The object of this study is the process of segmentation of images from unmanned aerial vehicles. It was established that segmentation methods based on k-means and a genetic algorithm work qualitatively on images from space observation systems. It is proposed to use segmentation methods based on k-means and a genetic algorithm for segmenting images from unmanned aerial vehicles. The main stages of image segmentation methods based on k-means and genetic algorithm have been determined.

An experimental study of segmentation of images from unmanned aerial vehicles was carried out. Unlike known ones, image segmentation by a k-means-based method that successfully works on images from space surveillance systems cannot be directly applied to image segmentation from unmanned aerial vehicles. Unlike known ones, image segmentation by a method based on a genetic algorithm that successfully works on images from space surveillance systems also cannot be directly applied to image segmentation from unmanned aerial vehicles.

The quality of segmentation of images from unmanned aerial vehicles by methods based on k-means and a genetic algorithm was assessed. It was established that:

– the average level of first-kind errors is 70 % and 51 % when segmenting an image from an unmanned aerial vehicle using methods based on k-means and a genetic algorithm, respectively;

– average level of second-kind errors is 61 % and 43 % when segmenting an image from an unmanned aerial vehicle using methods based on k-means and a genetic algorithm, respectively.

It was concluded that further research must be carried out to develop methods for segmenting images from unmanned aerial vehicles

Keywords: unmanned aerial vehicle, image segmentation, experimental research, k-means, genetic algorithm

METHODS OF UAVS IMAGES SEGMENTATION BASED ON K-MEANS AND A GENETIC ALGORITHM

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1. Introduction

In the modern world, unmanned aerial vehicles (UAVs) are widely used to solve heterogeneous problems. These are, for example, the tasks of communication, reconnaissance and surveillance, cargo transportation, protection of the state border, demining, environmental monitoring, control of maritime navigation, etc. [1]. However, UAVs are most widely used for reconnaissance and surveillance, including in the interests of solving military tasks [2].

Reconnaissance and surveillance in the interests of solving military tasks using UAVs have several advantages over space shooting. These are the following main advantages [3, 4]:

– high resolution of the image obtained with the help of UAVs;

– low shooting height above the Earth's surface;

– the possibility of conducting a detailed survey of objects or areas of interest;

– the possibility of perspective shooting (shooting at an angle to the horizon);

– the possibility of obtaining panoramic images;

– the ability to choose the time of day, weather conditions, observation area, etc. for shooting;

– the possibility of promptly obtaining the results of intelligence and surveillance;

– the ability to stream and receive streaming video;

– low cost of intelligence and surveillance results of ultra-high quality;

– environmental friendliness of UAV flights.

These advantages of reconnaissance and surveillance using UAVs determine the features of images from UAVs, in contrast to images from space reconnaissance and surveillance systems. The main feature of images from UAVs in the interests of reconnaissance and surveillance is their high resolution and much smaller (compared to images from space systems) image sizes.

When processing images from UAVs in the interests of reconnaissance and surveillance, strict requirements are put forward for the maximum completeness, accuracy, and reliability of information [5]. Such stringent requirements require the use of methods for processing, decrypting, and segmenting images from UAVs. Such methods should take into consideration the peculiarities of images from UAVs obtained in the interests of intelligence and surveillance.

Known methods of processing, decryption, and segmentation of images in the interests of intelligence and surveillance are focused mainly on images from space surveillance systems, for example [6]. Known methods do not take into consideration the peculiarities of images from UAVs obtained in the interests of reconnaissance and surveillance. Thus, the experimental study of methods for segmenting images from UAVs is relevant.

2. Literature review and problem statement

In [7], a method of segmentation of color images obtained from UAVs and represented in red-green-blue (RGB) color space is proposed. The method implies combining a set of textural features in a segmentation structure based on an active contour model without edges, with the representation of a set of levels and a filtering strategy for linked components. The advantage is the segmentation of images obtained from different types of UAVs, even from the simplest agricultural ones. The disadvantage is the use and acquisition of experimental data only for segmentation of crops in the image.

In [8], a method of image segmentation was proposed in order to identify safe landing zones of UAVs. The use of images captured by a single RGB camera located on a UAV is being investigated. The advantage is to work with the image, not with the video stream and without human intervention. The disadvantage is the use of this method to solve only the problem of distinguishing between safe and dangerous areas for landing UAVs.

In [9], the use of multispectral images obtained from UAVs for solving problems in the field of forestry is considered. The method, which is based on the growth of the region, is considered. The method is based on combining pixels or objects in the image. The advantage is the high speed when segmenting images of the same type, when the parameters are already configured. The disadvantage of the method is the need to establish such parameters as the degree of spectral and geometric homogeneity, scale parameter, compactness of objects, etc. Due to the lack of a generally accepted formula for setting these parameters, this method is semi-automatic.

Work [10] demonstrates the use of machine learning techniques to classify images obtained from UAVs. The essence of methods from [10] is to use ensemble decision trees with an object-oriented approach. The advantage of segmentation of images obtained from UAVs by the method is the high speed of image processing. The disadvantage is a limited classification only for certain limited objects of interest, namely: road, vineyard, asphalt, and roof.

In [11], a technique for using UAVs integrated with advanced digital hyperspectral light sensors and machine learning algorithms for monitoring coral reefs are proposed. The advantage is the fast and continuous processing of geospatial images, the results of which can determine not only the type of coral but also the signs of their discoloration. The disadvantage is the complexity of the technology of combining several data sets, namely, onboard RGB images and hyperspectral images with data from shooting in water and air.

In [12], segmentation and classification of orthophotos from UAVs using the method of reference vectors is proposed. The essence of this approach is in the combination of UAV orthophotography and machine learning models with a support vector machine (SVM). After segmentation using edge segmentation and a complete lambda algorithm, segmented objects are classified using the support vector method. The advantage is the high accuracy of classification but with the condition of processing digital images in high resolution. The disadvantage is the need to pre-use the method of highlighting boundaries.

In [13], the Random forest method was used to classify trees, grass, sand, gravel, and water surface in images from UAVs. The advantage is to achieve a fairly high accuracy of classification of these objects in images from UAVs. The disadvantage is the processing of only images of the annual landscape and the limited list of objects of interest for classification.

In [14], it is proposed to use the segmentation method with an online decision tree to increase the gradient (GBDT method). The advantages are the use of this method for images with the presence of combined objects, processing of an object of interest with various deformations. The disadvantage is the difficulty in determining the segmentation parameters.

In [15], a method of segmentation of the image of remote sensing of UAVs by combining super pixels with multifunctional distance measurement is proposed. The advantage of the method from [15] is that the criteria for choosing the original super pixel are both spectral, textural features, as well as the shapes and features of the plane. The disadvantage of the method is the need to establish the number of regions and the relationship of the merger with the achievement of the selected number of regions.

In [16], a method of segmentation of images of mango ecosystems obtained from UAVs using super pixels of simple linear iterative clustering SLIC is proposed. The advantage

of the method is a good result when delimiting areas of the image with similar information about the color and texture in the image area. The disadvantages are the limitations of the volume of the data set and the inflexibility of the classifications obtained.

In [17], a segmentation method is proposed for images of remote sensing of UAVs based on the textural features of the local binary pattern and improved medium displacement. The essence of the method is the joint use of textural features and boundaries in the image. The advantage of the method is the absence of the need for initial knowledge of the number of clusters and the possibility of segmenting both hyperspectral and panchromatic images. The disadvantage is the need for large cost of computing resources to calculate the mean shift vector and sensitivity to emissions – small areas in the image that require processing costs but do not carry information about the semantic structure of the image.

In [18], the segmentation of images of remote sensing of UAVs by the algorithm of combining regions using several fusion criteria is proposed. The advantage of the method is the use of many fusion criteria, which were developed to improve the accuracy of segmentation during the merging of regions. The disadvantage is that each of the merging criteria may have its drawbacks, which can cause errors in image segmentation.

In [19], for the identification of crops, a method of segmentation of images of remote sensing of UAVs using a deep segmentation network based on U-Net was proposed. The essence of the improved method is the replacement of the transposed convolutional layer in the U-Net sampling increase block with a subpixel convolutional layer in order to solve the problem of losing information about the structure of the boundaries and low accuracy of segmentation. The advantage of the method is the improved smoothness of the borders and the accuracy of pixels. The disadvantage of the method is the need to pre-process the obtained images from a data set from UAVs for training.

In [20], segmentation of images from drones using deep learning to map vegetation groups is proposed. Among deep learning networks, convolutional neural network (CNN) architecture was used as part of transfer learning. Experimental data showed that the combination of the SegNet and ResNet50 architecture gave the best results of semantic segmentation. The advantage is the high accuracy of segmentation. The disadvantage is the significantly increased set of training data, computation time, and equipment requirements compared to machine learning classifiers.

Paper [21] explores various semi-controlled models, such as pseudo-marking architecture, graph-based label propagation architecture, and deep-learning UNet-Autoencoder architecture that perform segmentation tasks in aerial photographs. The performance of each of the models improves as more specified data are provided for training. The disadvantage is the need for continuous training to obtain a high result of segmentation of aerial photographs.

In [22], the method of segmentation on images from space surveillance systems of disguised military equipment using a genetic algorithm is proposed. The advantage of the method is the selection of both disguised objects of interest and undisguised ones. The disadvantage of the proposed method is the processing of only color RGB images.

In [23], a method of segmentation based on the algorithm of a swarm of particles of images from space observation systems is proposed. The advantage of this method is to take into consideration the features of images obtained from

on-board surveillance systems, namely, the complexity of images. The disadvantage is to obtain experimental studies only for images from space observation systems.

In [24], a method of determining based on the algorithm for optimizing the ant colony of contours of objects of interest on a complexly structured color image is proposed. The advantage is the reduction of the first-kind errors and second-kind errors in determining the contours of objects in comparison with segmentation by known methods for determining contours. The disadvantage is re-segmentation, that is, the selection of a large number of small contours of objects of interest.

In [25], a two-stage method for determining the elements of urban infrastructure objects in images from air monitoring systems is proposed. The essence of the method is to apply the improved method of the boundary detector at the first stage and apply the method of searching for analytically given primitives in the second. The advantage is to take into consideration the features of image formation from air monitoring systems. The disadvantage is the definition of only elements of urban infrastructure objects that have geometric primitives such as a straight line.

In [26], a segmentation method using k-means clustering has been developed. The segments are refined, and textural features are analyzed in the image. The advantage is the reduction of segmentation time. The disadvantage is the dependence of the method on the choice of initial clusters.

In [27], a method of segmentation based on the clustering of C-means is proposed. To classify pixels, the minimum Euclidean distance and fuzzy entropy are used. The advantages are the absence of color changes and distortions during segmentation. The disadvantage is the sensitivity of the method to heterogeneous noise.

In [28], a segmentation method using fuzzy C-means clustering is proposed. The advantage is the absence of loss of textural information. The disadvantage is sensitivity to heterogeneous noise.

Thus, our review of known methods of segmentation of images from UAVs showed that these methods are focused mainly on the segmentation of planar objects or a predetermined class of objects. Segmentation methods developed to solve intelligence and surveillance problems work well on images from space surveillance systems.

For example, in [22], the method of segmentation of images from space surveillance systems of disguised military equipment using a genetic algorithm is proposed. The method provides a reduction in segmentation errors (of the first and second kinds) on average from 3 % to 15 %. In [27, 28], segmentation methods based on clustering of k-means and C-means are proposed.

Therefore, in the future, it is necessary to conduct experimental studies on the segmentation of images from UAVs using methods based on k-means and a genetic algorithm.

3. The aim and objectives of the study

The aim of this study is to develop methods for segmenting images from UAVs based on k-means and a genetic algorithm. This will make it possible to assess the quality of segmentation of images from UAVs based on k-means and a genetic algorithm.

To accomplish the aim, the following tasks have been set:
– to determine the main stages of image segmentation methods based on k-means and a genetic algorithm;

– to conduct an experimental study of segmentation of images from UAVs based on k-means and a genetic algorithm;

– to assess the quality of segmentation of images from UAVs using methods based on k-means and a genetic algorithm.

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4. The study materials and methods

The object of this study is the process of segmentation of images from UAVs using methods based on k-means and a genetic algorithm.

The main hypothesis of the study was to determine the possibility of segmenting images from UAVs using methods based on k-means and a genetic algorithm. The quality of segmentation is proposed to be assessed visually and by identifying errors of the first and second kinds.

During the study, the following research methods were used:

1) in determining the main stages of image segmentation methods based on k-means and a genetic algorithm:

– mathematical apparatus of matrix theory;
– methods of probability theory and mathematical statistics;
– methods of digital image processing;
– methods of system analysis;
– iterative methods;
– clustering methods;
– genetic methods;

2) when conducting an experimental study of segmentation of images from UAVs using methods based on k-means and a genetic algorithm:

– clustering methods;
– genetic methods;
– methods of digital image processing;
– methods of system analysis;
– methods of mathematical modulation;

3) when assessing the quality of segmentation of images from UAVs using methods based on k-means and a genetic algorithm:

– methods of mathematical modeling;
– methods of probability theory;
– methods of the theory of mathematical statistics;
– analytical and empirical methods of comparative research.

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

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

– optoelectronic image from UAVs is considered as the initial one;

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

– the image shows heterogeneous objects of interest;

– the size of the objects of interest can be compared with the size of the background objects;

– the influence of distorting factors (noise, rotation, and zooming) in the original image is not taken into consideration.

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5. Results of studying image segmentation by methods based on k-means and a genetic algorithm

5. 1. The main stages of image segmentation methods based on k-means and a genetic algorithm

To formalize the problem of image segmentation using methods based on k-means and aa genetic algorithm in the image $f(x, y)$ from UAVs, we shall use known expression (1) [22, 23]:

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

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

Segmentation of the original image from UAV $f(x, y)$ involves splitting the original image (expression (1)) into segments B_i, taking into consideration known condition (2) [22, 23]:

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

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

In expression (2), the predicate LP is defined by known condition (3) [22, 23]:

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

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

The result of segmenting the original image from UAV $f(x, y)$ is its separation (clustering) into heterogeneous objects of interest and background.

In general, the principle of operation of the method of segmentation of images from UAVs based on k-means is as follows [29, 30]. Each object O for partitioning into clusters is represented by a vector of characteristics – expression (4) [29, 30]:

$$O = \{c_1, c_2,..., c_n\}, \qquad (4)$$

where n is the dimension of the space of characteristics of the object.

The set M consists of the characteristic vectors $M = \{O_1, O_2,..., O_m\}$. The result is a cluster as a subset of close objects from the set M.

Such proximity is determined by comparing every two objects O from the set M. In order to compare objects with each other, it is necessary to determine the criterion of comparison. Such a criterion is selected depending on the implicit characteristics of the clusters and on the space of objects. The result of applying the selected criterion of comparison in the space of characteristics is the distance between objects x_i and y_i – the distance $d(x_i, y_i)$ [29, 30].

When segmenting images from UAVs based on k-means, the objects are the pixels of the image, and the characteristics of the object are the color intensity values of the pixel. The main purpose of the method of segmentation of images from UAVs based on k-means is to minimize the complete intra-cluster dispersion (expression (5)) [31, 32]:

$$D = \sum_{i=0}^{k} \sum_{O_j \in C_i} (O_j - \mu_i)^2, \qquad (5)$$

where C_i is the clusters in the image from UAV; O_j – vectors of object characteristics (pixel intensity); μ_i – «centers» of clusters.

The main stages of the method of segmentation of images from UAVs based on *k*-means are as follows:

1. Enter input data:

– the original image from UAV $f(X)$, where $X(x, y)$ is the pixel coordinates in the original image from the UAV $f(X)$;

– N – the size of the original image from the UAV $f(X)$ (determined by the number of pixels in the original image);

– k – the number of clusters in the segmented image $fs(X)$.

2. Select k pixels in the input image. This choice is performed randomly. At the first iteration of the algorithm, the selected pixels are considered the «centers» of future clusters. Each cluster has only one such «center».

3. Choose the criterion of comparison (metric).

When applying the *k*-means algorithm to solve the problem of image segmentation, the Manhattan metric (distance of urban quarters) (expression (6)) was selected as a metric [33]:

$$d\left(x_i, y_i\right) = \sum_{i=1}^{n} |x_i - y_i|, \tag{6}$$

where x_i and y_i values are the color intensity of pixels with coordinates (x, y).

4. Distribute all pixels in an image into clusters. To do this, calculate the distance from each «center» of the cluster to the pixel according to the selected metric and attribute this pixel of the image to the cluster whose distance to the «center» is minimal.

5. Recalculation of each «center» of the cluster as the arithmetic average of all pixels of the cluster.

6. Appointment of new «centers» of clusters.

Points 4–6 are repeated until one of the stopping conditions is met, the stopping conditions are [33]:

– performing the maximum number of iterations;

– invariance of the «centers» of clusters over a certain number of iterations.

The main stages of the method of segmentation of images from UAVs based on the genetic algorithm are shown in Fig. 1 [22]. Fig. 1 shows the main stages of the method of segmentation of disguised military equipment in images from space surveillance systems using a genetic algorithm [22]. Therefore, when citing the main stages of the method of segmentation of images from UAVs based on a genetic algorithm, we shall use the results reported in [22, 34, 35].

The method of segmentation of images from UAVs based on the genetic algorithm involves the following steps [22]:

1. Enter source data:

– the original image from the UAV $f(X)$, where $X(x, y)$ is the pixel coordinates in the original image from the UAV $f(X)$;

– N – the size of the original image from the UAV $f(X)$ (determined by the number of pixels in the original image);

– K – number of segments in the segmented image $fs(X)$;

– w – the initial value of the genetic algorithm (determines the number of chromosomes in the population);

– L – the initial value of the genetic algorithm (determines the number of generations in the evolutionary process);

– P_c – the initial value of the genetic algorithm (determines the probability of performing a crossover operator);

– P_m – the initial value of the genetic algorithm (determines the probability of performing a mutational operator).

2. Initialization of the initial value of generations (generation numbers) ($l=1$).

3. Initialization of the initial value of the chromosome number ($t=1$).

4. Determining the segmentation variant (determined randomly, the vector $g_l^t = \left(g_{l1}^t, g_{l2}^t, \ldots g_{lK}^t\right)$ is used where

$t = \overline{1, w}$ (*t* is the number of the chromosome in the population). In the segmented image $fs(X)$, the number of components of the vector g_l^t is equal to the number of segments. As noted in [34], it is advisable to use a decimal number system when encoding the values of the chromosome component. At the same time, it is advisable to use the integer value of the component g_{lr}^t (of the *r*-th gene in the chromosome) for encoding the segment number [34]. To the number of the segment, in accordance with [34], we shall attribute the *r*-th pixel of the original image from the UAV $f(X)$. This *r*-th pixel will be in the interval $[1, K]$.

5. The next step is to calculate the function $\phi(g_l^t)$. Here are some explanations regarding the function $\phi(g_l^t)$. In [22, 34, 35] it is noted that it is possible that operators of selection, crossover, mutations of chromosomes of the genetic algorithm are applied to pixels of segments of the original image from UAV $f(X)$ that do not correspond to the number of segments K. In [22, 34, 35] it is also noted that such an event has a high probability. This is due to the fact that during the formation of the initial population of chromosomes, the choice of component values is random. At the same time, the formation of the initial population of chromosomes is influenced by other genetic operators [22, 34, 35]. The function $\phi(g_l^t)$ (expression (7)):

$$\phi\left(g_l^t\right) = \begin{cases} 1, \text{ if } \exists r \in [1, N] \text{ what } g_{lr}^t = j \text{ for } \forall j \in [1, K]; \\ 0, \text{ if } \exists j \in [1, K] \text{ what } \overline{\exists} r \in [1, N], \text{ for } g_{lr}^t = j; \end{cases} \tag{7}$$

excludes such an event. When checking condition (7), the chromosome is either removed (in the case of $\phi(g_l^t) = 0$) or continues to work (in the case $\phi(g_l^t) = 1$).

For the process of programming and implementing the genetic algorithm, we introduce, in accordance with [22, 34, 35], the filtering operator $Fil(g_l^t)$ (expression (8)):

$$Fil\left(g_l^t\right) = \begin{cases} g_l^t, \text{ if } \phi\left(g_l^t\right) = 1; \\ 0, \text{ if } \phi\left(g_l^t\right) = 0. \end{cases} \tag{8}$$

According to expression (8), the filtering operator $Fil(g_l^t)$ is performed with respect to the chromosome and puts in line with the chromosome either an empty set or itself.

6. Calculation of the objective function $\mu(g_l^t)$ from expression (9):

$$\mu\left(g_l^t\right) = \frac{\dfrac{1}{K}\sum\limits_{j=1}^{K}\left(\dfrac{1}{k_j}\sum\limits_{p=1}^{k_j} d^2\left(\mathbf{X}_j^p; \mathbf{X}_{0_j}\right)\right)}{\dfrac{1}{C_K^2}\sum\limits_{i=1}^{K-1}\left(\sum\limits_{j=i+1}^{K} d^2\left(\mathbf{X}_{0_i}; \mathbf{X}_{0_j}\right)\right)}, \tag{9}$$

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

Steps 7–10 (Fig. 1) are clearly set out in [22, 34, 35] and do not require further clarification and comment.

11. Using the operator *Sel*. This operator searches for the parent chromosomes. The search is carried out by the «virtual roulette» procedure according to the principle of «only the best survives». The essence of such a search is set forth in [22, 34, 35]. As a result, chromosomes that have a higher value of the objective function (4) are more likely to be selected.
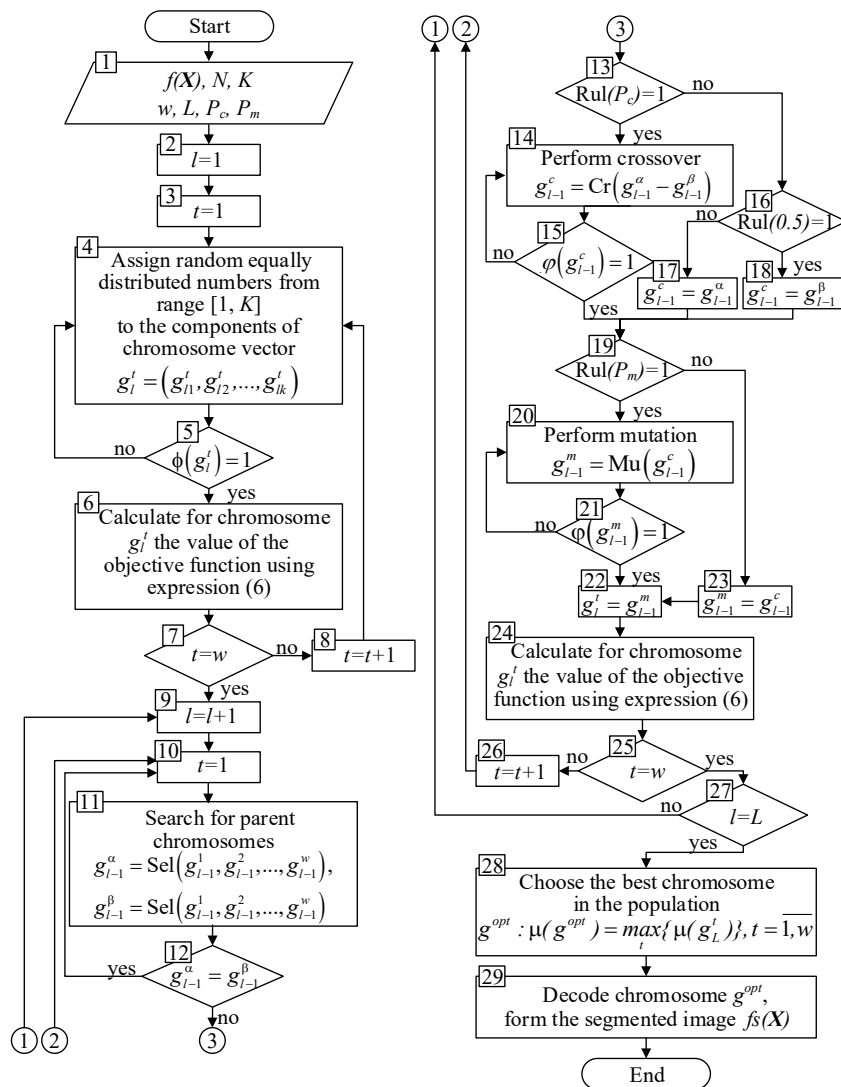
Fig. 1. The main stages of the method of segmentation of images from an unmanned aerial vehicle based on a genetic algorithm

Stage 12 is clearly set out in [22, 34, 35] and does not require further clarification and comment.

13. Calculation of the function $Rul(P_c)$. If the probability of an event is P_c, then for such an event the function $Rul(P_c)$ is equal to unity.

14. Entering the Cr operator (crossover operator). The crossover operator was introduced for chromosome g_{l-1}^{α} and g_{l-1}^{β} crossing. The result of the Cr operator is the appearance of a new chromosome. It is this chromosome that moves to the new population.

Stages 15–19 are shown in Fig. 1.

20. A mutation of the «gene» with the number $r_m \in [1,k]$.

Steps 21–28 (Fig. 1) are clearly set forth in [22, 34, 35] and do not require further clarification and comment.

29. Obtaining a segmented image $fs(X)$. The segmented image $fs(X)$ is obtained by decoding the chromosome.

As indicated above (in the limitations and assumptions adopted in the study), the original image from the UAV $fs(X)$ is represented in the RGB color space. Thus, as indicated in [22], one must first select the brightness channels of the original image (brightness channel Red, brightness channel Green, brightness channel Blue). Accordingly, the stages of the method of segmentation of images from UAVs based on the genetic algorithm (Fig. 1) must be carried out for each brightness channel (Red, Green, Blue). After that, it is necessary to combine the channels and get a segmented image $fs(X)$.

Thus, the method of segmentation of images from UAVs based on the genetic algorithm involves:

– selection of brightness channels (Red, Green, Blue) of the RGB color space of the representation of the original image;

– in each brightness channel (Red, Green, Blue), the use of a genetic algorithm, the combination of brightness channels.

5. 2. Methods of segmentation of images from an unmanned aerial vehicle based on k-means and a genetic algorithm

The color image from UAV was considered as the original one (Fig. 2 [36, 37]).

This is the original optoelectronic image obtained from UAV R 18 (Ukraine). The image is represented in the color space RGB. Image size – (1980×1480) pixels. The image shows objects of interest – buildings, military equipment, traces of military equipment, etc.

Fig. 3 shows a segmented image from the UAV (Fig. 2) using the k-means-based method.

Fig. 2. Original color image from an unmanned aerial vehicle [36, 37]
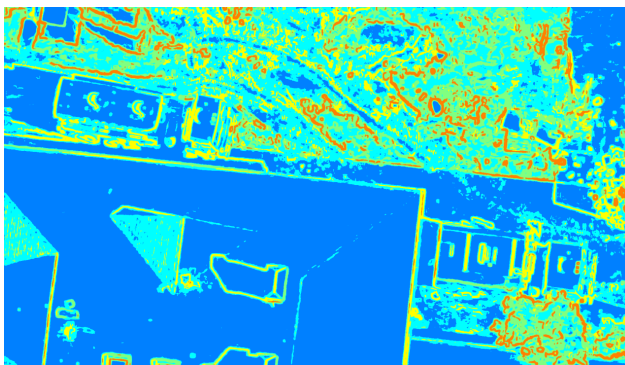

Fig. 3. Segmented image by the k-means-based method after combining the brightness channels of the Red-Green-Blue color space

In Fig. 3, different segments are highlighted in different colors (blue, blue, red, yellow). The number of segments is 4. From the analysis of Fig. 3, it was established that there is no clear boundary between different objects of interest. In Fig. 3, unlike [22, 24], there are no clearly distinguished structures, military equipment, traces of military equipment, etc.

The analysis of Fig. 3 shows that image segmentation by the k-means-based method, which successfully works on images from space surveillance systems [22, 24, 38], cannot be directly applied to image segmentation from UAVs.

Fig. 4 shows a segmented image from the UAV (Fig. 2) by a method based on a genetic algorithm.

In Fig. 4, by analogy with Fig. 3, different segments are highlighted in different colors (blue, blue, red, yellow). The number of segments is also 4. From the analysis of Fig. 4, it was found that, by analogy with Fig. 3, there is no clear boundary between different objects of interest. A comparative visual analysis of Fig. 3, 4 shows the better visual quality of Fig. 4 (compared to Fig. 3). In Fig. 4, in contrast to [22, 24], there are also no clearly distinguished structures, military equipment, traces of military equipment, etc.
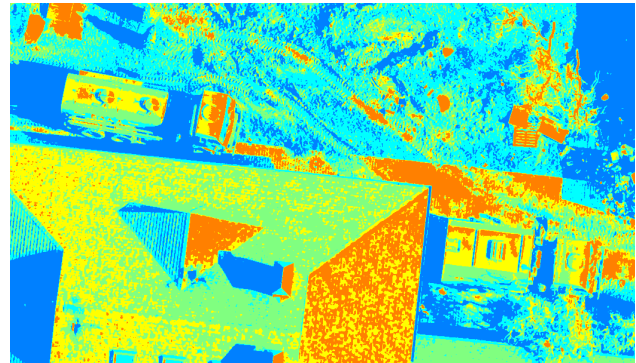

Fig. 4. Segmented image by a method based on a genetic algorithm after combining the brightness channels of the Red-Green-Blue color space

It is known [22, 24, 38] that the segmentation methods based on a genetic algorithm are successfully used on images from space observation systems. The analysis of Fig. 4 reveals that segmentation of the image by the method based on the genetic algorithm cannot be directly applied to the segmentation of the image from the UAV.

5. 3. Evaluation of image segmentation quality with UAV methods based on k-means and a genetic algorithm

To quantify the quality of image segmentation from UAV by methods based on k-means and a genetic algorithm, we calculate the segmentation first-kind errors and second-kind errors [22, 24, 39, 40]. The segmentation first-kind errors (α_1) and second-kind errors (β_2) are calculated from expressions (10), (11), respectively [22, 24, 39, 40]:

$$\alpha_1 = \frac{S_1\big(fs(\mathbf{X})\big)}{S_2\big(f(\mathbf{X})\big)}, \qquad (10)$$

$$\beta_2 = 1 - \frac{S_3\big(fs(\mathbf{X})\big)}{S_4\big(f(\mathbf{X})\big)}, \qquad (11)$$

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

The calculation of segmentation first-kind errors (α_1) and second-kind errors (β_2) is given in Tables 1, 3, and Fig. 5, 6. In Fig. 5, 6, the green curve corresponds to the method of segmenting the image from UAVs based on k-means ($k=4$). The blue curve corresponds to the method of segmenting the image from UAVs based on the genetic algorithm.

The results of calculating segmentation first-kind errors I (α_1) are given in Table 1 and Fig. 5. The number of implementations of segmentation methods is ten.

Table 1

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

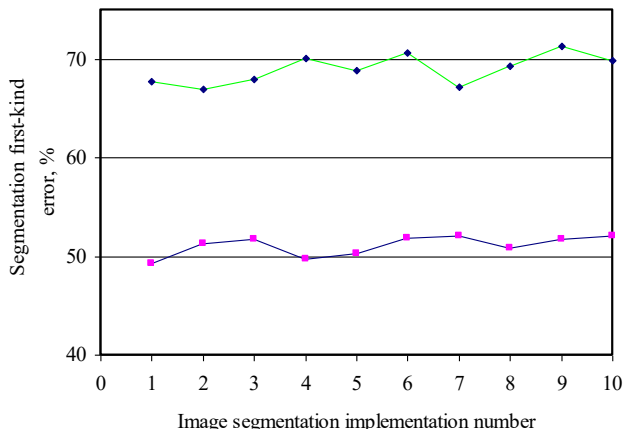| The name of the segmentation method	Segmentation first-kind error, %									
	Image segmentation process number									
	1	2	3	4	5	6	7	8	9	10
Segmentation method based on k-means	67.7	66.9	68.0	70.1	68.9	70.6	67.2	69.3	71.3	69.9
Segmentation method based on genetic algorithm	49.3	51.3	51.7	49.7	50.3	51.9	52.1	50.8	51.7	52.1

Fig. 5. Calculation of the segmentation error of the first kind in the implementation of image segmentation methods from 1 to 10

The results of the calculation of segmentation second-kind errors (β_2) are given in Table 2 and Fig. 6. The number of implementations of segmentation methods is ten.

Table 2

The results of the calculation of the segmentation second-kind errors (β_2)

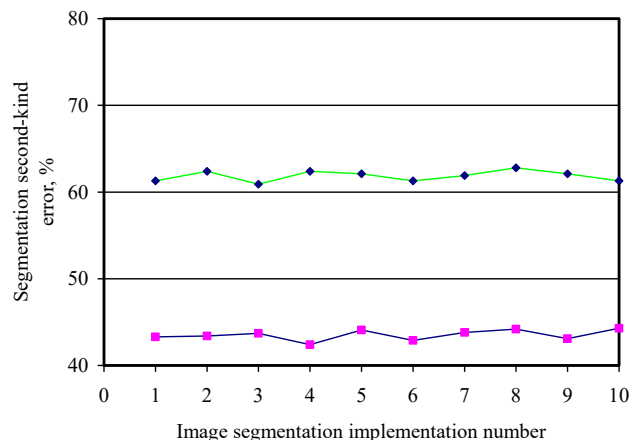| The name of the segmentation method	Segmentation second-kind error, %									
	Image segmentation process number									
	1	2	3	4	5	6	7	8	9	10
Segmentation method based on k-means	61.3	62.4	60.9	62.4	62.1	61.3	61.9	62.8	62.1	61.3
Segmentation method based on genetic algorithm	43.3	43.4	43.7	42.4	44.1	42.9	43.8	44.2	43.1	44.3

Fig. 6. Calculation of the segmentation error of the second kind in the implementation of image segmentation methods from 1 to 10

Our analysis of Tables 1, 2, Fig. 5, 6 revealed the following:
– the average level of errors of the first kind is on average 70 % when segmenting an image with a UAV using a k-means method and on average 51 % when segmenting an image from a UAV using a method based on a genetic algorithm;
– the average level of errors of the second kind is on average 61 % when segmenting the image with UAVs using the k-means method and on average 43 % when segmenting the image with UAVs using the method based on the genetic algorithm.

The determined level of first-kind errors and second-kind errors of image segmentation acquired from UAV by methods based on k-means and genetic algorithm is quite high and does not meet the specified requirements [1, 2].

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

The main stages of image segmentation methods based on k-means and genetic algorithm have been determined. It was established that the main purpose of the method of segmentation of images from UAVs based on k-means is to minimize the complete intracluster dispersion – expression (5).

The main stages of the method of segmentation of images from UAVs based on k-means are as follows:
– input of initial data;
– selection of k pixels on the input image;
– selection of the comparison criterion (metrics);
– distribution of all pixels of the image into clusters;
– recalculation of each «center» of the cluster as the arithmetic average of all pixels of the cluster;
– appointment of new «centers» of clusters.

The method of segmentation of images from UAVs based on the genetic algorithm involves the selection of brightness channels of the RGB color space of the representation of the original image, in each brightness channel of the application of the genetic algorithm, the combination of brightness channels.

An experimental study of segmentation of images from UAVs by methods based on k-means and a genetic algorithm was carried out (Fig. 2–4). The analysis of Fig. 3 shows that k-means-based image segmentation, which successfully works on images from space surveillance systems, cannot be directly applied to image segmentation from UAVs. A comparative visual analysis of Fig. 3, 4 shows the better visual quality of Fig. 4 (compared to Fig. 3). In Fig. 4, buildings, military equipment, traces of military equipment, etc. are also not clearly distinguished. From the analysis of Fig. 4, it can be seen that segmentation of the image by a method based on a genetic algorithm that successfully works on images from space surveillance systems also cannot be directly applied to segmentation of the image from the UAV.

The quality of segmentation of images from UAVs based on k-means and a genetic algorithm was assessed. From the analysis of Tables 1, 2, Fig. 5, 6, it was found that:
– the average level of the first-kind errors is 70 % and 51 % when segmenting an image with UAVs using methods based on k-means and a genetic algorithm, respectively;
– the average level of errors of the second kind is 61 % and 43 % when segmenting the image with UAVs using methods based on k-means and genetic algorithm, respectively.

During the study, the following limitations and assumptions were adopted:
– optoelectronic image from UAVs is considered as the initial one;
– the original image is represented in the RGB color space;
– the image shows heterogeneous objects of interest;

– the size of the objects of interest can be compared with the size of the background objects;

– the influence of distorting factors (noise, rotation, and zooming) in the original image is not taken into consideration.

Image segmentation methods can be implemented in software and hardware systems for processing images from UAVs.

The disadvantages of the methods of segmentation of images from UAVs based on k-means and a genetic algorithm are the high level of errors of the first kind and second kind.

Further research may address the development of methods for segmenting images from UAVs based on algorithms that provide a low level of errors of the first kind and second kind. When implementing segmentation methods in practice, the peculiarities of image formation from UAVs must be taken into consideration.

7. Conclusions

1. The main stages of image segmentation methods based on k-means and a genetic algorithm have been determined.

The main stages of the method of segmentation of images from UAVs based on k-means are as follows:

– input of initial data;

– the selection on the input image of k pixels;

– selection of the comparison criterion (metrics);

– the distribution of all pixels of the image into clusters;

– recalculation of each «center» of the cluster as the arithmetic average of all pixels of the cluster;

– appointment of new «centers» of clusters.

The method of segmentation of images from UAVs based on the genetic algorithm involves the selection of brightness channels of the RGB color space of the representation of the original image, in each brightness channel of the application of the genetic algorithm, the combination of brightness channels.

2. An experimental study of segmentation of images from UAVs using methods based on k-means and a genetic algorithm was carried out. Unlike known ones, image segmentation by a k-means-based method that successfully works on images from space surveillance systems cannot be directly applied to image segmentation from UAVs. Unlike known ones, image segmentation by a method based on a genetic algorithm that successfully works on images from space surveillance systems also cannot be directly applied to image segmentation from UAVs.

3. The quality of segmentation of images from UAVs based on k-means and a genetic algorithm was assessed. It was established that:

– the average level of errors of the first kind is 70 % and 51 % when segmenting an image with UAVs using methods based on k-means and a genetic algorithm, respectively;

– the average level of errors of the second kind is 61 % and 43 % when segmenting the image with UAVs using methods based on k-means and genetic algorithm, respectively.

Conflict of interest

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.

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