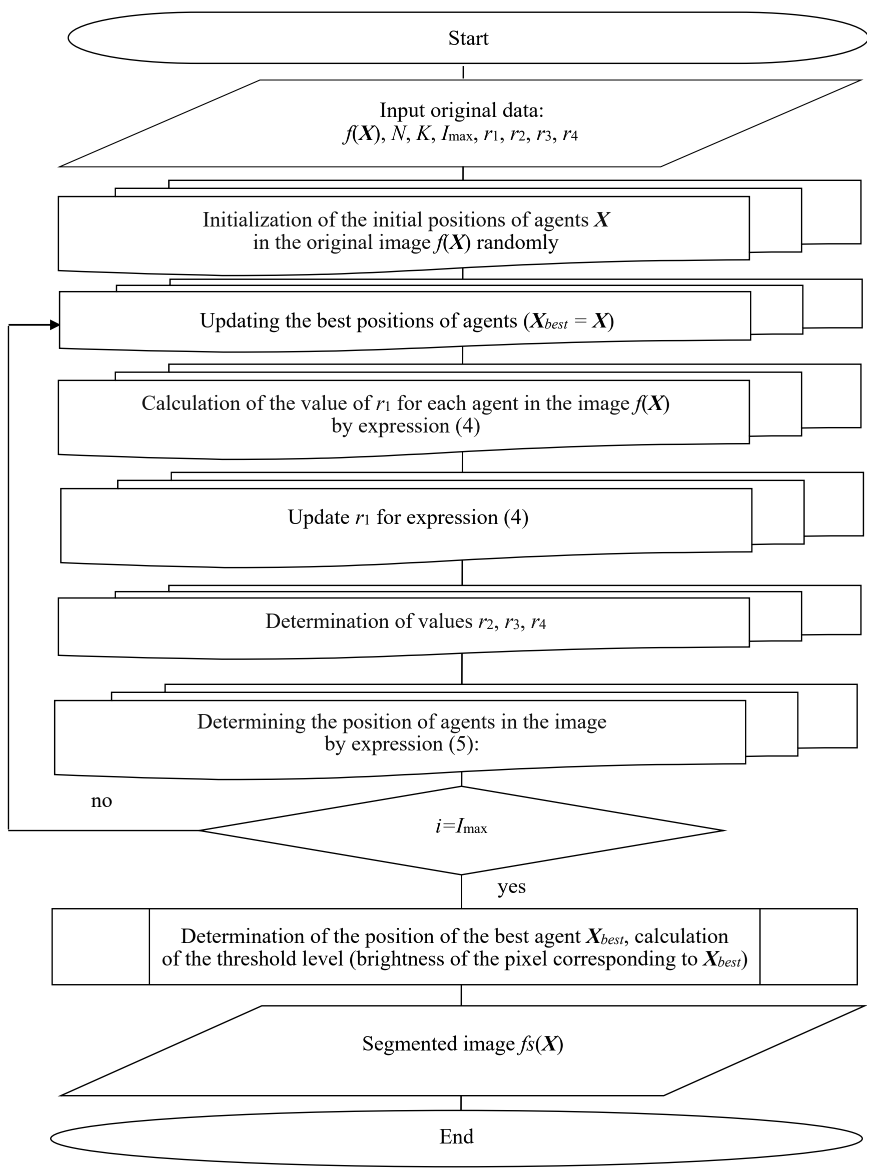

Fig. 1. The main stages of the method of segmentation of images acquired from space optoelectronic surveillance systems based on the Sine-Cosine algorithm

6. Checking the stopping condition of the Sine-Cosine algorithm. The condition for termination implies meeting condition (6):

$$i = I_{\max}. \qquad (6)$$

7. Determining the optimal segmentation threshold – brightness of a pixel with coordinates $\mathbf{X}_{best}^{I_{\max}}$.

8. Obtaining a segmented image $fs(\boldsymbol{X})$.

If the original image $f(\boldsymbol{X})$ is represented in the RGB color space, then it is first necessary to select the brightness channels Red, Green, and Blue in the original image. So, the main stages of the method of segmentation of images from space optoelectronic surveillance systems based on the Sine-Cosine algorithm (Fig. 1) must be carried out for each brightness channel (Red, Green, and Blue). After that, the brightness channels (Red, Green, and Blue) are combined, and an augmented image $fs(\boldsymbol{X})$ is obtained.

Thus, the method of segmentation of images acquired from space optoelectronic observation systems based on the Sine-Cosine algorithm involves determining the threshold level; in it, unlike in the known ones, the following is carried out:

– preliminary selection of brightness channels of RGB color space in the original image;

– calculation of the maximum distance of movement of agents in the image in each brightness channel;

– calculation of the values that determine the movement of agents in the image in each brightness channel;

– determining the position of agents in the image using trigonometric functions of the sine and cosine in each brightness channel.

5. 2. Segmentation of images by the method based on the Sine-Cosine algorithm

As a source image, we shall consider a color image (RGB color space) from the WorldView-2 space optoelectronic observation system (USA) (Fig. 2) [29]. The objects of interest in Fig. 2 are the objects of military equipment. Image size in Fig. 2 is (1868×1348) pixels.

Fig. 2. Original color image (RGB Color Space) from the WorldView-2 Space Optoelectronic Surveillance System (USA) [29]

Fig. 3 shows the image segmented with an improved method based on the Sine-Cosine algorithm. The image in Fig. 3 is represented after combining the brightness channels (Red, Green, Blue) of the RGB color space.

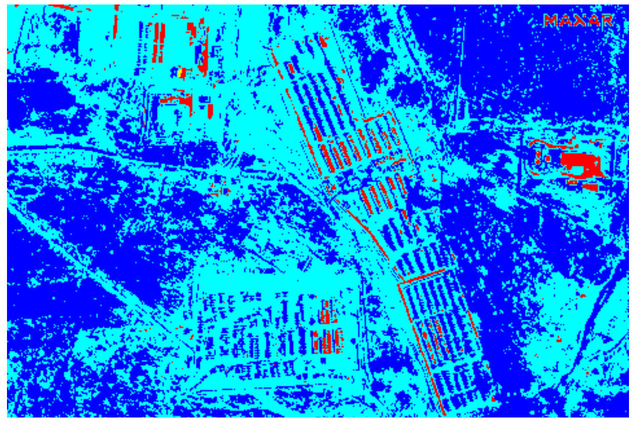

Fig. 3. Segmented image by an improved method based on the Sine-Cosine algorithm

The number of segments selected was $K=4$. This number of segments is due to the fact that segmentation is carried out into:

– objects of interest;

– objects of interest under snow cover;

– background objects;

– undefined areas of the image (anomalous areas).

In Fig. 3, the objects of interest are marked with blue, the objects of interest under a snow cover are marked in red, background objects are marked with blue, indefinite areas of the image (anomalous areas) are marked with yellow.

Our analysis of Fig. 3 reveals that the improved method of segmentation of images acquired from space optoelectronic surveillance systems based on the Sine-Cosine algorithm makes it possible to segment images.

5. 3. Evaluation of image segmentation by the method based on the Sine-Cosine algorithm

We shall calculate the segmentation errors of the I and II kinds [26, 28, 30, 31] for the well-known segmentation method and the improved segmentation method based on the Sine-Cosine algorithm. These segmentation errors of the I (α_1) and II (β_2) kinds are calculated using expressions (7), (8), respectively [26, 28, 30, 31]:

$$\alpha_1 = \frac{S_1\left(fs(\mathbf{X})\right)}{S_2\left(f(\mathbf{X})\right)}, \qquad (7)$$

$$\beta_2 = 1 - \frac{S_3\left(fs(\mathbf{X})\right)}{S_4\left(f(\mathbf{X})\right)}, \qquad (8)$$

where $S_1(fs(\boldsymbol{X}))$ is the background plane mistakenly assigned to the objects of interest in the segmented image $fs(\boldsymbol{X})$; $S_2(f(\boldsymbol{X}))$ – the background plane of the original image $f(\boldsymbol{X})$; $S_3(fs(\boldsymbol{X}))$ is the plane of correctly segmented objects of interest in the segmented image $fs(\boldsymbol{X})$; $S_4(f(\boldsymbol{X}))$ – the plane of objects of interest in the original image $f(\boldsymbol{X})$.

We shall calculate segmentation errors of the first and second kinds for the well-known segmentation method and the improved segmentation method based on the Sine-Cosine algorithm. As a well-known method of segmentation, we choose the method of segmentation of images acquired from space optoelectronic observation systems based on the particle swarm algorithm [28].

The image segmented by a known method based on the particle swarm algorithm is shown in Fig. 4 [28].

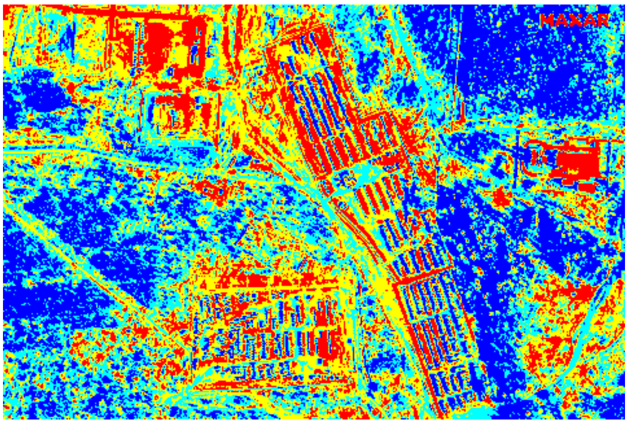

Fig. 4. The image segmented by a method based on a swarm of particles [28]

Tables 1, 2 give the result of the calculation of segmentation errors of I (α_1) and II (β_2) kinds, respectively.

Table 1

Results of the calculation of segmentation errors of the first kind (α_1)

The name of the segmentation method	Image segmentation process number									
	1	2	3	4	5	6	7	8	9	10
Segmentation method based on the particle swarm algorithm	24.9	27.3	24.7	25.4	26.1	25.5	27.1	24.6	25.4	26.1
An improved segmentation method based on the Sine-Cosine algorithm	19.3	20.8	20.2	19.1	19.8	20.6	21.1	19.8	19.5	20.1

Table 2

Results of the calculation of segmentation errors of the second kind (β_2)

The name of the segmentation method	Image segmentation process number									
	1	2	3	4	5	6	7	8	9	10
Segmentation method based on the particle swarm algorithm	22.9	23.1	22.2	23.6	24.1	22.2	23.6	22.6	22.9	23.2
An improved segmentation method based on the Sine-Cosine algorithm	18.9	19.2	19.4	18.2	18.3	19.0	19.4	18.2	18.6	18.3

Fig. 5, 6 show the dependence of segmentation errors of the first kind (α_1) and the second kind (β_2), respectively, for different implementations (from 1 to 10).

In Fig. 5, 6, the green curve corresponds to the segmentation method based on the particle swarm algorithm. The blue curve corresponds to the improved image segmentation method based on the Sine-Cosine algorithm.

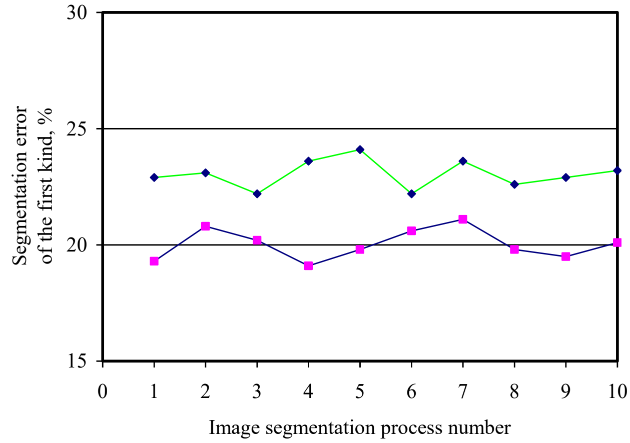

Fig. 5. Value of segmentation error of the first kind for a known segmentation method and the improved segmentation method based on the Sine-Cosine algorithm

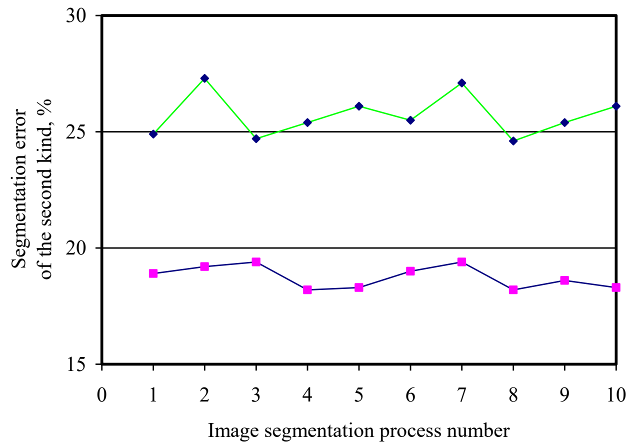

Fig. 6. Value of segmentation error of the second kind for a known segmentation method and the improved segmentation method based on the Sine-Cosine algorithm

The analysis of Tables 1, 2, and Fig. 5, 6 revealed that the improved segmentation method based on the Sine-Cosine algorithm reduces the segmentation error of the first kind by an average of 21 % and the segmentation error of the second kind by an average of 17 %. This is made possible by using the Sine-Cosine algorithm.

6. Discussion of results of the study on improving the method of segmentation using the genetic algorithm

The method of segmentation of images acquired from space optoelectronic surveillance systems based on the Sine-Cosine algorithm involves determining the threshold level; in it, unlike in the known ones, the following is carried out:

– preliminary selection of brightness channels of RGB color space in the original image;

– in each brightness channel, the calculation of the maximum distance of movement of agents in the image;

– in each brightness channel, the calculation of values that determine the movement of agents in the image;

– in each brightness channel, determining the position of agents in the image using trigonometric functions of the sine and cosine.

An experimental study into the segmentation of images from space optoelectronic surveillance systems based on the Sine-Cosine algorithm was carried out (Fig. 2, 3).

The analysis of Fig. 3 reveals that the improved method of segmentation of images acquired from space optoelectronic surveillance systems based on Sine-Cosine algorithm allows for image segmentation. In this case, it highlights the objects of interest, snow-covered objects of interest, background objects, and undefined areas of the image (anomalous areas).

The quality of image segmentation was assessed using the Sine-Cosine algorithm-based method. The analysis of Tables 1, 2, and Fig. 5, 6 revealed that the improved method of segmentation based on the Sine-Cosine algorithm reduces the segmentation error of the first kind by an average of 21 % and the segmentation error of the first kind by an average of 17 %.

The uniqueness of this study is the use of the Sine-Cosine algorithm for segmenting complexly structured images acquired from space optoelectronic surveillance systems.

Methods of image segmentation can be implemented in software and hardware systems of image processing from space optoelectronic surveillance systems.

The disadvantage of the method is the deterioration of the quality of segmentation when exposed to heterogeneous distorting factors on the original image.

Further studies may involve comparing the quality of segmentation by the method based on the Sine-Cosine algorithm with segmentation methods based on evolutionary algorithms (for example, genetic ones).

7. Conclusions

1. The method of segmentation of images acquired from space optoelectronic observation systems based on the Sine-Cosine algorithm involves determining the threshold level; in it, unlike in the known ones, the following is carried out:

– preliminary selection of brightness channels of RGB color space in the original image;

– in each brightness channel, the calculation of the maximum distance of movement of agents in the image;

– in each brightness channel, the calculation of values that determine the movement of agents in the image;

– in each brightness channel, determining the position of agents in the image using trigonometric functions of the sine and cosine.

2. An experimental study into the segmentation of images from space optoelectronic surveillance systems based on the Sine-Cosine algorithm was carried out. objects and undefined areas of the image (anomalous areas). It was established that the improved method for segmenting images from space optical-electronic surveillance systems based on the Sine-Cosine algorithm allows image segmentation. In this case, the objects of interest, objects of interest under snow cover, background objects, and undefined areas of the image (abnormal areas) are highlighted.

3. The quality of image segmentation was assessed using the Sine-Cosine algorithm-based method. It was found that the improved segmentation method based on the Sine-Cosine algorithm reduces the segmentation error of the first kind by an average of 21 % and the segmentation error of the second kind by an average of 17 %.

Conflict of interests

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

References

1. Olejnik, A., Kiszkowiak, Ł., Rogólski, R., Chmaj, G., Radomski, M., Majcher, M., Omen, Ł. (2020). The Use of Unmanned Aerial Vehicles in Remote Sensing Systems. Sensors, 20 (7), 2003. doi: https://doi.org/10.3390/s20072003
2. Olejnik, A., Kiszkowiak, L., Rogolski, R., Chmaj, G., Radomski, M., Majcher, M., Omen, L. (2019). Precise Remote Sensing Using Unmanned Helicopter. 2019 IEEE 5th International Workshop on Metrology for AeroSpace (MetroAeroSpace). doi: https://doi.org/10.1109/metroaerospace.2019.8869657
3. Sharad, W. (2021). The development of the earth remote sensing from satellite. MECHANICS OF GYROSCOPIC SYSTEMS, 40, 46–54. doi: https://doi.org/10.20535/0203-3771402020248768
4. Favorskaya, M. N., Zotin, A. G. (2021). Semantic segmentation of multispectral satellite images for land use analysis based on embedded information. Procedia Computer Science, 192, 1504–1513. doi: https://doi.org/10.1016/j.procs.2021.08.154
5. Khudov, H., Khizhnyak, I., Misiuk, D., Shamrai, N., Chepurnyi, V., Ruban, I. et. al. (2021). The Improved Mathematical Model for Interpretation of Satellite Imagery. 2021 IEEE 8th International Conference on Problems of Infocommunications, Science and Technology (PIC S&T). doi: https://doi.org/10.1109/picst54195.2021.9772162
6. Khudov, H., Makoveichuk, O., Khizhnyak, I., Shamrai, B., Glukhov, S., Lunov, O. et. al. (2022). The Method for Determining Informative Zones on Images from On-Board Surveillance Systems. International Journal of Emerging Technology and Advanced Engineering, 12 (8), 61–69. doi: https://doi.org/10.46338/ijetae0822_08
7. Ruban, I., Khudov, H., Makoveichuk, O., Khizhnyak, I., Khudov, V., Maliuha, V. et. al. (2021). The Development of a Forecasting Model for the Situation Based on Space Images. 2021 IEEE 16th International Conference on Computer Sciences and Information Technologies (CSIT). doi: https://doi.org/10.1109/csit52700.2021.9648685
8. Niu, Z., Li, H. (2019). Research and analysis of threshold segmentation algorithms in image processing. Journal of Physics: Conference Series, 1237 (2), 022122. doi: https://doi.org/10.1088/1742-6596/1237/2/022122
9. Li, D., Wang, Y. (2018). Application of an improved threshold segmentation method in SEM material analysis. IOP Conference Series: Materials Science and Engineering, 322, 022057. doi: https://doi.org/10.1088/1757-899x/322/2/022057

10. Jha, S. K., Bannerjee, P., Banik, S. (2013). Random Walks based Image Segmentation Using Color Space Graphs. Procedia Technology, 10, 271–278. doi: https://doi.org/10.1016/j.protcy.2013.12.361
11. Al-Azawi, R. J., Al-Jubouri, Q. S., Mohammed, Y. A. (2019). Enhanced Algorithm of Superpixel Segmentation Using Simple Linear Iterative Clustering. 2019 12th International Conference on Developments in ESystems Engineering (DeSE). doi: https://doi.org/10.1109/dese.2019.00038
12. Nguyen, N. T. T., Le, P. B. (2022). Topological Voting Method for Image Segmentation. Journal of Imaging, 8 (2), 16. doi: https://doi.org/10.3390/jimaging8020016
13. Saglam, A., Baykan, N. A. (2017). Sequential image segmentation based on minimum spanning tree representation. Pattern Recognition Letters, 87, 155–162. doi: https://doi.org/10.1016/j.patrec.2016.06.001
14. Pestunov, I. A., Rylov, S. A., Berikov, V. B. (2015). Hierarchical clustering algorithms for segmentation of multispectral images. Optoelectronics, Instrumentation and Data Processing, 51 (4), 329–338. doi: https://doi.org/10.3103/s8756699015040020
15. Pesaresi, M., Benediktsson, J. A. (2001). A new approach for the morphological segmentation of high-resolution satellite imagery. IEEE Transactions on Geoscience and Remote Sensing, 39 (2), 309–320. doi: https://doi.org/10.1109/36.905239
16. Neupane, B., Horanont, T., Aryal, J. (2021). Deep Learning-Based Semantic Segmentation of Urban Features in Satellite Images: A Review and Meta-Analysis. Remote Sensing, 13 (4), 808. doi: https://doi.org/10.3390/rs13040808
17. Avenash, R., Viswanath, P. (2019). Semantic Segmentation of Satellite Images using a Modified CNN with Hard-Swish Activation Function. Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications. doi: https://doi.org/10.5220/0007469604130420
18. Long, J., Shelhamer, E., Darrell, T. (2015). Fully convolutional networks for semantic segmentation. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). doi: https://doi.org/10.1109/cvpr.2015.7298965
19. Lyu, Y., Vosselman, G., Xia, G.-S., Yilmaz, A., Yang, M. Y. (2020). UAVid: A semantic segmentation dataset for UAV imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 165, 108–119. doi: https://doi.org/10.1016/j.isprsjprs.2020.05.009
20. Wang, Y., Lyu, Y., Cao, Y., Yang, M. Y. (2019). Deep Learning for Semantic Segmentation of UAV Videos. IGARSS 2019 – 2019 IEEE International Geoscience and Remote Sensing Symposium. doi: https://doi.org/10.1109/igarss.2019.8899786
21. Ibrahim, N. S., Sharun, S. M., Osman, M. K., Mohamed, S. B., S. Abdullah, S. H. Y. (2021). The application of UAV images in flood detection using image segmentation techniques. Indonesian Journal of Electrical Engineering and Computer Science, 23 (2), 1219. doi: https://doi.org/10.11591/ijeecs.v23.i2.pp1219-1226
22. Li, H., Tang, Y., Liu, Q., Ding, H., Jing, L., Lin, Q. (2014). A novel multi-resolution segmentation algorithm for highresolution remote sensing imagery based on minimum spanning tree and minimum heterogeneity criterion. 2014 IEEE Geoscience and Remote Sensing Symposium. doi: https://doi.org/10.1109/igarss.2014.6947070
23. Lopez, J., Branch, J. W., Chen, G. (2019). Line-based image segmentation method: a new approach to segment VHSR remote sensing images automatically. European Journal of Remote Sensing, 52 (1), 613–631. doi: https://doi.org/10.1080/22797254.2019.1699449
24. Xue, Y., Zhao, J., Zhang, M. (2021). A Watershed-Segmentation-Based Improved Algorithm for Extracting Cultivated Land Boundaries. Remote Sensing, 13 (5), 939. doi: https://doi.org/10.3390/rs13050939
25. Khudov, H., Makoveichuk, O., Butko, I., Gyrenko, I., Stryhun, V., Bilous, O. 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)), 6–14. doi: https://doi.org/10.15587/1729-4061.2022.259759
26. Ruban, I., Khudov, H., Makoveichuk, O., Khudov, V., Kalimulin, T., Glukhov, S. et. al. (2022). Methods of UAVs images segmentation based on k-means and a genetic algorithm. Eastern-European Journal of Enterprise Technologies, 4 (9 (118)), 30–40. doi: https://doi.org/10.15587/1729-4061.2022.263387
27. Mirjalili, S. (2016). SCA: A Sine Cosine Algorithm for solving optimization problems. Knowledge-Based Systems, 96, 120–133. doi: https://doi.org/10.1016/j.knosys.2015.12.022
28. Khudov, H., Makoveichuk, O., Khizhnyak, I., Oleksenko, O., Khazhanets, Y., Solomonenko, Y. et. al. (2022). Devising a method for segmenting complex structured images acquired from space observation systems based on the particle swarm algorithm. Eastern-European Journal of Enterprise Technologies, 2 (9 (116)), 6–13. doi: https://doi.org/10.15587/1729-4061.2022.255203
29. Satellite Imagery. Available at: https://www.maxar.com/products/satellite-imagery
30. Khudov, G. V. (2003). Features of optimization of two-alternative decisions by joint search and detection of objects. Problemy Upravleniya I Informatiki (Avtomatika), 5, 51–59. Available at: https://www.researchgate.net/publication/291431400_Features_of_optimization_of_two-alternative_decisions_by_joint_search_and_detection_of_objects
31. Khudov, H., Makoveichuk, O., Misiuk, D., Pievtsov, H., Khizhnyak, I., Solomonenko, Y. et. al. (2022). Devising a method for processing the image of a vehicle's license plate when shooting with a smartphone camera. Eastern-European Journal of Enterprise Technologies, 1 (2 (115)), 6–21. doi: https://doi.org/10.15587/1729-4061.2022.252310