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DEVISING A METHOD FOR SEGMENTING COMPLEX STRUCTURED IMAGES ACQUIRED FROM SPACE OBSERVATION SYSTEMS BASED ON THE PARTICLE SWARM ALGORITHM

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This paper considers the improved method for segmenting complex structured images acquired from space observation systems based on the particle swarm algorithm. Unlike known ones, the method for segmenting complex structured images based on the particle swarm algorithm involves the following:

– highlighting brightness channels in the Red-Green-Blue color space;

– using a particle swarm method in the image in each channel of brightness of the RGB color space;

– image segmentation is reduced to calculating the objective function, moving speed, and a new location for each swarm particle in the image in each RGB color space brightness channel.

Experimental studies have been conducted on the segmentation of a complex structured image by a method based on the particle swarm algorithm. It was established that the improved segmentation method based on the particle swarm algorithm makes it possible to segment complex structured images acquired from space surveillance systems.

A comparison of the quality of segmenting a complex structured image was carried out. The comparative visual analysis of well-known and improved segmentation methods indicates the following:

– the improved segmentation method based on the particle swarm algorithm highlights more objects of interest (objects of military equipment);

– the well-known k-means method assigns some objects of interest (especially those partially covered with snow) to the snow cover (marked in blue);

– the improved segmentation method also associates some objects of interest that are almost completely covered with snow with the snow cover (marked in blue).

It has been established that the improved segmentation method based on the particle swarm algorithm reduces segmentation errors of the first kind by an average of 12 % and reduces segmentation errors of the second kind by an average of 8 %

Keywords: segmentation, complex structured image, space surveillance system, particle swarm, errors of the first and second kind

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1. Introduction

Under modern conditions, the number of users of information from space surveillance systems is increasing. Information from such systems is used, for example, in monitoring urban infrastructure, agriculture, cartography, military operations, etc. [1]. The most important stage in processing an image acquired from onboard surveillance systems is segmentation.

The peculiarity of images acquired from space surveillance systems is their complex structure [2]. The complex structure is due to the features in forming images from space surveillance systems, the influence of atmospheric factors, the movement of the carrier of surveillance equipment, etc. Features of images from onboard surveillance systems are also a significant number of elements of distinction, heterogeneity and morphological complexity of a large number of objects of interest, low contrast of objects of interest compared to the background. These features greatly complicate the segmentation of complex structured images acquired from space surveillance systems.

Using existing methods for segmenting complex structured images acquired from space surveillance systems is not effective. Therefore, research on devising a method for segmenting complex structured images acquired from space surveillance systems is relevant.

2. Literature review and problem statement

It is proposed in [3] to use the *k*-means method to segment images. The advantage of [3] is the simplicity and speed of the method. The disadvantage of [3] is the dependence on the choice of initial values, and significant segmentation time at high *k* values. This, in turn, leads to segmentation errors (significant errors of the first and second kind).

Paper [4] proposes an adaptive method of image segmentation based on the *k*-means algorithm, which avoids interactive input of the value *k*. In method [4], the input image is converted to the Lightness color space before segmentation. The disadvantage of the method reported in [4] is the need to convert into the color space Lightness and conduct morphological processing as an intermediate stage of the method.

Methods of spatial differentiation are proposed in [5] for the selection of contours. The methods from [5] are effective for segmenting objects of interest of impressive size, subject to a small number of background objects. The disadvantage of [5] is their inefficiency in segmenting complex structured objects.

The methods for highlighting the contours of objects using the operators by Sobel, Prewitt, Kirsch, Wallis, and Roberts are considered in [6]. Those methods are effective with a small number of objects of interest. The main disadvantage is the large time cost.

The classical method of Otsu is proposed in [7] for image segmentation. The classical Otsu method is effective in segmenting simple images, such as medical ones. However, this method has problems finding a threshold value for more complex structured images, which leads to a non-completely segmented image.

In [8], a hybrid Otsu method of image segmentation with an algorithm for optimizing fruit flies based on memory is proposed. The experimental results show that this method produces better results in segmenting images in shades of gray with the presence of noise "salt and pepper". The disadvantage is the difficulty in finding a threshold value for segmenting color images.

In [9], an improved method of Otsu – 2D Otsu is proposed. The advantage of this method is the increased resistance to the "salt and pepper" noise together with the technology of distribution of images based on adaptive energy for segmenting an image with uneven lighting. The disadvantage is the failure to take into consideration image artifacts regarding uneven lighting and noises of other origins.

An improved Canny method for segmenting a noisy image is proposed in [10]. The method employs a medium filter to preserve small details of the image and eliminate noise. The disadvantage is not taking into consideration the complex structure of the image, the presence of a large number of selected edges, and high time costs.

Paper [11] provides an overview of the methods for segmenting heterogeneous images using deep learning neural networks. The methods from [11] are effective for segmenting images of small size. The disadvantage is the considerable time to train neural networks.

In [12], the methods of segmentation of medical images based on neural networks of deep learning are considered. It is established that those methods are effective for segmenting histological images and images of the human brain. The disadvantage is the ability to use them only to segment medical images.

It is proposed in [13] to use the CNN convolutional neural network to segment images of remote sensing of the Earth. The methods from [13] are effective for segmenting plane objects of interest in images of remote sensing of the Earth. The disadvantage is the considerable time to build a training sample, training, and retraining the neural network.

In [14], a multimodal method based on particle swarm optimization is proposed for image segmentation, which includes three successive stages. The advantage of the method is the automatic determination of the number of clusters. The disadvantage is that a given method is effective only for simple images.

Paper [15] proposes the use of a basic particle swarm algorithm to segment an image. The method from [15] randomly assigns the centers of the swarm, and the best value of the objective function is initialized on the histogram of the image. The disadvantage is a sharp coincidence in the early stages of the search process and, as a result, the impossibility of obtaining significant improvements in this process.

In [16], a method for determining objects on tone aerospace images based on ant algorithms is proposed. The method is effective in selecting the contours of objects of interest with a small number of such objects. In a complex structured image acquired from the space surveillance system, applying the method from [16] leads to the presence of a significant number of "garbage" objects.

Study [17] provides an overview of image segmentation methods based on hybrid ant algorithms. It is established that the use of hybrid ant algorithms enables the selection of contours of objects of interest without breaks, as well as an acceptable performance of the method. A disadvantage is a significant number of "garbage" objects when segmenting complex structured images and uncertainty of convergence time when solving an optimization problem.

Thus, our review of known methods for segmenting images acquired from onboard surveillance systems revealed their inefficiency given the complex structure of such images. Therefore, for the further study of segmenting images from onboard surveillance systems, it is advisable to choose the method of particle swarm. The main advantages of the particle swarm method are low algorithmic complexity, efficiency for global optimization, lack of fixation in local optimums, etc.

Therefore, devising a method for segmenting complex structured images acquired from space surveillance systems based on the particle swarm algorithm may solve the problem associated with the limitations of known methods for segmenting images from onboard surveillance systems given the complex structure of such images.

3. The aim and objectives of the study

The aim of this study is to improve a method for segmenting complex structured images acquired from space surveillance systems through the use of the particle swarm algorithm. This will reduce the value of errors of the first and second kind when segmenting complex structured images acquired from space surveillance systems.

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

– to define the main stages in the method for segmenting complex structured images acquired from space surveillance systems based on the particle swarm algorithm;

– to segment a complex structured image acquired from the space surveillance system by a method based on the particle swarm algorithm;

– to conduct a comparative assessment of the quality of segmentation of a complex structured image by the known and devised methods based on the particle swarm algorithm.

4. The study materials and methods

The object of our research is the process of segmenting complex structured images acquired from space surveillance systems.

The basic hypothesis of this study assumed that the use of the particle swarm algorithm when improving the method for segmenting complex structured images acquired from space surveillance systems would reduce the value of segmentation errors of the first and second kind.

During the study, the following research methods were used: a mathematical apparatus of matrix theory; the methods of probability theory and mathematical statistics; the methods of image processing theory; the methods of system analysis; swarm methods; the methods of image processing theory; the methods of mathematical modeling. When validating the proposed solutions, analytical and empirical methods of comparative research were employed.

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

– a complex structured typical image acquired from a space system of optoelectronic observation is considered the original image;

– the original image is represented in the Red-Green-Blue (RGB) color space;

– the image depicts heterogeneous objects of interest;

– the objects of interest are different in spatial structure;

– the size of the objects of interest is much smaller than the size of the background objects;

– the effects of noise, rotation, and zoom in the original image are not taken into consideration.

5. Results of the study on devising a segmentation method based on the particle swarm algorithm

5. 1. The basic stages of the method for segmenting complex structured images based on the particle swarm algorithm

The formalization of the task to segment a complex structured image acquired from a cosmic observation system $f(x, y)$ is represented by expression (1) [18]:

$$f(x,y) \to fs(x,y), \tag{1}$$

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

Segmenting a complex structured image acquired from a space surveillance system (1) involves splitting the original image $f(x, y)$ into B_i segments. In this case, the splitting of the original image $f(x, y)$ into segments must satisfy the following condition (2) [18]:

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

where B: $B=\{B_1, B_2,..., B_K\}$ are segments in the segmented image $fs(x, y)$; K is their number, (i=1, 2,..., K); LP is a predicate.

The predicate LP is equal to "1" when a pair of points from each B_i segment satisfies the following expression (3) [18]:

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

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

The result of the segmentation of a complex structured image acquired from a space surveillance system is the division of an image into objects of interest and other objects (background). The basic stages in the method for segmenting complex structured images based on the particle swarm algorithm are shown in Fig. 1.

The method for segmenting complex structured images based on the particle swarm algorithm involves the following stages:

1. Enter the source data – the original image $f(\boldsymbol{X})$, where $\boldsymbol{X}(x,y)$ is the coordinates of a pixel in the image.

2. Highlight brightness channels in an RGB color space (R brightness channel, G brightness channel, B brightness channel).

3. Initiate a swarm of particles in the image in each channel of brightness within the RGB color space. The initial positions of the particles are determined by the vector of the particle positions on the first iteration $\boldsymbol{X}_{i1}(x_{i1},y_{i1})$, where i=1, 2, ..., S; S is the total number of particles in a swarm.

4. Calculate the objective function for each swarm particle in the image in each brightness channel within the RGB color space.

We shall select a function from the following expression (4) [16, 19] as the objective function:

$$\varphi_j(X) = \sum_{m=1}^{S} \sum_{i=1}^{N} \left(D_i^m(j) \right), \tag{4}$$

where m is the current number of the swarm particle; N is the size of the original image; j is the iteration number.

The function $D_i^m(j)$ determines the route area. This takes into consideration the difference in the bright spots of neighboring pixels for the m-th swarm particle at the i-th point of the image on the j-th iteration [16, 19]. The function $D_i^m(j)$ is determined from the following expression (5) [16, 19]:

$$D_i^m(j) = \left|\Delta x_i^m(j)\right| + \left|\Delta y_i^m(j)\right| + k\left|\Delta f_i^m(j)\right|, \tag{5}$$

where $\left|\Delta x_i^m(j)\right|$, $\left|\Delta y_i^m(j)\right|$ is the movement of the m-th particle of the swarm at the i-th point of the image on the j-th iteration on the axes x and y, respectively;

– k – a coefficient that takes into consideration the difference in scales on the x and y axes and the brightness of the pixels of the image and different units of measurement of elementary displacements and brightness. If the brightness takes values from the range [0..255], then k=1;

– $\left|\Delta f_i^m(j)\right|$ is the difference in the bright spots of neighboring pixels for the m-th particle of the swarm at the i-th point of the image on the j-th iteration. The function $\left|\Delta f_i^m(j)\right|$ is determined from the following expression (6) [16, 19]:

$$\left|\Delta f_i^m(j)\right| = \left|f\left(x_i^m(j), y_i^m(j)\right) - f\left(x_{i-1}^m(j), y_{i-1}^m(j)\right)\right|. \tag{6}$$

Thus, taking into consideration expressions (5), (6), the objective function $\varphi_j(X)$ on the j-th iteration can be calculated from expression (7):

$$\varphi_j(X) = \sum_{m=1}^{S}\sum_{i=1}^{N}\left(\begin{array}{l}\left|\Delta x_i^m(j)\right| + \left|\Delta y_i^m(j)\right| + \\ +k\left(\left|f\left(\begin{array}{l}x_i^m(j), y_i^m(j) - \\ -f\left(x_{i-1}^m(j), y_{i-1}^m\right)\end{array}\right)\right|\right)\end{array}\right). \tag{7}$$

5. Compare the current value of the objective function for each swarm particle with the best value of the objective function in the image in each RGB color space channel.

The best position (gbest) on the j-th iteration is calculated from the following expression (8):

$$X_j^{gbest}(x,y) = \\ = \begin{cases} X_{j-1}(x,y), \\ \text{if } \varphi\left(X_{j+1}(x,y) \geq \varphi\left(X_j\right)\right); \\ X_{j+1}(x,y), \\ \text{if } \varphi\left(X_{j+1}(x,y) < \varphi\left(X_j\right)\right). \end{cases} \tag{8}$$

6. Calculate the value of the move rate and new location for each swarm particle in the image in each brightness channel of the RGB color space.

The speed of movement of each particle of the swarm is determined from the following expression (9):

$$v_{i,j+1}(x,y) = wv_{i,j}(x,y) + \\ +c_1 r_{1,j}\begin{bmatrix}\mathbf{X}_{i,j}^{gbest}(x,y) - \\ -\mathbf{X}_{i,j}(x,y)\end{bmatrix} + \\ +c_2 r_{2,j}\begin{bmatrix}\mathbf{X}_{i,j}^{pbest}(x,y) - \\ -\mathbf{X}_{i,j}(x,y)\end{bmatrix}, \tag{9}$$

where w is the coefficient of inertia (empirical coefficient). It detects changes in speed and manages the discovery of new areas and the search in the vicinity of a promising area; $v_{i,j}(x,y)$ is the value of the velocity of the particle i in iteration j; $\boldsymbol{X}_{i,j}(x,y)$ is the vector of coordinates of the particle i in iteration j; $\mathbf{X}_{i,j}^{pbest}(x,y)$ is the vector of coordinates of the particle with the best value of the objective function among all values of the objective function on the j-th iteration (global optimum). $\mathbf{X}_{i,j}^{pbest}(x,y)$ is determined from the following expression (10):

$$\mathbf{X}_{i,j}^{pbest}(x,y) \in \left\{\mathbf{X}_{i,1}(x,y), \ldots, \mathbf{X}_{i,J}(x,y)\right\}, \\ \text{for } \varphi\left(\mathbf{X}_{i,j+1}^{pbest}(x,y)\right) = \min\left\{\begin{array}{l}\varphi\left(\mathbf{X}_{i,1}(x,y)\right), \ldots, \\ , \varphi\left(\mathbf{X}_{i,J}(x,y)\right)\end{array}\right\}, \tag{10}$$

where J is the total number of iterations; c_1, c_2 are the acceleration coefficients; $r_{1,j}$, $r_{2,j}$ are the random coefficients that take values in the range [0, 1].

7. Move each swarm particle in an image in each RGB color space brightness channel. The coordinates of the swarm particles on the j-th iteration are determined from the following expression (11):

$$\boldsymbol{X}_{i,(j+1)}(x,y) = \boldsymbol{X}_{i,j}(x,y) + v_{i,j}(x,y). \tag{11}$$

8. Check the condition for achieving a criterion for stopping the iterative process. Calculations are repeated until a specified number of iterations is achieved or until the speed increase is close enough to zero.

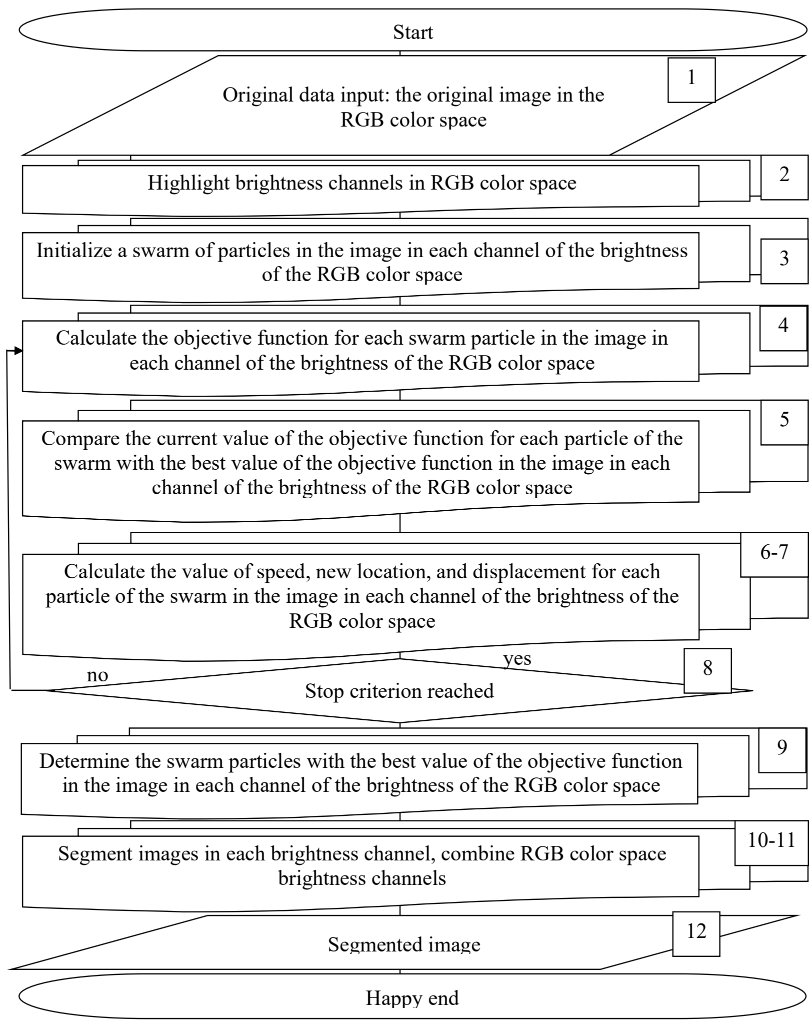

Fig. 1. Basic stages in the method for segmenting complex structured images based on the particle swarm algorithm

9. Determine swarm particles with the best value of the objective function in the image in each brightness channel of the RGB color space.

10. Split images in each RGB color space brightness channel into segments.

11. Combine the brightness channels of the RGB color space.

12. Obtain a segmented image $fs(x, y)$.

Thus, unlike known methods, the method for segmenting complex structured images based on the particle swarm algorithm involves the following:

– selection of brightness channels in the RGB color space;

– using the particle swarm method in the image in each channel of brightness of the RGB color space;

– an image segmentation is reduced to calculating the objective function, moving speed, and a new location for each swarm particle in the image in each RGB color space brightness channel.

5. 2. Segmentation of a complex structured image by a method based on the particle swarm algorithm

A color image below (Fig. 2 [20]) is to be considered an original image.

This is an original optoelectrical image acquired from the WorldView-2 spacecraft (United States) and provided by MAXAR (USA). The image is represented in the RGB color space. The image size is (1868×1348) pixels. The original image from the cosmic system of optoelectronic observation (Fig. 2) is a complex structured image. The objects of interest in the image are pieces of military equipment.

Fig. 3 shows a segmented image after combining the brightness channels of the RGB color space.

Fig. 2. Original color image [20]

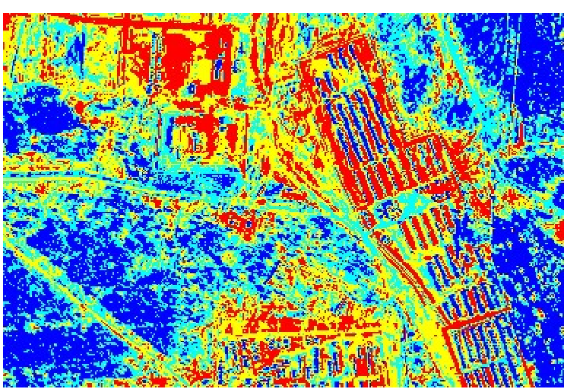

Fig. 3. Segmented image after combining RGB color space brightness channels

In Fig. 3, different segments are highlighted in different colors for clarity. The number of segments is 4. The objects of interest (pieces of military equipment) are highlighted in red. Our analysis of Fig. 3 shows that the improved segmentation method based on the particle swarm algorithm makes it possible to segment complex structured images acquired from space surveillance systems.

5. 3. Assessing the quality of image segmentation by the known and improved methods

To compare the quality of segmenting a complex structured image, we shall consider the following methods: the known method of k-means (k=4); the improved method for segmenting complex structured images acquired from space surveillance systems based on the particle swarm algorithm.

To assess the visual quality, Fig. 4 shows the image segmented by the known k-means method (k=4).

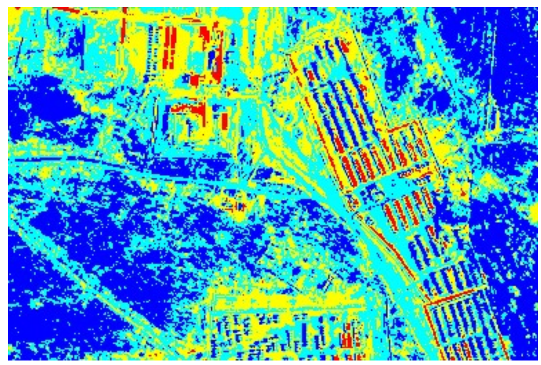

Fig. 4. The image segmented by the known k-means method (k=4)

The comparative analysis of Figs. 3, 4 reveals the following:

– the improved segmentation method based on the particle swarm algorithm highlights more objects of interest (pieces of military equipment);

– the known k-means method assigns some objects of interest (especially those that are partially covered with snow) with snow cover (blue);

– the improved segmentation method based on the particle swarm algorithm also associates some objects of interest that are almost completely covered with snow with the snow cover (blue).

To quantify the quality of image segmentation by the known and improved methods, we shall use segmentation errors of the first and second kinds [16, 18, 21]. Segmentation errors of the first kind (α_1) and the second kind (β_2) are determined by the criterion of maximum likelihood [22]. The criterion of maximum likelihood derives from the generalized criterion of minimum average risk [22]. Segmentation errors of the first kind (α_1) and the second kind (β_2) are calculated from the following expressions (12), (13), respectively [22]:

$$\alpha_1 = \frac{S_1\left(fs(\mathbf{X})\right)}{S_2\left(f(\mathbf{X})\right)}, \quad (12)$$

$$\beta_2 = 1 - \frac{S_3\left(fs(\mathbf{X})\right)}{S_4\left(f(\mathbf{X})\right)}, \quad (13)$$

where $S_1(fs(\boldsymbol{X}))$ is the plane of the background, which is mistakenly attributed to the objects of interest (pieces of military equipment) in the segmented image $fs(\boldsymbol{X})$; $S_2(f(\boldsymbol{X}))$ is the background plane of the original image $f(\boldsymbol{X})$; $S_3(fs(\boldsymbol{X}))$ is the plane of correctly segmented objects of interest (pieces of military equipment) in the segmented image $fs(\boldsymbol{X})$; $S_4(f(\boldsymbol{X}))$ is the plane of objects of interest (pieces of military equipment) in the original image $f(\boldsymbol{X})$.

The results of calculating segmentation errors of the first kind (α_1) and the second kind (β_2) are given in Table 1, Fig. 5, Table 2, and Fig. 6. In Fig. 5, 6, the bottom curve (blue) corresponds to the known k-means method (k=4), and the upper curve (green) corresponds to the improved method.

Table 1 and Fig. 5 show the results of calculating the segmentation errors of the first kind (α_1). Fig. 5 demonstrates the results of estimating errors of the first kind with ten implementations of segmentation of a complex structured image.

Table 2 and Fig. 6 show the results of calculating segmentation errors of the second kind (β_2). Fig. 6 demonstrates the results of estimating errors of the second kind with ten implementations of segmenting a complex structured image.

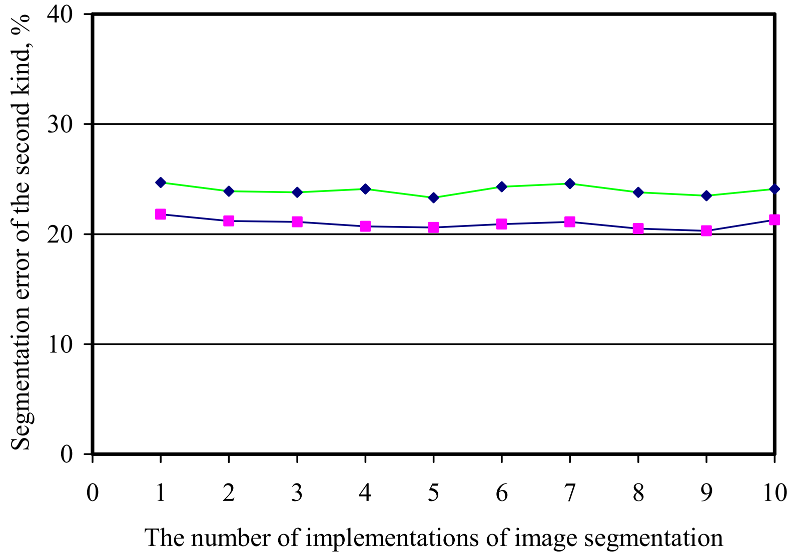

Fig. 6. Calculating a segmentation error of the second kind at the implementations of image segmentation from 1 to 10

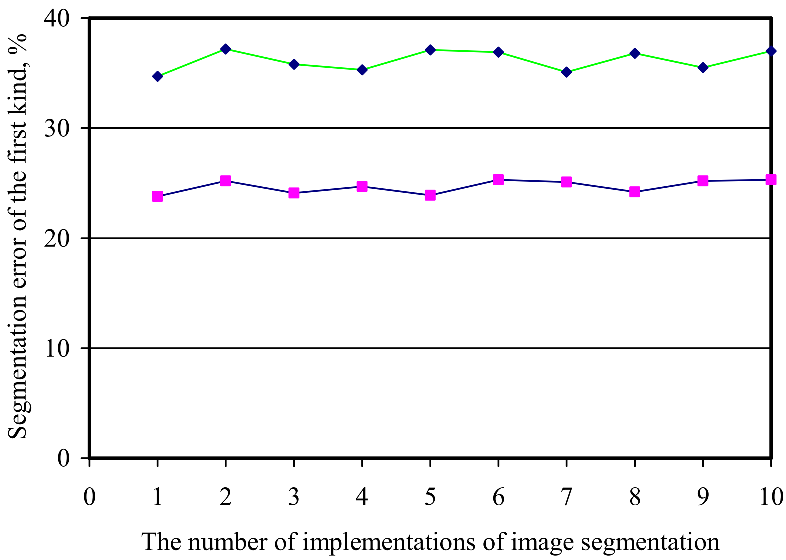

Fig. 5. Calculating a segmentation error of the first kind with the implementation of image segmentation from 1 to 10

Our analysis of Tables 1, 2, Fig. 5, 6 has established that the improved segmentation method based on the particle swarm algorithm reduces segmentation errors of the first kind by an average of 12 % and reduces segmentation errors of the second kind by an average of 8 %.

6. Discussion of results of the study on devising a segmentation method based on the particle swarm algorithm

Unlike known methods, our method for segmenting complex structured images based on the particle swarm algorithm involves:

– the selection of brightness channels in the RGB color space;

– using the particle swarm method in the image in each channel of brightness of the RGB color space;

– an image segmentation is reduced to calculating the objective function, moving speed, and a new location for each swarm particle in the image in each RGB color space brightness channel.

Table 1

The results of calculating segmentation errors of the first kind (α_1)

Name of the segmentation method	Segmentation error of the first kind (α_1), %									
	Image segmentation process number									
	1	2	3	4	5	6	7	8	9	10
Known k-means method (k=4)	34.7	37.2	35.8	35.3	37.1	36.9	35.1	36.8	35.5	37.0
Improved segmentation method based on the particle swarm algorithm	23.8	25.2	24.3	24.7	23.9	25.3	25.1	24.2	25.2	25.3

Table 2

The results of calculating segmentation errors of the second kind (β_2)

Name of the segmentation method	Segmentation error of the second kind (β_2), %									
	Image segmentation process number									
	1	2	3	4	5	6	7	8	9	10
Known k-means method (k=4)	24.7	23.9	23.8	24.1	23.3	24.3	24.6	23.8	23.5	24.1
Improved segmentation method based on particle swarm algorithm	21.8	21.2	21.1	20.7	20.6	20.9	21.1	20.5	20.3	21.3

Experimental studies have been conducted on the segmentation of a complex structured image by a method based on the particle swarm algorithm. A comparison of the quality of segmentation of a complex structured image is carried out. It was established (Tables 1, 2, Fig. 5, 6) that the improved segmentation method based on the particle swarm algorithm reduces segmentation errors of the first kind by an average of 12 % and reduces segmentation errors of the second kind by an average of 8 %.

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

– a complex structured typical image acquired from a space system of optoelectronic observation is considered the original image;

– the original image is represented in the color space Red-Green-Blue (RGB);

– the image presents heterogeneous objects of interest;

– the objects of interest are different in spatial structure;

– the size of the objects of interest is much smaller than the size of the background objects;

– the effects of noise, rotation, and zoom in the original image are not taken into consideration.

The improved method for segmenting complex structured images based on the particle swarm algorithm can be implemented in software and hardware systems for processing complex structured images acquired from space surveillance systems.

The disadvantages of the improved method for segmenting complex structured images based on the particle swarm algorithm are the difficulty in selecting the parameters for the method – the inertia coefficient, acceleration coefficients, and some random coefficients.

Further research should focus on determining the optimal value of the number of segments when segmenting a complex structured image acquired from a space observation system by a method based on the particle swarm algorithm.

7. Conclusions

1. The basic stages in the method for segmenting complex structured images acquired from space observation systems based on the particle swarm algorithm have been determined. Unlike known methods, our method for segmenting complex structured images based on the particle swarm algorithm involves:

– the selection of brightness channels in the RGB color space;

– using the particle swarm method in the image in each channel of brightness of the RGB color space;

– an image segmentation is reduced to calculating the objective function, moving speed, and a new location for each swarm particle in the image in each RGB color space brightness channel.

2. Experimental studies have been conducted on the segmentation of a complex structured image by a method based on the particle swarm algorithm. It is established that the improved segmentation method based on the particle swarm algorithm makes it possible to segment complex structured images acquired from space surveillance systems.

3. We have compared the quality of segmenting a complex structured image. It is established that the improved segmentation method based on the particle swarm algorithm reduces segmentation errors of the first kind by an average of 12 % and reduces segmentation errors of the second kind by an average of 8 %.

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