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DEVISING A METHOD FOR SEGMENTING CAMOUFLAGED MILITARY EQUIPMENT ON IMAGES FROM SPACE SURVEILLANCE SYSTEMS USING A GENETIC ALGORITHM

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The object of this research is the process of segmentation of camouflaged military equipment in images from space surveillance systems.

The method of segmentation of camouflaged military equipment in images from space surveillance systems has been improved using a genetic algorithm. Unlike known methods, the method of segmentation of camouflaged military equipment using a genetic algorithm involves the following:

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

– the use of a genetic algorithm in the image in each channel of brightness of the RGB color space;

– image segmentation is reduced to the formation of generations and populations of chromosomes, the calculation of the objective function, selection, crossing, mutation, and decoding of chromosomes in each brightness channel of the Red-Green-Blue color space.

Experimental studies were conducted on the segmentation of camouflaged military equipment using a genetic algorithm. It is established that the improved method of segmentation using a genetic algorithm makes it possible to segment images from space surveillance systems.

A comparison of the quality of segmentation was carried out. It is established that the improved method of segmentation using a genetic algorithm reduces segmentation errors in the following way:

– compared to the known k-means method, by an average of 15 % of errors of the first kind and an average of 7 % of errors of the second kind;

– compared to the method of segmentation based on the algorithm of swarm of particles, by an average of 3.8 % of errors of the first kind and an average of 2.9 % of errors of the second kind.

The improved segmentation method using a genetic algorithm can be implemented in software and hardware imaging systems from space surveillance systems

Keywords: optoelectronic image, camouflaged military equipment, genetic algorithm, chromosome population

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1. Introduction

The modern experience of the leading countries of the world indicates an increase in attention to the integrated conduct of all types of intelligence and surveillance. At the same time, considerable attention is paid to the conduct of observation using space systems [1]. Space surveillance systems should promptly provide political, military authorities, as well as the armed forces with the necessary information with maximum completeness, accuracy, and reliability.

The requirements of consumers of information from space surveillance systems regarding its completeness, reliability, accuracy, and reliability require the use of appropriate methods for processing and segmenting optoelectronic images. This is especially important and relevant when conducting surveillance under the conditions of using a wide arsenal of camouflage tools and measures [3]. At the same time, a wide arsenal of camouflage tools and measures is applied, first of all, to military objects [3].

The complexity of the use of known methods of segmentation of optoelectronic images from space surveillance systems is determined by a significant decrease in the visibility of military facilities. Using segmentation methods requires selecting textured objects with a large range of possible color values. That requires additional study, determining, and consideration of the characteristics and features of masking tools, their characteristic features, etc. Consequently, the use of well-known methods of segmentation of camouflaged military equipment in images from space surveillance systems is not effective. Therefore, research into the development of a method of segmentation of camouflaged military equipment in images from space surveillance systems is relevant.

2. Literature review and problem statement

Paper [4] states that camouflage nets are used to shelter buildings, structures, military equipment, etc. Owing to this cover, the color contrast of the objects of interest on the surrounding background becomes lower. In [4], it is noted that segmentation methods based on the basic properties of the brightness signal – on breakage, give a large number of "noisy" objects. Therefore, in the presence of a constant texture of the camouflage grid, for segmentation of such images, in [4], segmentation methods based on statistical description of textures are proposed. The essence of methods [4] is to calculate the numerical characteristics of the texture. In this case, the texture is a quantitative characteristic of the distribution of intensity values in the image area. The disadvantage of [4] is their inefficiency in the case of segmentation of objects masked by a natural background.

In [5], the method of segmentation of the image using the indicators of the texture energy of Lawes is proposed. In the first stage, the mask calculates the local average for each pixel in the image in order to eliminate the effects of the intensity of lighting. In the second stage, sixteen formed masks of size (5×5) are applied to the image in parallel. These masks are formed in order to isolate different components of textures and receive resultant energy indicators. As a result, each element in the image is represented by a vector of textured features. These textured features are the energy characteristics of Lawes. The advantage of the method [5] is the selection of all texture features in the image. The disadvantage of the method [5] is the need to choose the size of the mask depending on the type of image at the first stage and the need to work with sixteen masks on the image simultaneously on the second.

In [6], the method of segmentation is proposed, based on the calculation of the matrix of matches. The essence of this method is to analyze for each pixel the image of signs formed on the basis of a matrix of coincidences, in which statistical information is collected about the mutual arrangement of bright spots in the vicinity of this pixel. The advantage of the method [6] is the use of a small amount of memory. The disadvantages [6] are:

– the need to select a displacement vector between pixels with different brightness;

– determining the characteristic features that are most effective for solving a specific problem;

– the need for texture standards and computing costs.

Paper [7] proposes an automatic segmentation method based on the k-mean clustering method in order to clarify the classes in the image and match the texture features. Since the process of calculating the matrix of matching gray levels requires an increase in computing resources, it is proposed to use an indexed list for quick access to elements. This approach significantly optimizes an algorithm called an indexed list of gray-level matches. The advantage of [7] is to reduce the computational segmentation time. The disadvantage of [7] is dependence on the choice of initial clusters.

In [8], the method of segmentation using fuzzy clustering of C-averages is considered, with the help of which clusters and their labels are automatically selected. Fuzzy entropy is used to determine the number of clusters. Image pixels are classified by the corresponding clusters based on the minimum Euclidean distance. The advantages of [8] are the lack of a priori information for the segmentation of the color area; in addition, there is no obvious distortion or color change after segmentation. The disadvantage of [8] is the failure to take into consideration local information in the context of the image, which makes it sensitive to additive noise and impairs the characteristics of the pixels of the image.

In [9], an improved image segmentation method based on a fuzzy local binary C-medium pattern is proposed. In addition to using the gray level match matrix and its application to segment images, an algorithm for selecting the iteration threshold is additionally introduced. It also uses a local binary template. The advantage of [9] is to reduce the loss of information about texture, better accuracy, and reliability. The disadvantage of [9] is sensitivity to noise of different origins.

In [10], to segment the image on the basis of the Voronoi mosaic, a set of polygons is built, polygons with common properties are selected and combined in the region. To study the general properties, signs are used – moments of polygons. The advantage of [10] is their ability to clearly select contours. The disadvantage of [10] is low performance.

In [11], it is proposed to segment using the Haahr mosaic method, which consists of constructing primitives, assembling mosaics of primitives, and analyzing mosaic elements. Primitives are obtained by applying spatial filtering to the image and selecting points of local maximums to which the build-up method is applied. The resulting eight-connected components are taken as primitives. The advantage of [11] is its performance. The disadvantage of [11] is their poor results in the presence of a combination of textured and untextured areas.

In [12], the algorithm for calculating the fractal dimension of digital images is proposed, depending on the choice of the evaluation method. A comparison of the fractal dimension of the images was carried out and it was proved that the fractal dimension is a good tool for measuring the texture of the image. The disadvantage of [12] is that not all textures stand out for the dimension of the fractal. Therefore, it is necessary to evaluate the fractality of the texture before including it in the system of signs.

In [13], the method of segmentation by spectral measures of texture, which are calculated by the Fourier spectrum, is proposed. Paper [13] proposes an approach to calculating texture distortion descriptors in the frequency area. New texture characteristic descriptors have been introduced that describe how a unit of texture is repeated globally throughout the image, such as the linearity of pattern formation and the direction of repetition. The method [13] is good to use in the presence of prior information. The disadvantage of [13] is the presence of fine texture on the segmented image.

Paper [14] proposes methods in which convolutional neural network (CNN) functions are used to produce traits, and the support vector machine is used as a classifier for texture classification. The effectiveness of using CNN functions derived from various pre-trained models ResNet50, ResNet101, DenseNet201, AlexNet, Inceptionv3 and classification using the SVM classifier are investigated. The results of the method [14] showed high accuracy in the selection of texture objects. The advantage of [14] is also a short time of calculation. The disadvantage of [14] is the need for primary training of the convolutional neural network.

In [15], a modified feature selection algorithm for classifying and recognizing color textures is proposed, which combines functions derived from local binary patterns (LBPs) and convolutional neural networks (CNN). The goal [15] is to obtain discriminatory information, which leads to better texture classification results. CNN classified images based on global traits that describe the image as a whole. LBP classifies images based on local features describing key points in an image. The advantage of [15] is that the use of LBP improves classification tasks compared to using CNN only. The disadvantage of [15] is that a deep neural network intensively uses memory and requires a large amount of data to be trained.

In [16], an improved method of segmentation of complex structured images from space observation systems based on the algorithm of a swarm of particles is proposed. Experimental studies on segmentation by the method [16] have shown that disguised objects of interest are allocated to a separate segment. The advantages of [16] are the low algorithmic complexity of the method, the lack of fixation in local optimums, and the efficiency of processing complex images. The disadvantage of [16] is the difficulty in selecting the parameters of the method – coefficients of acceleration, inertia, and some random coefficients.

Paper [17] analyzes methods for detecting and classifying vessels on cosmic optical images. The advantages of methods [17] are the ability to combine optical data with other data sources, taking into consideration heterogeneous factors that greatly affect the accuracy of the vessel's detection. The disadvantages of [17] are the lack of recommendations for choosing the most appropriate method of detecting ships and the impossibility of working under the conditions of disguise of ships.

In [18], the methods of image processing from on-board surveillance systems are proposed. Unlike known methods that focus on a particular class of objects, such as a building and a road, the advantage of methods [18] is their application in more general categories of objects. The disadvantage of [18] is the possibility of their application to large plane objects (airport, urban infrastructure, etc.).

In [19], the information technology to highlight objects of military equipment is proposed. A segment map of the image, its construction and use of fuzzy logical detection systems are proposed. The advantage of [19] is the ability to solve a problem under the conditions of uncertainty of input data. The disadvantage of [19] is the ability to work on aircraft objects.

In [20], the method of segmentation of images based on a swarm of particles is proposed. The advantage of [20] is the ability to determine the optimal number of clusters. The disadvantage of [20] is the effectiveness of the method for segmenting simple images.

In [21], the method of segmentation based on the basic algorithm of a swarm of particles is proposed. The method [21] makes it possible to determine the centers of the swarm and the optimal value of the objective function. The disadvantage of [21] is its instability in the early stages of solving the optimization problem.

In [22], it is proposed to apply ant algorithms for segmentation into tone aerospace images. The method [22] is effective in the presence of single objects of interest in the image. The disadvantage of the method [22] is the impossibility of its use for the segmentation of disguised objects of interest.

In [23], a comprehensive review of image segmentation was conducted. Clustering methods, performance parameters, and control data sets are considered. Two main methods of clustering are investigated, namely hierarchical and distribution methods of clustering. Since distribution clustering is better in terms of computation, further research is conducted in terms of methods belonging to this class. In addition, clustering methods are divided into three categories, namely K-medium-based methods, histogram-based methods, and meta-heuristics-based methods. The disadvantages of [23] are the impossibility of their use for segmentation of disguised military facilities.

Thus, when analyzing known methods of segmentation of images, their inefficiency is established under the conditions of segmentation of disguised military equipment in images from space surveillance systems. It is established that the camouflage color of military equipment leads to the proximity of its color characteristics to the color characteristics of the background. In this case, there is also a large number of textures in the image.

Therefore, the development of a method for segmenting camouflaged military equipment in images from space surveillance systems is relevant.

3. The aim and objectives of the study

The aim of this study is to improve the method of segmentation of camouflaged military equipment in images from space surveillance systems based on a genetic algorithm. This will reduce the value of errors of the first and second kind of segmentation of camouflaged military equipment in images from space surveillance systems.

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

– to determine the main stages of the method of segmentation of camouflaged military equipment in images from space surveillance systems based on a genetic algorithm;

– to perform the segmentation of camouflaged military equipment in images from space surveillance systems based on a genetic algorithm;

– to conduct a comparative assessment of the quality of segmentation of camouflaged military equipment in images from space surveillance systems by the well-known and developed method based on a genetic algorithm.

4. The study materials and methods

The object of this research is the process of segmentation of camouflaged military equipment in images from space surveillance systems.

The main hypothesis of the study assumes that the use of a genetic algorithm in improving the method of segmentation of camouflaged military equipment in images from space surveillance systems will reduce the value of segmentation errors of the first and second kind.

During the study, the following research methods were used:

– in determining the main stages of the segmentation method: methods of digital image processing, methods of probability theory, methods of the theory of mathematical statistics, iterative methods, genetic methods, methods of system analysis, mathematical apparatus of matrix theory;

– when segmenting camouflaged military equipment on images from space surveillance systems based on a genetic algorithm: methods of digital image processing, genetic methods, methods of system analysis;

– in carrying out a comparative assessment of the quality of segmentation: analytical and empirical methods of comparative research, methods of mathematical modeling, methods of probability theory, methods of the theory of mathematical statistics.

Analytical and empirical methods of comparative research were used in validation of the proposed solutions.

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

– as the output image, we considered images from the space system of optoelectronic electronic observation;

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

– the image shows heterogeneous objects of military equipment, including camouflaged;

– the camouflaged object is understood as the object of military equipment located under the snow;

– the size of military equipment objects is taken 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 the development of a segmentation method using the genetic algorithm

5. 1. The main stages of the method of segmentation of camouflaged military equipment using a genetic algorithm

To formalize the task of segmenting camouflaged military equipment in the image $f(x, y)$ from the space surveillance system, we shall use expression (1) [16, 24]:

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

where $f(x, y)$ is the original image; $fs(x, y)$ – segmented image.

Segmentation of the image $f(x, y)$ involves splitting the original image (1) into B_i segments, taking into consideration condition (2) [16, 24]:

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

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

The predicate LP is determined by condition (3) [16, 24]:

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

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

The result of segmenting the image $f(x, y)$ is its division into objects of interest and background (or other objects).

The main stages of the method of segmentation of camouflaged military equipment based on a genetic algorithm are shown in Fig. 1. In Fig.1, some notations are borrowed from [25, 26]

The method of segmentation of camouflaged military equipment in images from space surveillance systems using a genetic algorithm involves the following main stages:

1. Enter source data:

– the original image $f(\boldsymbol{X})$, where $\boldsymbol{X}(x, y)$ is the pixel coordinates in the image;

– N is the number of pixels in the image $f(\boldsymbol{X})$ (determined by the size of the image);

– K is the number of segments (i=1, 2,..., K);

– w is the number of chromosomes in the population;

– L is the number of generations in the process of evolution;

– P_c is the probability of performing a genetic crossover operator;

– P_m is the probability of performing a genetic mutation operator.

2. Initialization of the generation number (l=1).

3. Initialization of chromosome number in the population (t=1).

4. Random definition of one of the possible segmentation options. As one of the possible segmentation options, the vector $g_l^t = (g_{l1}^t, g_{l2}^t, ... g_{lK}^t)$, is used, where $t = \overline{1,w}$ (t is the number of the chromosome in the population). The number of components of the vector g_l^t is equal to the number of segments. When encoding the values of the components of the chromosome in accordance with [25], we shall use a decimal number system. The whole value of the component g_{lr}^t (r-th gene in chromosome) encodes the segment number, which should include the r-th pixel of the image and is in the interval [1, K].

5. Calculate function $\phi(g_l^t)$ using expression (4):

$$\phi(g_l^t) = \\ = \begin{cases} 1, \text{ if } \exists \mathrm{r} \in [1,\mathrm{N}] \text{ what } \mathrm{g}_{lr}^t = j \text{ for } \forall \mathrm{j} \in [1,\mathrm{K}]; \\ 0, \text{ if } \exists j \in [1,\mathrm{K}] \text{ what } \overline{\exists} \mathrm{r} \in [1,\mathrm{N}], \text{ for } \mathrm{g}_{lr}^t = j. \end{cases} \tag{4}$$

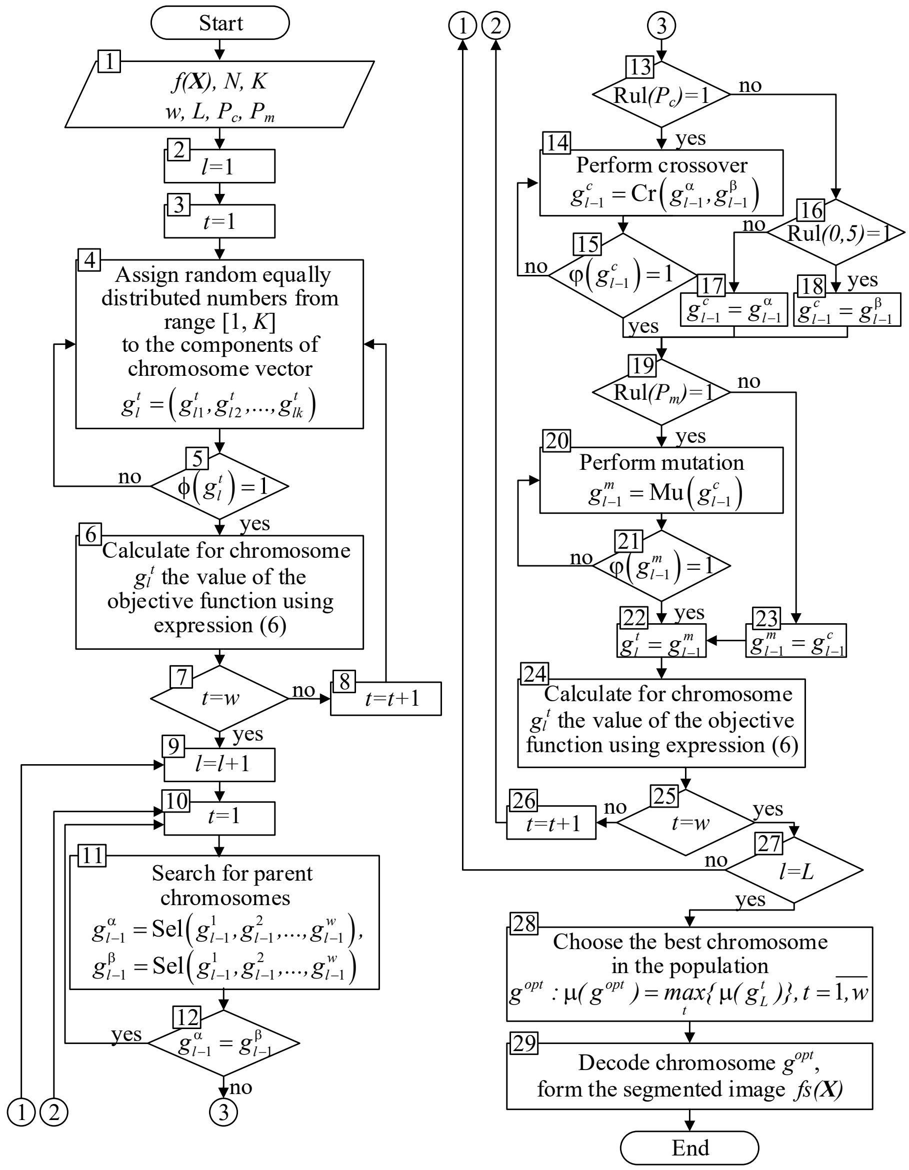

Fig. 1. The main stages of the method of segmentation of camouflaged military equipment in images from space surveillance systems using a genetic algorithm

The function $\phi\left(g_l^t\right)$ was introduced for the following reasons. It is known [25, 26] that the genetic algorithm uses operators of selection, crossover, mutations of chromosomes. At the same time, it is possible when these operators can be applied to pixels of segments that do not correspond to a certain number of segments K. The probability of such an event is quite high due to the random nature of the choice of component values in the formation of the initial population of chromosomes. This is also influenced by the work of other genetic operators.

To exclude such an event, a function $\phi\left(g_l^t\right)$ (expression (4)) is entered. As a result of satisfying the condition (4) chromosome either continues to participate in the method at $\phi\left(g_l^t\right)=1$, or it is removed when $\phi\left(g_l^t\right)=0$.

If you enter a filtration operator $Fil\left(g_l^t\right)$, it matches to the chromosome in relation to which it is performed, either itself or an empty set (expression (5)):

$$Fil\left(g_l^t\right)=\begin{cases} g_l^t, \text{ if } \phi\left(g_l^t\right)=1; \\ 0, \text{ if } \phi\left(g_l^t\right)=0. \end{cases} \quad (5)$$

6. Calculation of the objective function $\mu\left(g_l^t\right)$ by expression (6):

$$\mu\left(g_l^t\right)=\frac{\frac{1}{K}\sum_{j=1}^{K}\left(\frac{1}{k_j}\sum_{p=1}^{k_j} d^2\left(\mathbf{X}_j^p;\mathbf{X}_{0_j}\right)\right)}{\frac{1}{C_K^2}\sum_{i=1}^{K-1}\left(\sum_{j=i+1}^{K} d^2\left(\mathbf{X}_{0_i};\mathbf{X}_{0_j}\right)\right)}, \quad (6)$$

where k_j is the number of pixels belonging to the j-th segment; $\mathbf{X}_{0j}$ – coordinates of the point of the center of the j-th segment in the pixel brightness space; $d\left(\mathbf{X}_j^p;\mathbf{X}_{0_j}\right)$ – Euclidean distance from the input image of pixels with coordinates $\mathbf{X}_j^p$ in the brightness space to the center of its j-th segment; C_K^2 – the number of connections from K to 2; – the square of the distance between the centers of the i-th and j-th segments.

Stages 7–10 that are shown in Fig. 1 are understandable and need no further explanation.

11. Search for parent chromosomes. The *Sel* selection operator is introduced. Operator *Sel* selects the chromosome

for further recovery according to the principle of "survival of the best" using the "virtual roulette" procedure [25, 26]. This procedure allows chromosomes with a greater value of the objective function to be selected more likely.

Stage 12 needs no comment.

13. We entered the function $Rul(P_c)$, which takes the value of one in the case of an event, the probability of which is P_c.

14. Cross two chromosomes g^{α}_{l-1} and g^{β}_{l-1} using the crossover operator *Cr*. The result is a new chromosome that moves to a new population.

Stages 15–19 are shown in Fig. 1.

20. A mutation of the "gene" with the number $r_m \epsilon [1,k]$ is performed.

Stages 21–28 are shown in Fig. 1.

29. Due to the decoding of the chromosome, a segmented image is formed $fs(x, y)$.

In the case of the representation of the original image in the color space Red-Green-Blue (RGB), a preliminary selection of brightness channels is performed (brightness channel R, brightness channel G, brightness channel B), the stages of the method (Fig. 1) are carried out for each brightness channel and channels are combined.

Thus, unlike the well-known ones, the method of segmentation of camouflaged military equipment in images from space surveillance systems using a genetic algorithm involves:

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

– the use of a genetic algorithm in the image in each channel of brightness of the RGB color space;

– image segmentation is reduced to the formation of generations and populations of chromosomes, in the population, the calculation of the objective function, selection, crossing, mutation, and decoding of chromosomes in each channel of brightness of the RGB color space.

5. 2. Segmentation of camouflaged military equipment in images using a genetic algorithm

As a source image, we shall consider a color image (Fig. 2 [16, 27]).

Fig. 2. Original color image [16, 20]

This original optoelectronic image is presented on the website of MAXAR (United States of America (USA)). The image was acquired from the WorldView-2 spacecraft ((USA) and is represented in the RGB color space. The image size is1868×1348 pixels.

The image shows objects of military equipment, some of them camouflaged under snow.

Fig. 3 demonstrates a segmented image by an improved method using a genetic algorithm after combining the brightness channels of the RGB color space.

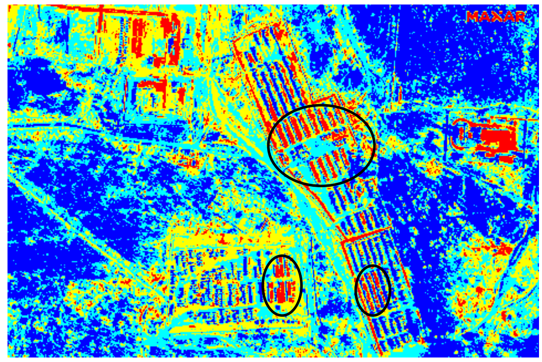

Fig. 3. Segmented image by advanced method using genetic algorithm after combining RGB color brightness channels

For clarity, in Fig. 3, different segments are highlighted in different colors. The number of segments is 4. Objects of military equipment are highlighted in red. Ellipses mark military equipment camouflaged as snow (white).

The analysis of Fig. 3 reveals that the improved method of segmentation of camouflaged military equipment in images using a genetic algorithm makes it possible to segment images from space surveillance systems.

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

To compare the quality of segmentation of camouflaged military equipment, we shall consider the following methods:

– a known method of k-means (k=4);

– a method of segmentation based on the algorithm of a swarm of particles [16];

– the improved method using a genetic algorithm.

To assess the visual quality, Fig. 4 shows a segmented image by the known method of k-means (k=4) [16].

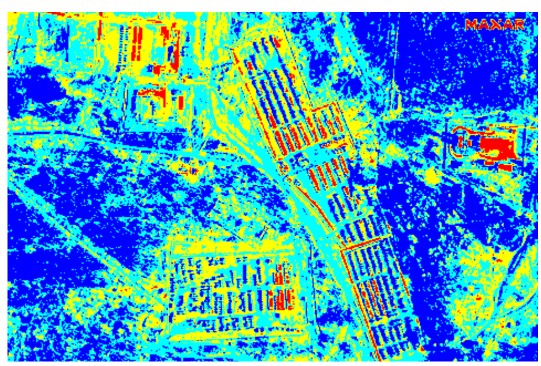

Fig. 4. Segmented image by the known k-means method (k=4) [16]

Fig. 5 depicts a segmented image by the segmentation method based on the particle swarm algorithm [16].

The comparative visual analysis of Fig. 3 to 5 indicates the following:

– the well-known k-means method refers objects of military equipment camouflaged as snow to the background (blue);

– the method of segmentation based on the particle swarm algorithm distinguishes some camouflaged military equipment but has a lack of re-segmentation;

– the improved method of segmentation using a genetic algorithm makes it possible to segment camouflaged military objects.

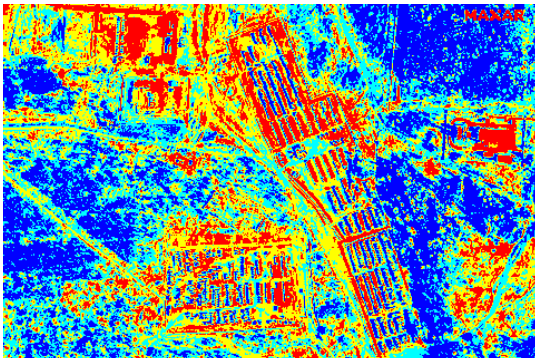

Fig. 5. Segmented image by the segmentation method based on particle swarm algorithm [16]

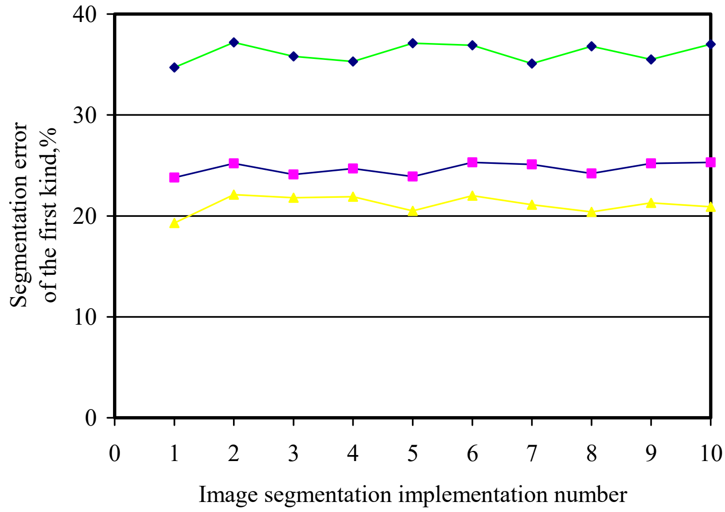

Fig. 6. Calculation of the error of segmentation of the first kind in the implementations of image segmentation from 1 to 10

We shall quantify the quality of image segmentation by the above segmentation methods. The segmentation indicator is the segmentation errors of the I and II kinds [16, 28, 29]. Segmentation errors of the first (α_1) and second (β_2) kinds are calculated from expressions (7), (8), respectively [16, 28, 29]:

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

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

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

The results of the calculation of segmentation errors of the first (α_1) and second (β_2) kinds are given in Tables 1, 2, shown in Fig. 6, 7. In Fig. 6, 7, the green curve corresponds to the known method of k-means (k=4), the blue curve corresponds to the method based on a swarm of particles, and the yellow curve corresponds to the method using a genetic algorithm.

Table 1 and Fig. 6 show the results of calculating the errors of segmentation of the first (α_1) kind. Fig. 6 demonstrates the results of the evaluation of errors of the first kind with ten implementations of segmentation of the original image.

Table 2 and in Fig. 7 show the results of calculating errors of segmentation of the second (β_2) kind. Fig. 7 demonstrates the results of the assessment of errors of the second kind with ten implementations of segmentation of the original image.

The analysis of Tables 1, 2, and Fig. 6, 7 revealed that the improved segmentation method using a genetic algorithm reduces segmentation errors:

– compared to the known k-means method, by an average of 15 % of errors of the first kind and an average of 7 % of errors of the second kind;

– compared to the method of segmentation based on the algorithm of a swarm of particles, by an average of 3.8 % of errors of the first kind and an average of 2.9 % of errors of the second kind.

Table 1

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

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 method of k-means (k=4)	34.7	37.2	35.8	35.3	37.1	36.9	35.1	36.8	35.5	37.0
Segmentation method based on particle swarm algorithm	23.8	25.2	24.3	24.7	23.9	25.3	25.1	24.2	25.2	25.3
Segmentation method using a genetic algorithm	19.3	22.1	21.8	21.9	20.5	22.0	21.1	20.4	21.3	20.9

Table 2

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

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 method of k-means (k=4)	24.7	23.9	23.8	24.1	23.3	24.3	24.6	23.8	23.5	24.1
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
Segmentation method using a genetic algorithm	18.6	19.0	19.2	18.8	19.3	18.9	19.0	19.2	18.7	19.4

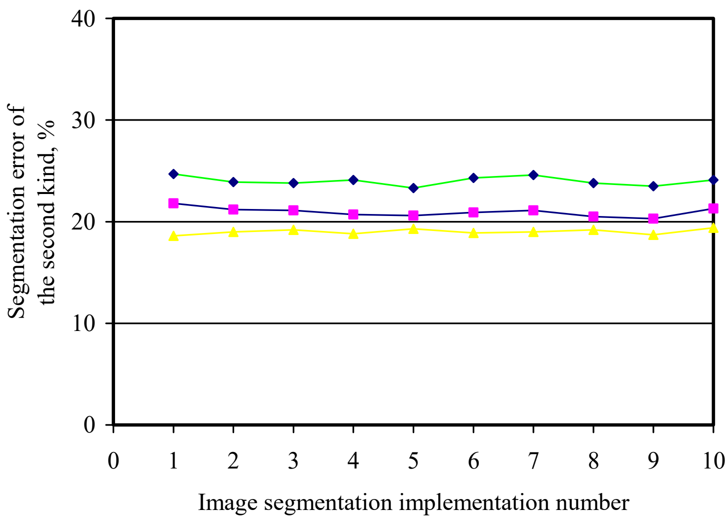

Fig. 7. Calculation of the error of segmentation of the second kind in the implementations of image segmentation from 1 to 10

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

Unlike the well-known ones, the method of segmentation of camouflaged military equipment in images from space surveillance systems using a genetic algorithm involves:

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

– the use of a genetic algorithm in the image in each channel of brightness of the RGB color space;

– image segmentation is reduced to the formation of generations and populations of chromosomes, in the population, the calculation of the objective function, selection, crossing, mutation, and decoding of chromosomes in each channel of brightness of the RGB color space.

Experimental studies were conducted on the segmentation of camouflaged military equipment in images from space surveillance systems using a genetic algorithm. The comparison of the quality of segmentation was carried out. It is established (Tables 1, 2, Fig. 6, 7) that the improved method of segmentation using a genetic algorithm reduces segmentation errors:

– compared to the known *k*-means method, by an average of 15 % of errors of the first kind and an average of 7 % of errors of the second kind;

– compared to the method of segmentation based on the algorithm of a swarm of particles, by an average of 3.8 % of errors of the first kind and an average of 2.9 % of errors of the second kind.

This is made possible by the use of a genetic algorithm when segmenting camouflaged military equipment in images.

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

– as the output image, we considered images from the space system of optoelectronic observation;

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

– the image shows heterogeneous objects of military equipment, including camouflaged;

– the camouflaged object is understood as the object of military equipment located under the snow;

– the size of military equipment objects is accepted 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 segmentation method using a genetic algorithm can be implemented in software and hardware imaging systems from space surveillance systems.

The disadvantages of the improved method of segmentation using a genetic algorithm are considerable time to perform operations.

Further research may be aimed at determining the value of the number of segments when segmenting an image from a space surveillance system.

7. Conclusions

1. The main stages of the segmentation method using the genetic algorithm have been determined. Unlike the well-known ones, the method of segmentation of camouflaged military equipment in images from space surveillance systems using a genetic algorithm involves:

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

– the use of a genetic algorithm in the image in each channel of brightness of the RGB color space;

– image segmentation is reduced to the formation of generations and populations of chromosomes, in the population, the calculation of the objective function, selection, crossing, mutation, and decoding of chromosomes in each channel of brightness of the RGB color space.

2. Experimental studies were conducted on the segmentation of camouflaged military equipment in images from space surveillance systems using a genetic algorithm. It is established that the improved method of segmentation using a genetic algorithm makes it possible to segment images from space surveillance systems.

3. The comparison of the quality of segmentation was carried out. It is established that the improved method of segmentation using a genetic algorithm reduces segmentation errors:

– compared to the known *k*-means method, by an average of 15 % of errors of the first kind and an average of 7 % of errors of the second kind;

– compared to the method of segmentation based on the algorithm of a swarm of particles, by an average of 3.8 % of errors of the first kind and an average of 2.9 % of errors of the second kind.

References

1. Harrison, T., Strohmeyer, M. (2022). Commercial Space Remote Sensing and Its Role in National Security. CSIS Briefs. Available at: https://csis-website-prod.s3.amazonaws.com/s3fs-public/publication/220202_Harrison_Commercial_Space.pdf?VgV9.43i5ZGs8JDAYDtz0KNbkEnXpH21
2. Military Imaging and Surveillance Technology (MIST) (Archived). Available at: https://www.darpa.mil/program/military-imaging-and-surveillance-technology

3. Harrison, T., Reid, C. (2022). Battle Networks and the Future Force. CSIS Briefs. Available at: https://csis-website-prod.s3.amazonaws.com/s3fs-public/publication/220304_Harrison_Battle_Networks_3.pdf?gIu7lDrCNMQmOByzH0IOIfCeWErbzv7J
4. Armi, L., Fekri-Ershad, S. (2019). Texture image analysis and texture classification methods - A review. International Online Journal of Image Processing and Pattern Recognition, 2 (1), 1–29. doi: https://doi.org/10.48550/arXiv.1904.06554
5. Kvyetnyy, R., Sofina, O., Olesenko, A., Komada, P., Sikora, J., Kalizhanova, A., Smailova, S. (2017). Method of image texture segmentation using Laws' energy measures. SPIE Proceedings. doi: https://doi.org/10.1117/12.2280891
6. Cai, Z., Hu, Q., Deng, X., Li, S. (2019). Reversible image watermarking based on texture analysis of grey level co-occurrence matrix. International Journal of Computational Science and Engineering, 19 (1), 83. doi: https://doi.org/10.1504/ijcse.2019.10020959
7. De O. Bastos, L., Liatsis, P., Conci, A. (2008). Automatic texture segmentation based on k-means clustering and efficient calculation of co-occurrence features. 2008 15th International Conference on Systems, Signals and Image Processing. doi: https://doi.org/10.1109/iwssip.2008.4604387
8. Hung, C.-C., Song, E., Lan, Y. (2019). Image Texture, Texture Features, and Image Texture Classification and Segmentation. Image Texture Analysis, 3–14. doi: https://doi.org/10.1007/978-3-030-13773-1_1
9. Tian, Y., Li, Y., Liu, D., Luo, R. (2016). FCM texture image segmentation method based on the local binary pattern. 2016 12th World Congress on Intelligent Control and Automation (WCICA). doi: https://doi.org/10.1109/wcica.2016.7578571
10. Jing, Z., Wei, D., Youhui, Z. (2012). An Algorithm for Scanned Document Image Segmentation Based on Voronoi Diagram. 2012 International Conference on Computer Science and Electronics Engineering. doi: https://doi.org/10.1109/iccsee.2012.144
11. Cheng, R., Zhang, Y., Wang, G., Zhao, Y., Khusravsho, R. (2017). Haar-Like Multi-Granularity Texture Features for Pedestrian Detection. International Journal of Image and Graphics, 17 (04), 1750023. doi: https://doi.org/10.1142/s0219467817500231
12. Shanmugavadivu, P., Sivakumar, V. (2012). Fractal Dimension Based Texture Analysis of Digital Images. Procedia Engineering, 38, 2981–2986. doi: https://doi.org/10.1016/j.proeng.2012.06.348
13. Hu, X., Ensor, A. (2018). Fourier Spectrum Image Texture Analysis. 2018 International Conference on Image and Vision Computing New Zealand (IVCNZ). doi: https://doi.org/10.1109/ivcnz.2018.8634740
14. Simon, P., Uma, V. (2020). Deep Learning based Feature Extraction for Texture Classification. Procedia Computer Science, 171, 1680–1687. doi: https://doi.org/10.1016/j.procs.2020.04.180
15. Hosny, K. M., Magdy, T., Lashin, N. A., Apostolidis, K., Papakostas, G. A. (2021). Refined Color Texture Classification Using CNN and Local Binary Pattern. Mathematical Problems in Engineering, 2021, 1–15. doi: https://doi.org/10.1155/2021/5567489
16. 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
17. Kanjir, U., Greidanus, H., Oštir, K. (2018). Vessel detection and classification from spaceborne optical images: A literature survey. Remote Sensing of Environment, 207, 1–26. doi: https://doi.org/10.1016/j.rse.2017.12.033
18. Cheng, G., Han, J. (2016). A survey on object detection in optical remote sensing images. ISPRS Journal of Photogrammetry and Remote Sensing, 117, 11–28. doi: https://doi.org/10.1016/j.isprsjprs.2016.03.014
19. Berezina, S., Solonets, O., Lee, K., Bortsova, M. (2021). An information technique for segmentation of military assets in conditions of uncertainty of initial data. Information Processing Systems, 4 (167), 6–18. doi: https://doi.org/10.30748/soi.2021.167.01
20. Farshi, T. R., Drake, J. H., Özcan, E. (2020). A multimodal particle swarm optimization-based approach for image segmentation. Expert Systems with Applications, 149, 113233. doi: https://doi.org/10.1016/j.eswa.2020.113233
21. Lokhande, N. M., Pujeri, R. V. (2018). Novel Image Segmentation Using Particle Swarm Optimization. Proceedings of the 2018 8th International Conference on Biomedical Engineering and Technology - ICBET '18. doi: https://doi.org/10.1145/3208955.3208962
22. Ruban, I., Khudov, H., Makoveichuk, O., Chomik, M., Khudov, V., Khizhnyak, I. et. al. (2019). Construction of methods for determining the contours of objects on tonal aerospace images based on the ant algorithms. Eastern-European Journal of Enterprise Technologies, 5 (9 (101)), 25–34. doi: https://doi.org/10.15587/1729-4061.2019.177817
23. Mittal, H., Pandey, A. C., Saraswat, M., Kumar, S., Pal, R., Modwel, G. (2021). A comprehensive survey of image segmentation: clustering methods, performance parameters, and benchmark datasets. Multimedia Tools and Applications. doi: https://doi.org/10.1007/s11042-021-10594-9
24. Ruban, I., Khudov, H. (2019). Swarm Methods of Image Segmentation. Studies in Computational Intelligence, 53–99. doi: https://doi.org/10.1007/978-3-030-35480-0_2
25. Anfyorov, M. A. (2019). Genetic clustering algorithm. Russian Technological Journal, 7 (6), 134–150. doi: https://doi.org/10.32362/2500-316x-2019-7-6-134-150
26. Oleksenko, O., Khudov, H., Petrenko, K., Horobets, Y., Kolianda, V., Solomonenko, Y. (2021). The Development of the Method of Radar Observation System Construction of the Airspace on the Basis of Genetic Algorithm. International Journal of Emerging Technology and Advanced Engineering, 11 (8), 23–30. doi: https://doi.org/10.46338/ijetae0821_04
27. Satellite Imagery. Available at: https://www.maxar.com/products/satellite-imagery
28. 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
29. 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