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DEVELOPMENT OF AN IMAGE SEGMENTATION METHOD FROM UNMANNED AERIAL VEHICLES BASED ON THE PARTICLE SWARM OPTIMIZATION ALGORITHM

The object of research is the process of segmenting images from an unmanned aerial vehicle based on the particle swarm algorithm.

One of the most problematic areas in segmenting images from unmanned aerial vehicles is the reduction in the efficiency of known segmentation methods. In addition, most methods do not accurately recognize small objects that occupy a small part of the image.

The method of segmenting images from an unmanned aerial vehicle based on the particle swarm algorithm has been improved, in which, unlike the known ones, the following is performed:

– the source image is converted to the appropriate color space;

– the channel is selected for further analysis;

– the particle swarm is initialized on the source image in each channel selected for further analysis;

– the objective function is calculated for each particle of the swarm in the image in each selected channel;

– the current value of the objective function for each particle of the swarm is compared with the best value of the objective function in the image in each selected channel;

– calculating the velocity value and new location for each swarm particle in the image;

– moving each swarm particle in the image in each selected channel;

– determining the swarm particles with the best value of the objective function in the image in each channel;

– combining the channels and forming the resulting image.

During the study, it was found that the segmented image by the improved method based on the particle swarm algorithm has better visual quality compared to the known segmentation method. It was found that the improved segmentation method based on the particle swarm algorithm provides an average reduction in segmentation errors of the I kind by 11% and an average reduction in segmentation errors of the II kind by 9%.

***Keywords**: segmentation, unmanned aerial vehicle, swarm intelligence, particle swarm algorithm, k-means.*

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1. Introduction

Over the past decade, the use of unmanned aerial vehicles (UAVs) for image collection has become an important component of modern remote sensing technologies. Due to their high resolution, flexibility in use, and the ability to quickly cover large areas, UAVs have been successfully used in agriculture, forestry, and water management, environmental protection, emergency situations, etc. [1]. Images obtained using UAVs have the advantages of high spatial resolution and contain a large amount of detailed information about specific areas, which gives them an advantage over satellite and aerial photographs [2]. However, for the full use of images obtained from UAVs, their effective processing is necessary.

One of the most important stages of image processing is the stage of its segmentation. Segmentation consists in dividing the image into homogeneous areas or classes of pixels according to certain characteristics. The quality of segmentation directly affects the detection of various objects of interest.

In [3], the authors investigated a method for segmenting orthomosaic images of plants from UAVs based on deep learning. The Real-Enhanced Super-Resolution Generative Adversarial Network (Real-ESRGAN) algorithm was used to improve the quality of UAV images for semi-automated annotation. The results showed that the detection accuracy (mAP50 value) was 0.902 for You Only Look Once, version 8 (YOLOv8) and 0.920 for Mask Region-Based Convolutional Neural Network (R-CNN), respectively. Image restoration using Real-ESRGAN partially improved the accuracy. It was shown that in the presence of several types of weeds, the accuracy generally decreased. Another drawback of [3] is the limited ability of the methods to generalize in conditions of high object variability.

In [4], a comparative analysis of the effectiveness of the YOLOv8 and Mask R-CNN deep learning models is presented on the example of image segmentation in complex conditions of agricultural gardens. It was found that these models are qualitative in relation to plant segmentation. The disadvantage of [4] is that both models are mainly focused on segmenting only plants. The quality of segmentation is significantly reduced when there is overlap of vegetation, variation of shapes or merging of plants with the background. In [5], a method for segmenting tree crown images based on a regional convolutional neural network (R-CNN) is proposed, which uses a modified UNet++ architecture with a feature compression and activation block – the Multi-Scale Enhanced Unit (MSEU) R-CNN model. The accuracy of object boundary detection and segmentation by the AP50 metric is 96.6% and 96.2%, respectively, the average detection accuracy is 73.0%, and the F1-measure is 69.4%, which exceeds the corresponding indicators of the base model by 3.4%, 2.4%, 4.9% and 3.5%. Compared with the box-instant segmentation (BoxInst) and conditional convolutional networks (CondInst) models, the MSEU R-CNN model demonstrates better segmentation accuracy and higher speed than the previous leader, Mask R-CNN. The disadvantage [5] is that the model has difficulty generalizing under complex or heterogeneous conditions typical of natural tree canopies, especially when densely planted or intersecting objects.

In [6], typical models of weed control robots built or proposed in the last 30 years are reviewed, as well as several open data sets for weed detection tasks. Key technologies such as image preprocessing, image segmentation, navigation line extraction, and weed recognition based on machine learning or deep learning algorithms for robotic weed control systems are discussed. The research results showed that in each component of the robotic system, weed recognition and weed control remain numerous shortcomings that need to be addressed. However, due to the variability of the environment and the complexity of the system, machine vision-based robots are still in the early stages of development. In the study [7], a new method for segmenting images obtained from UAVs and interpreting the fire front within the ignition zone is proposed. The YOLOv7-tiny model was improved by integrating the Convolutional Block Attention Module, which combines channel and spatial attention mechanisms to improve the model's focus on fire areas and improve the accuracy of image segmentation. Experimental results showed that the proposed method improved the detection and segmentation accuracy by 3.8% and 3.6%, respectively, compared to existing approaches. The method achieved an average segmentation rate of 64.72 frames/s, which is well above the minimum threshold of 30 frames/s required for real-time. A disadvantage of [7] is that the use of the simplified YOLOv7-tiny model potentially limits the depth of analysis of complex visual scenes with a large number of obstacles, smoke, or unstable lighting, which are typical of fire areas. In [8], a new algorithm is proposed that is capable of monitoring small forest areas in real time using streaming video. The proposed algorithm is an improvement of the EdgeFireSmoke method and uses an artificial neural network in combination with a deep learning method. The EdgeFireSmoke++ algorithm achieved forest fire detection accuracy of 95.41% and 95.49% for two different metrics on a validated dataset. During real-time experiments, in particular using IP cameras, the algorithm showed excellent results, reaching 33 frames per second. However, the algorithm proposed in [8] is mainly focused on monitoring small forest areas, which limits its application for large-scale or regional monitoring, where much larger data volumes are required. In [9], for segmenting weed plant images in remotely sensed rice field images, the authors propose to use a new segmentation model called Coarse-to-Fine Feature Fusion Network (CTFFNet), which combines a convolutional neural network (CNN) and a transformer. The authors developed two feature extraction modules using a transformer and a residual CNN, which generate global semantic features and local visual features. The experiments demonstrate that compared to individual CNN or Transformer models, CTFFNet achieves the best segmentation accuracy when dealing with complex and variable shapes of plant (weed) objects, with a Mean Intersection over Union (MIoU) of 72.8%, which significantly improves segmentation performance. The main drawback of [9] is the rather complex structure of the model from a computational point of view.

In [10], a new method for improving the segmentation of UAV-derived rice plant images in the field is proposed, namely Weighted Skip-Connection Feature Fusion (WSFF). Based on this method, a new model called Weakly-Supervised U-Net (WSUNet) was developed, which combines WSFF and the basic UNet architecture. The authors generated two sets of UAV-derived rice plant images. These two sets, as well as an additional set of cell nucleus images, were used to compare the performance of the UNet, WSUNet, and UNet++ models. The mean Intersection over Union (mIOU) and mean pixel classification accuracy (mPA) were used as evaluation metrics. In terms of mIOU, the WSUNet model outperformed UNet on all datasets, while the maximum improvement on the rice plant image set was 2.84%. The average inference speed of WSUNet on the processor was 2.1 times higher than that of UNet++. However, the limited volume and diversity of the used datasets, focused mainly on monoculture plants (rice), casts doubt on the model's ability to generalize to other types of crops or shooting conditions, which is the main drawback [10]. In [11], the authors developed an image segmentation network that is capable of extracting features of large-scale variations in urban ground buildings. A new composite transformer network was proposed for segmenting UAV images of urban buildings. The accuracy of urban building segmentation could be significantly improved, and large-scale variation objects were successfully segmented from UAV images. Experimental results demonstrated the effectiveness of the developed network structure and the superiority of the proposed network over state-of-the-art methods. In particular, 53.2% mIoU was achieved on the Unmanned Aerial Vehicle video dataset (UAVid) and 77.6% mIoU on the Urban Drone Dataset, version 6 (UDD6), respectively. The main drawback of [11] is the high computational cost.

In [12], a method for segmenting fire images captured by UAVs is developed. A new benchmark for testing typical methods is Unsupervised Domain Adaptation (UDA) and an efficient Colour-Mix platform is proposed to improve the performance of the segmentation method equivalent to the fully supervised level. Experimental evaluations demonstrate the limitations of current UDA systems and the advantage of the Colour-MiX platform in handling various fire conditions. The Colour-MiX system is simple but effective enough to improve the performance of a neural network without using complex methods. However, the main drawback of [12] is the instability of the platform when changing such shooting parameters as sensor type, flight altitude or noise level.

Therefore, although deep learning methods provide high accuracy, they require significant computational resources and large volumes of labeled data, which limits their application in real-time conditions or on devices with limited computing power. Known image segmentation methods, such as threshold algorithms, clustering, methods based on contour extraction, demonstrate low efficiency in conditions of complex background, non-uniform illumination or noise, typical of images obtained from UAVs [13–16].

In connection with the above, there is a growing interest in heuristic and meta-heuristic approaches, in particular in swarm intelligence methods, which have proven their effectiveness in image optimization and processing tasks.

In [17], it was proposed to use a hybrid approach for segmenting images obtained from UAVs, which combines the efficiency of pixel clustering (k-means) with the ability of genetic algorithms to globally optimize parameters. The advantage of [17] is that there is no need to manually determine the number of clusters and cluster centers, as is

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inherent in classical *k*-means, and no prior training is required, as is usually necessary for deep models. The disadvantage of [17] is the lack of consideration of spatial relationships between pixels and the lack of guarantees of a global optimum – the possibility of convergence to a local optimal solution, especially without careful parameter tuning.

To eliminate the shortcomings of the method [17], in [18] an improved segmentation method based on a genetic algorithm was proposed, the main idea of which is to evolutionary "train" an operator that best performs segmentation of images with a complex structure. The main advantages, in addition to eliminating the shortcomings of the previous method, are that [18] can be applied to images of different nature (medical, satellite, from UAVs, etc.) without changing the basic architecture. The main disadvantage of [18] is the significant need for time and resources to achieve the optimal solution. In [19], a segmentation method was proposed based on one of the swarm intelligence methods – the firefly algorithm. This metaheuristic approach is inspired by the behavior of fireflies in nature, in particular their ability to find each other using light signals. Optimization occurs by moving fireflies to brighter (better) solutions from the point of view of the selected objective function. The main advantages of [19] are automatic search for the best solution, parallel computations, and fast convergence of the algorithm. The main disadvantage of [19] is the possibility of getting stuck in local extrema, especially on complex images without additional heuristics. In [20], the authors proposed the use of another algorithm of swarm intelligence, namely a simple ant algorithm, which was inspired by the behavior of ants in nature during food search. Pheromone traces are used as a mechanism for highlighting the most significant pixels belonging to different segments in the image. The advantages of [20] are the simplicity of calculations, which does not require significant computing power, and the possibility of its implementation on simple computing devices, which is important for processing images obtained from UAVs. However, the main disadvantages [20] are the limited quality of segmentation – inferior to modern methods based on deep learning when processing images with complex scenes and sensitivity to the input parameters of the method.

Segmentation of images obtained from UAVs by known methods is complicated due to the features of such images [21]. These are:

– constant change in flight altitude;
– different viewing angles;
– change in lighting;
– presence of noise;
– complexity of the landscape.

These features lead to a decrease in the efficiency of known segmentation methods that work well with other types of images. In addition, most methods do not accurately recognize small objects that occupy a small part of the image.

Analysis of known works [19, 20] showed that the use of segmentation methods based on swarm intelligence algorithms allows segmentation of images from UAVs. However, the methods proposed in [19, 20] have certain drawbacks and cannot be directly applied to UAV image segmentation.

Therefore, it is relevant to develop a method for segmenting UAV images based on other swarm intelligence methods.

The particle swarm algorithm was chosen as the swarm intelligence algorithm for developing a method for segmenting UAV images in this work. The choice of the particle swarm algorithm is due to the following properties [22, 23]:

– self-organization – allows for flexible adaptation to the image structure without the need for clearly defined rules;
– positive feedback – a group of agents is able to gather around pixels with similar characteristics, which corresponds to objects of interest in the image;
– negative feedback – this prevents excessive concentration of agents in certain areas, contributing to maintaining a stable segment structure and uniform image coverage;
– stochastic variability – due to random components in the behavior of agents, the algorithm is able to avoid local minima and explore new, potentially better areas;
– information interaction between agents – the exchange of information about the best positions found allows for rapid coordination of collective behavior and achieving high-quality global image segmentation.

The aim of the research is to develop a method for segmenting images from an unmanned aerial vehicle based on the particle swarm algorithm.

2. Materials and Methods

The object of research is the process of segmenting images from an unmanned aerial vehicle based on the particle swarm algorithm.

The following scientific methods were used in the study:

– when analyzing known methods of segmenting images from UAVs: methods of comparative analysis, methods of digital image processing, methods of neural networks, methods of artificial intelligence;
– when developing a method of segmenting images from UAVs based on the particle swarm algorithm: methods of digital image processing, methods of probability theory and mathematical statistics, methods of matrix theory, methods of differential calculus, methods of swarm intelligence, methods of optimization theory;
– when processing images from UAVs: methods of digital image processing, methods of mathematical modeling, methods of probability theory and mathematical statistics, methods of matrix theory, methods of differential calculus, methods of swarm intelligence, methods of optimization theory, methods of comparative analysis.

The following was used for the study:

– hardware: Dell laptop Intel® Core™ i7-8650U CPU@ 1.90 GHz;
– software: high-level programming language Matlab 7 with application program package, interpreted object-oriented programming language Python 3.11.

3. Results and Discussion

3.1. Formulation of the image segmentation task

In general, the image segmentation obtained from an on-board UAV camera can be described as a transformation [20]

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

where $f(x, y)$ – the original image captured by the UAV optical system; $fs(x, y)$ – the result of the original image segmentation, which contains the selected areas of objects of interest (segments).

Segmentation consists in transforming the pixel space of the original image into a feature space, where each pixel is represented by a set of characteristics. The main feature is brightness or color, which are analyzed taking into account two key properties – homogeneity (uniformity) and contrast (discontinuity) between neighboring areas.

Therefore, the goal of segmentation is to divide the image $f(x, y)$ into a set $B = \{B_1, B_2, ..., B_k\}$ of disjoint segments, i. e. [20]

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

where $\boldsymbol{B}$ – the total number of segments; B_i – the area of pixels belonging to one segment.

To define segments, the predicate $LP(B_i)$ is introduced, which returns a true value if and only if all pairs of pixels within the segment B_i satisfy the homogeneity conditions

$$LP(B_i)=1 \Leftrightarrow$$
$$\Leftrightarrow \forall (x_m, y_m),...(x_1, y_1) \in B_i : d(f(x_m, y_m),...f(x_1, y_1)) \le T, \qquad (3)$$

where M – the number of pixels within the segment B_i; $d(...)$ – the distance function between vector features of pixels in a given color space; T – the threshold of similarity that determines the level of homogeneity within one segment.

Thus, an image segmentation from a UAV is based on finding such areas B and in which the local characteristics of pixels (in particular, color or brightness) are as similar as possible according to a given metric.

As a result of image segmentation obtained from the UAV optical system, the original image is divided into areas corresponding to artificial objects (in particular, objects of interest) and the natural background, which includes elements of the environment.

3.2. The main stages of the image segmentation method from an unmanned aerial vehicle based on the particle swarm algorithm

The main stages of the image segmentation methods from a UAV based on the particle swarm algorithm are shown in Fig. 1.

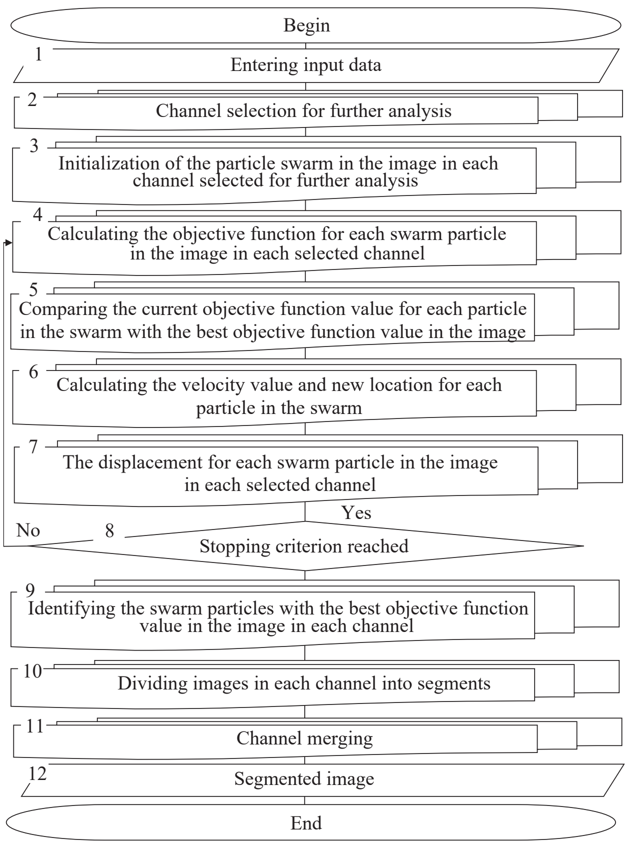

Fig. 1. The main stages of the UAV image segmentation method based on the particle swarm algorithm

Let's consider in detail the stages of the UAV image segmentation method based on the particle swarm algorithm.

1. *Input data input.*

At this stage:

– an image is obtained from the UAV camera: color or grayscale. The output image, which is recorded by the UAV optical system, is $f(x, y)$, where $X(x, y)$ are the pixel coordinates on the plane of the output image;

– the output image $f(x, y)$ is converted into the corresponding color space (for example, RGB, HSV or grayscale);

– information-significant channels are selected for further analysis (for example, the brightness channel or their combination).

2. *Channel selection for further analysis.*

3. *Initialization of the particle swarm on the output image $f(x, y)$ in each channel selected for further analysis.*

At this stage:

– the number of swarm particles is determined – S. In the proposed method, the total number of swarm particles is equal to the total number of pixels of the original image;

– random generation for each swarm particle of the initial coordinates in the image, which form the vector of its initial position at the first iteration

$$\mathbf{X}_{i_1}(x_{i_1}, y_{i_1}),$$

where $i = 1, 2, ..., S$.

4. *Calculation of the objective function for each particle of the swarm in the image in each selected channel.*

This stage begins the iterative process of the particle swarm algorithm. The iterative process of the particle swarm algorithm is characterized by high adaptability, the ability to globally search in the solution space, and an effective convergence control mechanism. Due to these properties, the algorithm is suitable for rapid and accurate processing of images, in particular those obtained from UAV optical sensors.

Within the iterative process, information is exchanged between particles by updating their velocities and positions (coordinates). During the update, the orientation is carried out both on the own experience of each particle (local optimum) and on the best global solution found among the entire swarm. This approach provides a balanced combination of exploitation of existing solutions and exploration of new areas of the space of possible solutions.

In order to find positions where pixels belong to the same object of interest or background class, the objective function is calculated for each particle of the swarm. The function of the form is chosen as an objective function

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

where $D_i^s(j)$ – the function describing the length of the route of the s-th particle of the swarm at the j-th iteration; j – the iteration number; N – the size of the original image $f(x, y)$.

The function $D_i^s(j)$ determines the total change in the position of the swarm particle and the corresponding change in the brightness of the pixels with which it interacts. At each iteration of the algorithm, the distance traveled by the swarm particle is taken into account, as well as local brightness gradients indicating a change in the intensity of pixel values in its immediate surroundings.

For the s-th particle of the swarm at a certain point in the image at the j-th iteration, the route section function is determined according to the expression

$$D_i^s(j) = \left|\Delta x_i^s(j)\right| + \left|\Delta y_i^s(j)\right| + k\left|\Delta f_i^s(j)\right|, \qquad (5)$$

where $\left|\Delta x_i^s(j)\right|$ – the displacement magnitude of the s-th particle of the swarm along the x-axis at the j-th iteration; $\left|\Delta y_i^s(j)\right|$ – the displacement magnitude of the s-th particle of the swarm along the y-axis at the j-th iteration; k – scale factor, which brings the spatial units of measurement and the brightness levels of pixels into line. If the brightness values are in the standard range [0...255], then $k = 1$ is assumed; $\left|\Delta f_i^s(j)\right|$ – absolute brightness difference between neighboring pixels with which the s-th particle of the swarm interacts at the j-th iteration in the i-th pixel of the image.

The last component of expression (5) is determined through the brightness contrast function

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

where $f(x,y)$ – function, which returns the brightness value of the pixel at the corresponding point of the image.

Taking into account all the above components, the generalized objective function, which accumulates the total estimates for all particles of the swarm at the *j*-th iteration, has the form

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

Function (7) allows the algorithm to assess the quality of image segmentation, focusing on both spatial particle movements and local brightness changes. Thus, swarm particles tend to move in directions where there is a significant change in image intensity, which indicates potential boundaries of objects in the interior.

5. *Comparison of the current value of the objective function for each swarm particle with the best value of the objective function in the image in each selected channel.*

At this stage of the particle swarm algorithm, the current value of the objective function for each particle is compared with the best value achieved in previous iterations, i. e., the global optimum in the population of swarm particles is evaluated and updated. This approach allows identifying the most effective (globally optimal) position of the swarm particle in the solution space, which maximally meets the optimization criterion. The evaluation is performed separately in each channel, which increases the accuracy of image segmentation.

The globally best particle position at the *j*-th iteration, denoted as $\mathbf{X}_j^{gbest}(x,y)$, is determined based on a comparison of the objective function values for the current and previous iterations according to the following expression

$$\boldsymbol{X}_j^{gbest}(x,y)=\begin{cases}\boldsymbol{X}_{j-1}(x,y), & \text{if } \varphi\left(\boldsymbol{X}_{j+1}(x,y)\geq\varphi\left(\boldsymbol{X}_j\right)\right);\\ \boldsymbol{X}_{j+1}(x,y), & \text{if } \varphi\left(\boldsymbol{X}_{j+1}(x,y)<\varphi\left(\boldsymbol{X}_j\right)\right),\end{cases} \quad (8)$$

where $\varphi(\mathbf{X})$ – the value of the objective function at the corresponding point in the solution space; $\mathbf{X}_{j-1}(x,y)$ – the coordinates of the particle at the previous (j–1)-th iteration; $\mathbf{X}_j(x,y)$ – the coordinates of the particle at the current *j*-th iteration.

Thus, if the new position of the swarm particle gives a better value of the objective function, it is updated as a new global best vector. Otherwise, the previous value is preserved. This allows the algorithm to gradually approach the global extremum without losing the most promising solutions found earlier.

6. *Calculation of the velocity value and new location for each swarm particle in the image.*

To determine the new coordinates of each swarm particle in the studied image within each channel selected for analysis, its movement velocity is calculated. This process is implemented according to the following formula

$$\begin{array}{l}v_{i,j+1}(x,y)=wv_{i,j}(x,y)+c_1r_{1,j}\left[\mathbf{X}_{i,j}^{gbest}(x,y)-\mathbf{X}_{i,j}(x,y)\right]+\\+c_2r_{2,j}\left[\mathbf{X}_{i,j}^{pbest}(x,y)-\mathbf{X}_{i,j}(x,y)\right],\end{array} \quad (9)$$

where w – the inertia coefficient, which is an empirically established parameter. This parameter affects the change in particle velocity, controlling the balance between searching for new areas and preserving already found promising areas in the image; $v_{i,j}(x,y)$ – velocity vector of the *i*-th particle of the swarm at the *j*-th iteration; $\mathbf{X}_{i,j}(x,y)$ – the coordinates of the *i*-th particle of the swarm at the *j*-th iteration; $\mathbf{X}_{i,j}^{gbest}(x,y)$ – the best position of the *i*-th particle within its own experience (local optimum); $\mathbf{X}_j^{gbest}(x,y)$ – globally the best position among all particles at the *j*-th iteration; c_1, c_2 – the acceleration coefficients that regulate the intensity of movement to the local and global extrema; $r_{1,j}, r_{2,j}$ – the random values from the interval [0,1] that ensure the stochastic nature of the algorithm.

The globally best position $\mathbf{X}_j^{gbest}(x,y)$ is determined according to the expression

$$X_j^{best}(x,y)=\arg\min\left\{\varphi\left(X_{1,j}(x,y)\right),...,\varphi\left(X_{J,j}(x,y)\right)\right\}, \quad (10)$$

where $\varphi(\cdot)$ – the objective function that evaluates the quality of the obtained solution; J – the total number of particles in the swarm.

Thus, the swarm optimizer algorithm adapts the position of each particle, taking into account its inertial characteristics, local achievements and collective experience of the swarm, which allows to effectively find optimal areas in the image.

7. *Movement for each swarm particle in the image in each selected channel.*

At each iteration of the computational process, all swarm particles are moved according to the updated velocities. This movement occurs separately in each selected channel. The new coordinates of each particle at the *j*-th iteration are determined as the sum of the previous position and the new velocity

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

This scheme provides dynamic adaptation to local image changes, allowing the swarm particles to effectively explore the space of possible solutions.

8. *Checking the conditions for the termination of the iteration process.*

The iterations are repeated until one of the termination conditions is met. This may be the achievement of a predetermined maximum number of iterations or the stabilization of the process, which is manifested in the minimum increase in particle velocity – when changes in position become insignificant. Thus, the algorithm stops when further changes do not lead to a noticeable improvement in the result.

9. *Determining the swarm particles with the best value of the objective function in the image in each channel.*

At the final stage of the analysis of the iteration process, a search is performed for particles that demonstrate the best values of the objective function. This allows identifying the most promising coordinates in the image – separately for each of the analyzed channels.

10. *Dividing the images in each channel into segments.*

After the optimization process is completed, the results are used to divide the image into separate segments in each analyzed channel. This approach ensures accurate localization of objects that have similar brightness characteristics.

11. *Combining channels and forming the resulting image.*

After dividing into segments in each channel, the results are merged, which allows obtaining a full-fledged segmented image.

12. *Outputting the segmented image.*

The result of processing is the construction of the result in the form of a segmented image, which contains information about the distribution of segments within the image, taking into account the characteristics of each analyzed channel.

Thus, the method of segmenting an image from an unmanned aerial vehicle based on the particle swarm algorithm has been improved, in which, unlike the known ones, the following is performed:

– conversion of the original image into the appropriate color space;
– selection of the channel for further analysis;
– initialization of the particle swarm on the original image in each channel selected for further analysis;
– calculating the objective function for each swarm particle in the image in each selected channel;
– comparing the current objective function value for each swarm particle with the best objective function value in the image in each selected channel;

– calculating the velocity value and new location for each swarm particle in the image;
– moving each swarm particle in the image in each selected channel;
– determining the swarm particles with the best objective function value in the image in each channel;
– combining the channels and forming the resulting image.

3.3. Segmentation of an image from an unmanned aerial vehicle based on the particle swarm algorithm

To verify the operation of the segmentation method based on the particle swarm algorithm, it is possible to segment an image from an UAV. The image (Fig. 2) [24] was selected as the source. This is an image from a DJI Mavic 3 Pro (DJI RC) UAV (China). The main characteristics of the UAV camera: wide-angle 4/3 Complementary Metal-Oxide-Semiconductor (CMOS) Hasselblad, 20 MP, RAW format, shooting speed 5.1 K/50 frames per second [25].

Fig. 2. Output image from UAV [24]

When performing segmentation, the following initial data and assumptions were made:
– the image from the DJI Mavic 3 Pro (DJI RC) UAV (China) is considered as the source;
– the initial image is presented in the Red-Green-Blue (RGB) color space;
– the image presents the object of interest;
– the size of the object of interest is smaller than the size of the background objects;
– the effects of noise, rotation and scaling on the original image are not taken into account;
– hardware: Dell laptop Intel® Core™ i7-8650U CPU@ 1.90 GHz;
– software: high-level programming language Matlab, interpreted object-oriented programming language Python 3.11.

The segmented image using the particle swarm algorithm is shown in Fig. 3.

In Fig. 3, the number of clusters for segmentation is 8. For clarity, different clusters are marked with different pseudocolors.

Analysis of Fig. 3 allows to draw a conclusion about the efficiency of the segmentation method based on the particle swarm algorithm.

For comparison, Fig. 4 shows an image segmented by the known k-means method [17, 26]. The number of clusters is also 8.

A comparative analysis of Fig. 3 and Fig. 4 indicates a better visual quality of the segmented image by the method based on the particle swarm algorithm. For example, it is possible to study the structure of the road surface, the features of a passenger car and a trailer, etc.

To quantitatively assess the quality of image segmentation by the known and improved method, it is possible to use segmentation errors of the I and II kinds [19]. Segmentation errors of the I (α_1) and II (β_2) kinds are calculated by expressions (12), (13) respectively [19]:

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

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

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

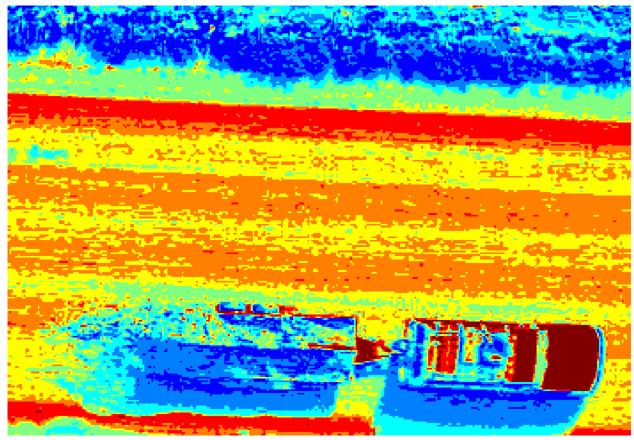

Fig. 3. Segmented image by the method based on the particle swarm algorithm

Fig. 4. Segmented image by the known k-means method

The results of calculating the segmentation errors of the first (α_1) and second (β_2) types are given in Table 1 and Table 2. In this case, taking into account the iterative nature of the particle swarm algorithm, the process of segmenting the original image was carried out 5 times. The estimation of segmentation errors of the first (α_1) and second (β_2) types was calculated for the known method (k-means) and the improved method based on the particle swarm algorithm. At the same time, segmentation errors of the I (α_1) (Table 1) and II (β_2) kind (Table 2) are constant and do not depend on the number of segmentation processes.

From the analysis of Table 1 and Table 2, it was found that the improved segmentation method based on the particle swarm algorithm provides a reduction in segmentation errors of the I kind by an average of 11% and a reduction in segmentation errors of the II kind by an average of 9%.

Table 1

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

Segmentation method name	Segmentation error of the I kind (α_1), %				
	Image segmentation process number				
	1	2	3	4	5
Well-known *k*-means method ($k=8$)	29.8	29.8	29.8	29.8	29.8
Improved segmentation method based on particle swarm algorithm	18.9	19.1	19.0	18.8	18.7

Table 2

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

Segmentation method name	Segmentation error of the I kind (α_1), %				
	Image segmentation process number				
	1	2	3	4	5
Well-known *k*-means method ($k=8$)	27.7	27.7	27.7	27.7	27.7
Improved segmentation method based on particle swarm algorithm	19.3	19.7	19.1	19.6	19.5

Practical significance. The practical significance of the improved segmentation method based on the particle swarm algorithm lies in the possibility of performing image segmentation from a UAV. At the same time, the visual quality of the segmented image is better compared to known methods.

Research limitations. The following limitations were adopted during the research:
- an optoelectronic image from a UAV is considered;
- the influence of distorting factors is not considered;
- the number of segments in the work is not optimized, but is selected experimentally;
- the *k*-means method is selected as the known one.

Prospects for further research. Prospects for further research are:
- conducting a quantitative comparison of the developed image segmentation method with other known segmentation methods;
- study of the operation of the segmentation method under the influence of distorting factors.

4. Conclusions

Thus, the method of segmenting an image from an unmanned aerial vehicle based on the particle swarm algorithm has been improved, in which, unlike the known ones, the following is performed:
- conversion of the original image into the corresponding color space;
- selection of a channel for further analysis;
- initialization of a particle swarm in the original image in each channel selected for further analysis;
- calculation of the objective function for each swarm particle in the image in each selected channel;
- comparison of the current objective function value for each swarm particle with the best objective function value in the image in each selected channel;
- calculation of the velocity value and new location for each swarm particle in the image;
- movement of each swarm particle in the image in each selected channel;
- determination of swarm particles with the best objective function value in the image in each channel;
- combination of channels and formation of the resulting image.

During the research, it was found that the segmented image by the improved method based on the particle swarm algorithm has better visual quality compared to the known segmentation method.

The research results will be useful in conducting practical segmentation of images from UAVs for various purposes.

Conflict of interest

The authors declare that they have no conflict of interest regarding this research, including financial, personal, authorship or other, which could affect the research and its results presented in this article.

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Data availability

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 presented work.

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