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DEVISING A SEGMENTATION METHOD FOR OPTOELECTRONIC IMAGERY FROM UNMANNED AERIAL VEHICLES BASED ON THE ARTIFICIAL BEE COLONY ALGORITHM

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This paper considers the process of segmenting an optoelectronic image acquired from an unmanned aerial vehicle based on the artificial bee colony algorithm. The principal hypothesis of this study assumes that the use of the artificial bee colony algorithm for segmenting an optoelectronic image acquired from an unmanned aerial vehicle could reduce segmentation errors of the first and second kinds.

A method for segmenting an optoelectronic image acquired from an unmanned aerial vehicle based on the artificial bee colony algorithm has been improved, which, unlike known ones, involves the following:

– initialization of the population of scout bees;

– calculation of the objective function;

– determining the best and promising positions;

– calculation of the optimal value of the segmentation threshold;

– image division into segments;

– checking the stopping criterion;

– bee migration;

– acquisition of a segmented image.

Experimental studies have been conducted on the segmentation of an optoelectronic image acquired from an unmanned aerial vehicle using a method based on the artificial bee colony algorithm. The visual quality of the segmented image makes it possible to conclude that segmentation using the artificial bee colony method is possible. Comparative analysis of segmented images (improved and known methods) indicates a clearer separation of the object of interest (car) using the method based on the artificial bee colony algorithm. The results of calculating segmentation errors of the first and second kind indicate a reduction in segmentation errors of the first kind by 9% and errors of the second kind by 7% when segmenting an optoelectronic image using the method based on the artificial bee colony algorithm

Keywords: segmentation, optoelectronic imagery, artificial bee colony algorithm, unmanned aerial vehicle

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1. Introduction

Over the past decades, space technologies have become an integral part of the global Earth observation system. Satellite monitoring provides large-scale coverage of territories, which makes it possible to obtain up-to-date data on environmental changes, urbanization, natural disasters, agricultural conditions, and other critically important processes. How-

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ever, despite their numerous advantages, satellite systems also have certain limitations, in particular dependence on weather conditions, limited spatial resolution, high launch and maintenance costs, as well as time delays between shooting sessions [1].

Given the above, the use of unmanned aerial vehicles (UAVs) as a mobile and affordable tool for observing objects is becoming increasingly relevant. UAVs allow for real-time monitoring with high detail, selectivity on demand, and, importantly, regardless of the satellite flight schedule. Their use is especially valuable in situations that require urgent response or monitoring of hard-to-reach areas. And the combination of satellite and UAV technologies forms a powerful hybrid monitoring system that combines global coverage with local accuracy. This approach allows for comprehensive, multi-level data analytics, which is especially relevant for environmental protection, agriculture, urban planning, security, and defense [2].

In modern practice of processing images acquired from airborne optical-electronic surveillance systems, both conventional segmentation algorithms and approaches based on deep learning technologies are used. Both classes of methods have their strengths, certain limitations, and specific areas of effective use, especially in the cases of image processing of increased complexity, which is typical for UAV images.

Classical segmentation methods are usually based on the analysis of pixel intensity, geometric characteristics, or statistical parameters of the image. Most of them have proven effective for both space and UAV images.

It is important to note that image processing methods that have already proven effective in the analysis of satellite data have a high potential for adaptation to the needs of processing images acquired from UAVs. Although images from UAVs have different characteristics, namely higher spatial resolution, different shooting geometry, dynamic scale, the principles of segmentation, classification, detection of objects of interest and analysis of changes remain relevant [3]. This creates conditions for the effective transfer of developed algorithms, in particular machine learning tools, deep learning and optimization approaches, to the processing of optoelectronic images acquired from UAVs.

Therefore, it is advisable to deeply analyze and adapt existing image segmentation methods that have demonstrated their effectiveness in processing images obtained from space reconnaissance and surveillance systems. A thorough study of such approaches makes it possible not only to ensure high accuracy of the selection of objects of interest in images acquired from UAVs but also reduce the time spent on developing new algorithms “from scratch”. Segmentation is one of the key stages of image processing, and the use of optimized and proven methods in a new context is a logical and effective way to improve the quality of automated analysis.

At the same time, despite the similarity of the general principles of image processing, the adaptation of existing methods to data acquired from UAVs is not only a relevant but also a critically important task. Images from UAVs are characterized by ultra-high spatial resolution, significant variability of perspective, as well as an increased presence of artifacts – noise, shadows, lighting, and background inhomogeneities. This necessitates the need to take into account the specificity of such data when setting up algorithms for processing optoelectronic images acquired from UAVs.

Thus, the adaptation process cannot be limited to the technical transfer of existing methods. It requires a deep conceptual rethinking: modification of pre-processing stages, careful selection of relevant input parameters, development, or refinement of criteria for assessing the quality of segmentation. In addition, it is necessary to optimize the methods themselves, taking into account the characteristics of the input data coming from the UAV, including topographic, atmospheric, and technical characteristics of the shooting. Therefore, the study aimed at devising a method for segmenting an optoelectronic image acquired from an unmanned aerial vehicle is a relevant task.

2. Literature review and problem statement

In [4], the k-means clustering method for segmenting satellite images is described. It is shown that the integration of additional validation metrics makes it possible to automatically determine the optimal number of clusters. This enables effective pixel grouping without the need for manual intervention. However, questions related to the sensitivity of the results to the quality of pre-processing (illumination normalization and noise reduction) remain open. The likely reason is objective difficulties associated with the background heterogeneity. Potential options for overcoming these problems are to improve the initialization of cluster centers and pre-extraction of features using the principal component analysis (PCA) method. This makes it possible to increase its resistance to image variability. Therefore, it is advisable to conduct research focused on adapting clustering methods to the features of UAV images.

In [5], the results of using the Otsu algorithm for automatic segmentation of remote sensing optical-electronic images are reported. It was found that the method makes it possible to effectively select objects of interest in images from space and airborne observation systems. The method provides automatic division into background and target areas without the need for manual selection of thresholds. At the same time, problems related to the sensitivity of the algorithm to noise and lighting inhomogeneities remain unsolved. This is especially true for images where the background and objects differ greatly. This is explained by the high contrast of the background and the presence of shadows, which are typical for images from UAVs. One way to increase the efficiency of this approach is to pre-filter images, for example, with a Gaussian filter, especially in the presence of uneven lighting and shadows. This option was used in [5] but its effectiveness is limited in complex images. Therefore, it seems reasonable to conduct a study on improving the stability of threshold segmentation methods for use in aerial photography.

In [6], a method for segmenting color images using watershed transformation (Watershed Segmentation), which is based on a morphological gradient, is proposed. It has been found that a combination of morphological preprocessing, filtering, and contour enhancement can avoid over-segmentation. However, there are technical difficulties such as:

– high computational complexity when processing large images;

– dependence of results on filter settings and morphological processing parameters;

– possibility of loss of accuracy in case of strong noise or non-uniform illumination.

The reason is the complex structure of the images and their high level of detail, typical for UAVs. A solution option is preliminary smoothing of the images (for example, using the Sobel filter [7]), as well as a combination with morphological filtering, which allows for effective processing of highly detailed aerial photographs with noise and complex structures. This is the approach used in [6] but its adaptation to a wide range of UAV images still requires further development. Thus, research aimed at improving the efficiency of watershed methods in the context of aerial photography is relevant.

In [7], a method for segmenting small aerial objects on optoelectronic images using a gradient approach is proposed. The method is characterized by high computational speed and ease of implementation, which makes it suitable for processing large data sets. At the same time, problems related to high sensitivity to noise and brightness fluctuations remain open, due to which the segmentation accuracy is significantly reduced under conditions of low contrast or the presence of atmospheric artifacts. The reason for this is the limited stability of gradient methods to changes in shooting conditions.

Thus, analysis revealed that classical segmentation methods have a number of limitations:

– efficiency significantly depends on high-quality pre-processing of images;

– high sensitivity to noise and unstable results under variable lighting conditions;

– limited ability to adapt to a wide variety of input data.

In contrast, the development of deep learning, in particular convolutional neural networks (CNN), has significantly improved the accuracy and reliability of segmentation, making it more resistant to the influence of complex image factors.

In [8], a modified U-Net architecture is proposed, supplemented with self-attention mechanisms and separable convolutions. This architecture is designed to improve semantic segmentation of aerial images. It is found that the proposed structure demonstrates high accuracy and context understanding, reduces parameters, and accelerates learning. However, there are unresolved issues related to the complexity of processing images with complex terrain, such as urban or heterogeneous landscapes. This is explained by the limited coverage of the global context within the model. One way to overcome this problem is to expand the field of view or pre-process the input image. All this indicates the need for further development of compact but effective CNN architectures for UAV images.

In [9], a classic U-Net architecture with a symmetric encoder-decoder structure with gaps between the corresponding levels is proposed. This makes it possible to preserve spatial information and achieving high object localization accuracy even in the cases of limited training data sets. At the same time, the problems associated with high resource intensity and sensitivity to class imbalance remain relevant. This requires additional tuning of the loss function with weight coefficients. In addition, the classic U-Net does not take into account the global context outside the local field of view. This may limit its effectiveness in analyzing large or complex images. Thus, the need to study optimized U-Net approaches for high-resolution UAV images is justified.

Analysis revealed that U-Net and other convolutional neural networks are actively used for segmenting satellite images of urban areas. They are used to recognize infrastructure, vegetation cover, and objects of artificial origin. However, they often require the use of data augmentation methods to increase the generalization ability of the model and avoid overtraining.

In [10], the results of the study on the improved DeepLabv3+ model are reported. The model combines the ability to process the global context with high accuracy in determining the boundaries of objects. Owing to the use of the Advanced Convolutional Pattern (ASPP) module and deep features, the model demonstrates resistance to background noise. The model maintains the stability of the results even in cases of non-uniform illumination. However, there are still difficulties associated with sensitivity to structural artifacts and irregular interference, especially in the absence of effective methods for expanding the training sample (data augmentation). Among the limitations of [10] is the high demand for computational resources. This complicates its use on limited hardware platforms. An alternative solution is to design lighter versions of the architecture or pre-optimize the data. A similar idea was partially implemented in [10] but its effectiveness under field conditions has not yet been fully proven. Therefore, research on devising segmentation methods for use on UAVs is advisable.

The basic limitations of methods based on deep learning are as follows:

– computational complexity;

– sensitivity to the quality and balance of the training set;

– the need to retrain the model, especially when working with small amounts of data.

In [11], a review of algorithms based on Graph Cuts for image segmentation is provided. Classical models are considered, in particular, minimization of energy functions that take into account data (data term) and smoothness of boundaries (smoothness term). Boykov-Kolmogorov approaches and other optimization options, implementation of maximum graph cutting (min-cut), as well as the use of multilayer extensions for complex segmentation of multichannel data are covered in detail. It is shown that such methods provide a global minimum of the energy function. This guarantees high accuracy of segmentation and the possibility of integrating additional conditions, such as a priori knowledge of the shape of objects of interest. However, difficulties remain associated with high computational complexity, the need for precise adjustment of weight coefficients in the energy function. This complicates automation and the tendency to local minima. An option for improvement is the implementation of global optimization methods that make it possible to work with high-dimensional parameter spaces.

Thus, analysis of existing approaches to image segmentation reveals that they have certain limitations:

– dependence on parameterization;

– sensitivity to noise;

– the need for large computational resources or the complexity of optimizing energy functions.

This justifies the feasibility of switching to optimization methods based on swarm intelligence approaches. Such methods make it possible to effectively find global solutions to problems with a large number of variables, which is relevant when processing images from UAVs.

Among modern optimization approaches, bioinspired algorithms occupy a special place, which are characterized by adaptability, ease of implementation, and the ability to globally search for optimal solutions. Study [12] considered the bioinspired algorithm Artificial Bee Colony (ABC), which models the behavior of a bee population when searching for food sources. It was proven that the algorithm provides an effective balance between global search and local refinement, making it possible to achieve high efficiency in segmenting structured images with a large number of variables. However, challenges remain related to the adaptation of ABC to the specificity of high-resolution UAV images, noise, and artifacts. This is due to the objective complexity of transforming metaheuristic methods to dynamic input data. One way to overcome these difficulties is to adaptively adjust the algorithm parameters. This approach was implemented in [12] but its effectiveness requires confirmation on a wider range of data. This indicates the feasibility of research on devising adaptive bioinspired segmentation methods for UAV images.

3. The aim and objectives of the study

The aim of our research is to devise a method for segmenting optical-electronic images acquired from UAVs based on the artificial bee colony algorithm. This will make it possible to reduce segmentation errors of the first and second kind.

To achieve this aim, the following objectives were accomplished:

– to define the main stages of the method for segmenting optical-electronic images acquired from UAVs based on the artificial bee colony algorithm;

– to conduct an experimental study on segmenting optical-electronic images acquired from UAVs using a method based on the artificial bee colony algorithm.

4. The study materials and methods

The object of our study is the process of segmenting an optoelectronic image from a UAV based on the artificial bee colony algorithm.

The principal hypothesis of the study assumed that the use of the artificial bee colony algorithm for segmenting an optoelectronic image acquired from a UAV could reduce segmentation errors of the first and second kind.

The following assumptions were accepted during the study:

– the image from the UAV is optoelectronic;

– the camera on the UAV is digital;

– the color space of the image representation is Red-Green-Blue (RGB);

– the influence of distorting factors is not considered;

– the Otsu method was chosen for comparison.

The following simplifications were adopted during the study:

– when selecting the initial optoelectronic image for the experiment, there is one object of interest on it;

– the color space of the image representation is RGB;

– the influence of distorting factors is not considered.

Our research involved the following:

– hardware: ASUSTeK COMPUTER INC model X550CC laptop, 3rd Gen processor DRAM Controller – 0154, NVIDIA GeForce GT 720M;

– software: high-level programming language and interactive environment for programming, numerical calculations, and visualization of results MATLAB R2017b.

The following general methods were applied in the research:

– digital image processing;

– mathematical apparatus of matrix theory;

– iterative methods;

– probability theory and mathematical statistics;

– systems analysis;

– swarm;

– artificial bee colony;

– mathematical modeling methods;

– analytical and empirical methods of comparative research.

5. Results of investigating a segmentation method based on the artificial bee colony algorithm

5. 1. Main stages of the segmentation method based on the artificial bee colony algorithm

In its classical form, the artificial bee colony algorithm is a bioinspired optimization method that simulates the behavior of real bees when searching for nectar sources. In the process of finding solutions, the bee population is divided into worker bees, observers, and scouts. This algorithm is characterized by a high ability for global optimization, adaptability, and relative simplicity of implementation.

In the context of image segmentation, a solution is a set of thresholds or cluster centers that determine the distribution of all image pixels into significant areas. Optimization of such parameters can be carried out using the artificial bee colony algorithm by maximizing or minimizing the corresponding objective function, which reflects the quality of segmentation [12].

The proposed method consists of the following stages:

Stage I: setting the input parameters.

$f(\boldsymbol{X})$ – input optoelectronic image;

$|S|$ – image size or number of pixels $f(X)$;

$|B|$ – total number of bees in the population;

c^b, c^p is the number of worker bees placed around each of the best and promising positions, respectively;

n^s, n^b, n^p – number of scout bees, best and promising, respectively;

rad – coefficient that determines the radius of bee scattering around the selected position;

r_x, r_y – size of the circle along the x-axis and y-axis, respectively, within which the best and promising positions are placed, i.e., the sizes of the search area along the x- and y-axes.

Stage II: preprocessing of the input image.

At this stage, pre-processing of the image is performed to improve its quality and ensure more effective subsequent segmentation. The main subtasks are noise reduction, brightness equalization, and contrast enhancement:

1. Noise filtering. Images acquired from UAVs often contain impulse or Gaussian noise caused by vibrations, atmospheric conditions, or signal transmission characteristics. To reduce the impact of noise, one of the following filters is used, depending on the shooting conditions:

1. 1. Median filter, which is effective for suppressing impulse noise without significantly blurring the contours.

1. 2. Gaussian filter, which reduces high-frequency components while preserving the overall structure of the image.

1. 3. Bilinear or bicubic smoothing, which is used to reduce artifacts when scaling.

2. Brightness normalization. Due to variable lighting conditions (sunlight, shadows, reflections from surfaces), images can have uneven brightness. To fix this problem, histogram normalization or local illumination equalization is performed. This makes it possible to reduce the influence of external factors and provide more stable segmentation results.

3. Contrast enhancement (if necessary). In some cases, histogram stretching or adaptive contrast equalization (for example, the Contrast Limited Adaptive Histogram Equaliza-

tion (CLAHE) method) is also used, which makes it possible to better detect details in dark or overexposed areas.

4. Color space conversion (optional). If segmentation is not performed in grayscale, it is possible to convert the image to HSV or Lab color space for better separation of objects by color or saturation.

The result of the preprocessing is an improved image suitable for further analysis and optimization of segmentation parameters using the artificial bee colony algorithm.

Stage III: Initialization of the scout bee population.

At this stage, the initial positions of the bees in the original image are determined, i.e., this is the initial population that explores the space. This process is performed only on the first iteration of the scout bee algorithm

$$X_{i1} = rand(f(\boldsymbol{X})), \quad (1)$$

where $\boldsymbol{X} = (x, y)$ is the vector representing the coordinates of the bees' positions;

$X_{i1} = (x_{i1}, y_{i1})$ are the coordinates of the positions of each of the n^s scouting bees at the first iteration;

$rand(f(\boldsymbol{X}))$ is an operator responsible for generating random values based on the function $f(\boldsymbol{X})$;

$i = 1,...,n^s$ is the index of each of the scouting bees.

Therefore, the result of this stage is a random generation of initial solutions, where each solution is a vector of segmentation thresholds.

Stage IV: calculation of the objective function.

At each iteration j, the quality of solutions corresponding to the current positions of the bees is evaluated. For each i-th bee, the value of the objective function $\varphi(X_{ij})$ is calculated, where $(i = 1,...,|B|)$. This algorithm is iterative, so we shall denote the index of the algorithm iterations by j.

This stage is critical for analyzing search efficiency and further decision-making regarding the movement of bees in the search space.

Stage V: determining the best and promising positions.

After calculating the objective function, the selection of bee positions that have the potential for further research is carried out. This involves forming a set of the best positions N_{ij}^b, and selecting promising positions N_{ij}^p according to the values of the objective function $\varphi(\boldsymbol{X}_{ij})$ obtained at the previous stage. This mechanism makes it possible to concentrate the search in those areas of the solution space where the extremum (maximum or minimum) of the objective function $\varphi(\boldsymbol{X}_{ij})$ is recorded.

Stage VI: calculation of the optimal value for a segmentation threshold.

Based on the objective function, the optimal value of the threshold t is determined, which makes it possible to divide the image into segments (for example, background/object).

Stage VII: dividing the image into segments.

Using the threshold value t, the image is divided into parts according to the pixel values.

Stage VIII: checking the stopping criterion.

At this stage, it is checked whether the conditions for completing the algorithm are met. The stopping criteria for the algorithm can be as follows:

– reaching the maximum permissible number of iterations;

– finding a solution that satisfies the requirement;

– no noticeable improvement in the value of the objective function $\varphi(\boldsymbol{X}_{ij})$ over a certain number of iterations.

If so, then the transition to the segmented image output stage is performed – stage X: segmented image output. If not, then the transition to the next stage (stage IX) is performed, after which the next iteration from stage IV begins.

Stage IX: bee migration.

After the best and most promising positions have been determined, the worker bees are directed to their surroundings. In particular, a certain number of worker bees are placed around each of the best positions, and the rest – in the area of the promising positions.

The positions of the worker bees are determined using mathematical expressions (2) and (3). In particular, formula (2) describes the vector of coordinates of bees placed in the vicinity of the best positions found in the current iteration

$$\mathbf{X}_{((i-1)c^b+k)j} = N_{i(j-1)}^b + Rnd \cdot rad, \quad (2)$$

where $I = 1, ..., n^b$;

$k = 1, ..., c^b$;

N_{ij}^b – coordinates of the best position for the i-th bee at the j-th iteration;

Rnd – a random value that models the stochastic nature of the bee movement.

At the same time, expression (3) is used to calculate the coordinates of the positions of worker bees heading to promising search areas

$$\mathbf{X}_{(n^b c^b+(i-1)c^b+k)j} = N_{i(j-1)}^p + Rnd \cdot rad, \quad (3)$$

where $i = 1, ..., n^p$;

$k = 1, ..., c^p$;

N_{ij}^p – coordinates of the prospective position for the i-th bee at the j-th iteration; other variables are similar to the previous expression.

Thus, the algorithm simulates the behavior of bees in nature where they explore the environment near the detected effective or potentially effective food sources, maintaining a balance between exploiting the best areas and exploring new ones.

At this stage of the algorithm, a certain number of scouts are sent to randomly generated coordinates. These coordinates are evenly distributed within the permissible range of values (i.e., within the entire solution space). This is formalized by expression (4)

$$\mathbf{X}_{(n^b c^b+n^p c^p+i)j} = rand\big(f(\mathbf{X})\big), \quad (4)$$

where $i = 1, ..., n^s$.

The function $rand(f(\boldsymbol{X}))$ generates a random position in the permissible range of the solution space.

So, at this stage, the bees' positions are updated, namely the worker bees move to the neighborhood of the best and most promising positions, and the scout bees look for new random positions.

These new positions form the basis for the next iteration.

Stage X: outputting a segmented image.

At the final stage of the algorithm, the end result is formed – a segmented image. The goal of the stage is to represent the image in a convenient form, where each segment is clearly highlighted, which significantly simplifies further processing, analysis, or recognition of objects.

This process involves the following:

1. Using the optimal threshold value t. The previously found optimal threshold value, which provides the best separation of objects in the image, is used for the final division of pixels into groups (classes).

2. Pixel classification. Each pixel of the input image is compared with the threshold value:

– if the pixel intensity is greater than or equal to the threshold – it belongs to one segment (for example, an object);

– if it is less – to another segment (for example, a background).

3. Construction of a new image matrix. Based on the classification of pixels, a new matrix is built that represents a segmented image, i.e., an image where objects and background are clearly separated.

4. Output of the result. The finished segmented image is output as a graphical result that can be saved, analyzed, or transmitted for further processing.

The block diagram of the algorithm underlying our method for segmenting an optoelectronic image acquired from a UAV based on the artificial bee colony algorithm is shown in Fig. 1.

The result of applying the method for segmenting optoelectronic images based on the artificial bee colony algorithm is:

– finding the coordinates of the optimal location of bees, at which the value of the objective function $\varphi(\mathbf{X}_{ij})$ reaches a maximum or minimum $\varphi\left(\mathbf{X}_{final}^{best}\right)$;

– calculating the optimal value of segmentation threshold t.

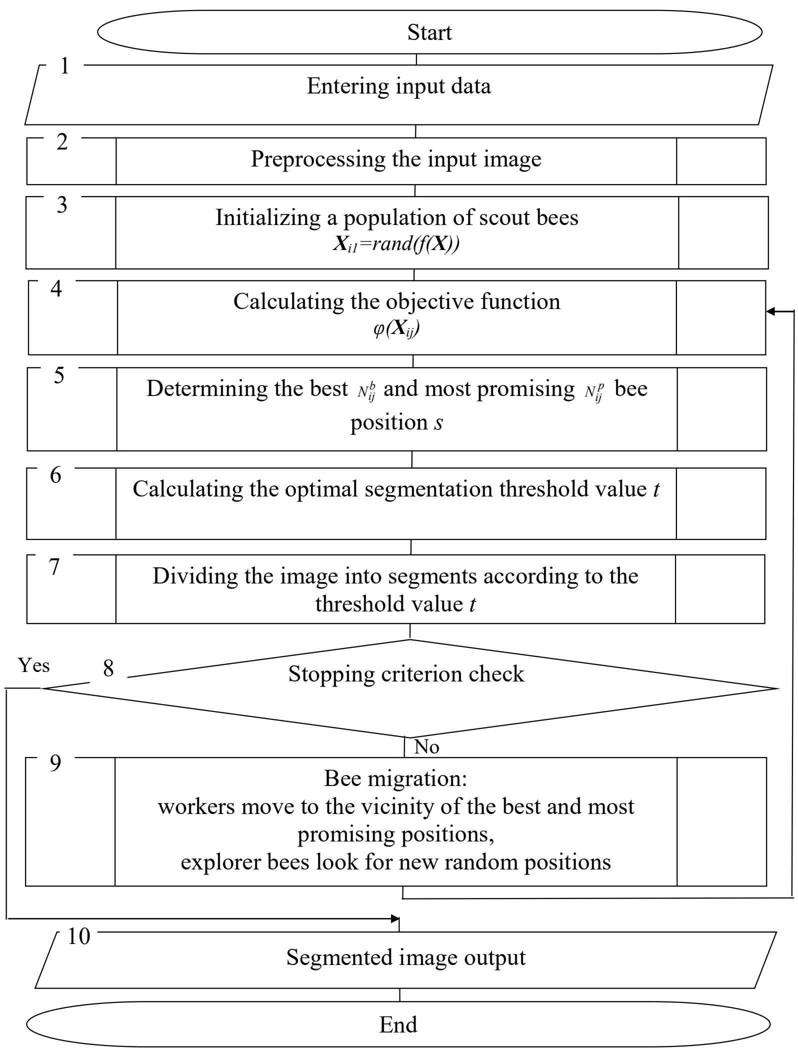

Fig. 1. Block diagram of the algorithm for the method of segmenting an optoelectronic image acquired from an unmanned aerial vehicle based on the artificial bee colony algorithm

Thus, the method of segmenting an optoelectronic image acquired from a UAV based on the artificial bee colony algorithm, unlike known ones, involves the following:

– initialization of the population of scout bees;

– calculation of the objective function;

– determining the best and promising positions;

– calculation of the optimal value of the segmentation threshold;

– image division into segments;

– checking the stopping criterion;

– bee migration;

– acquisition of a segmented image.

5. 2. Experimental study of image segmentation based on the artificial bee colony algorithm

Fig. 2 shows an optoelectronic image acquired from a UAV [13]. This is an optoelectronic image from a DJI Mavic 3 Pro (DJI RC) UAV (China). The image size is (1280 × 720) pixels. The DJI Mavic 3 Pro (DJI RC) UAV (China) is equipped with a wide-angle Complementary Metal-Oxide-Semiconductor (CMOS) Hasselblad camera, 20 MP, RAW format (4/3). The basic characteristics of the optoelectronic image (Fig. 2) are given in [14].

When conducting our experimental study on image segmentation (Fig. 2), the following initial data and assumptions were adopted:

– optoelectronic image is from the DJI Mavic 3 Pro (DJI RC) UAV (China);

– camera on the UAV is a Complementary Metal-Oxide-Semiconductor (CMOS) Hasselblad, 20 MP, RAW format (4/3), digital, wide-angle;

– color space of image representation – RGB;

– the influence of distorting factors is not considered;

– object of interest – car;

– image size $|S|$ is equal to $(1280 \times 720 = 921600)$ pixels;

– total number of bees in the population $|B| = 100$ pieces;

– number of worker bees around each of the best positions $c^b = 80$ pieces;

– number of worker bees around each of the promising positions $c^p = 0$ pieces;

– number of scouting bees $n^s = 20$ pieces;

– number of best bees $n^b = 5$ pieces;

– number of promising bees $n^p = 0$ pieces;

– coefficient that determines the radius of scattering of bees around the selected position $rad = 2$ pixels;

– size of the circle along the x axis (size of the search area along the x axis) $r_x = 5$ pixels;

– size of the circle along the y axis (size of the search area along the y axis) $r_y = 5$ pixels;

– condition for stopping the iterative process – invariance of the objective function over 5 iterations.

When conducting an experimental study, we selected the following:

– hardware: ASUSTeK COMPUTER INC model X550CC laptop, 3rd Gen processor DRAM Controller – 0154, NVIDIA GeForce GT 720M;

– software: the high-level programming language and interactive environment for programming, numerical calculations, and visualization of results MATLAB R2017b.

Fig. 3 shows a segmented optoelectronic image acquired from a UAV using the method based on the artificial bee colony algorithm.

Fig. 2. Optical-electronic image from the DJI Mavic 3 Pro UAV (DJI RC) (China) [13]

Fig. 3. Segmented optoelectronic imaging using an artificial bee colony algorithm

Fig. 3 shows the segmented object of interest – a car. The visual quality of the image (Fig. 3) makes it possible to conclude that segmentation can be performed using the method based on an artificial bee colony.

Fig. 4 shows a segmented optoelectronic image acquired from a UAV (Fig. 2) using the Otsu method [15–18] for comparison.

Fig. 4. Segmented optical-electronic imaging from a UAV using the Otsu method

Comparative analysis of Fig. 3, 4 reveals a clearer separation of the object of interest (car) by the method based on the artificial bee colony algorithm. In addition, in Fig. 3 there is no shadow effect from the object of interest (car).

Let us quantitatively evaluate the segmentation errors of the first (α_1) and second (β_2) kind (expressions (5), (6), respectively) [10, 19, 20]:

$$\alpha_1 = \frac{S_1\left(fs\left(\mathbf{X}\right)\right)}{S_2\left(f\left(\mathbf{X}\right)\right)}, \tag{5}$$

$$\beta_2 = 1 - \frac{S_3\left(fs\left(\mathbf{X}\right)\right)}{S_4\left(f\left(\mathbf{X}\right)\right)}, \tag{6}$$

where $\boldsymbol{X}(x, y)$ is the vector of pixel coordinates in the image;

$f(\boldsymbol{X})$ is the original image;

$fs(\boldsymbol{X})$ is the segmented image;

$S_1(fs(\boldsymbol{X}))$ is the number of background pixels incorrectly assigned to the object of interest in the image $fs(\boldsymbol{X})$;

$S_2(f(\boldsymbol{X}))$ is the number of background pixels in the image $(\boldsymbol{X})$;

$S_3(fs(\boldsymbol{X}))$ is the number of correctly segmented pixels of the object of interest in the image $fs(\boldsymbol{X})$;

$S_4(f(\boldsymbol{X}))$ is the number of pixels of the object of interest in the image $f(\boldsymbol{X})$.

The results of our calculating the segmentation errors of the first (α_1) and second (β_2) kinds are given in Table 1.

Table 1

Segmentation errors of the first (α_1) and second (α_1) kind

Segmentation method name	Segmentation error of the first kind (α_1), %	Segmentation error of the second kind (β_2), %
Segmentation method based on artificial bee colony algorithm	29.78	27.33
Otsu segmentation method	38.22	34.86

Analysis of Table 1 reveals a reduction in type I errors by 9% and type II errors by 7% when segmenting an optoelectronic image using the method based on the artificial bee colony algorithm.

6. Discussion of results related to devising a segmentation method based on the artificial bee colony algorithm

A method for segmenting an optoelectronic image acquired from a UAV based on the artificial bee colony algorithm has been improved, which, unlike known ones (for example, [4–12]), involves the following:

– initialization of the population of scout bees;
– calculation of the objective function;
– determining the best and promising positions;
– calculation of the optimal value of the segmentation threshold;
– image division into segments;
– checking the stopping criterion;
– bee migration;
– acquisition of a segmented image.

Experimental studies have been conducted on the segmentation of an optoelectronic image acquired from a UAV (Fig. 2) using the method based on the artificial bee colony algorithm (Fig. 3).

The visual quality of the image (Fig. 3) makes it possible to conclude that segmentation can be performed using the method based on an artificial bee colony. Fig. 4 shows a segmented optoelectronic image acquired from a UAV (Fig. 2) using the Otsu method for comparison.

Comparative analysis of Fig. 3, 4 reveals a clearer separation of the object of interest (car) using the method based on the artificial bee colony algorithm. In addition, Fig. 3 does not have a shadow effect from the object of interest (car).

The results of calculating the segmentation errors of the first (α_1) and second (β_2) types are given in Table 1. Analysis of Table 1 reveals a reduction in the errors of the first type by 9% and errors of the second type by 7% when segmenting the optoelectronic image using the method based on the artificial bee colony algorithm.

Our research limitations are as follows:

– the data given in Table 1 are valid when comparing the improved method and the Otsu method;

– the original image is undistorted.

This study in the future may tackle the quality of segmentation using other indicators and other known segmentation methods.

7. Conclusions

1. The basic stages of the method for segmenting an optoelectronic image acquired from a UAV based on the artificial bee colony algorithm are as follows:

– initialization of the population of scout bees;

– calculation of the objective function;

– determining the best and promising positions;

– calculation of the optimal value of the segmentation threshold;

– image division into segments;

– checking the stopping criterion;

– bee migration;

– acquisition of a segmented image.

2. Experimental studies have been conducted on the segmentation of an optoelectronic image acquired from a UAV using the method based on the artificial bee colony algorithm. Our results from calculating the segmentation errors of the first and second kinds indicate a reduction of the first kind errors by 9% and the second kind errors by 7% when segmenting an optoelectronic image using the method based on the artificial bee colony algorithm.

Conflicts of interest

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

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

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

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