UDC 004.932 doi: https://doi.org/10.20998/2522-9052.2025.3.02

Hennadii Khudov[1], Oleksandr Makoveichuk[2], Irina Khizhnyak[1], Valerii Varvarov[1], Fedir Zots[1]

[1] Ivan Kozhedub Kharkiv National Air Force University, Kharkiv, Ukraine
[2] Academician Yuri Bugay International Scientific and Technical University, Kyiv, Ukraine

EXPERIMENTAL STUDIES OF THE IMAGE SEGMENTATION METHOD QUALITY FROM UNMANNED AERIAL VEHICLES BASED ON THE ANT COLONY OPTIMIZATION ALGORITHM UNDER THE INFLUENCE OF ADDITIVE GAUSSIAN NOISE

Abstract. The **subject matter** of the article is experimental studies of the image segmentation method quality from UAVs based on the Ant Colony Optimization algorithm under the influence of additive Gaussian noise. The **goal** is to reduce the probability of first and second type errors in image segmentation by applying a segmentation method based on the Ant Colony Optimization algorithm under the influence of additive Gaussian noise. The **tasks** of the study are to evaluate the robustness and accuracy of the image segmentation method based on the Ant Colony Optimization algorithm under varying levels of additive Gaussian noise, and to compare its performance with the classical Sobel filter–based segmentation approach. **The methods used are** digital image processing techniques, statistical analysis of segmentation quality, implementation of the Ant Colony Optimization algorithm for image segmentation, modeling of noise-contaminated conditions, and comparison of segmentation errors of the first and second kinds. The following **results** are obtained: the method based on the Ant Colony Optimization algorithm demonstrates superior noise resistance and maintains higher accuracy than the Sobel filter approach. Specifically, it reduces first-kind segmentation errors by 14–23% and second-kind errors by 9–17%, depending on the level of noise. Visual and quantitative analysis confirms the effectiveness of the proposed method in processing UAV-acquired imagery affected by additive Gaussian noise. **Conclusions.** The experimental findings confirm that the method based on the Ant Colony Optimization algorithm outperforms conventional edge detection techniques, particularly under noisy conditions, providing improved accuracy and robustness across a range of noise intensities.

Keywords: UAV imagery; image segmentation; additive Gaussian noise; Ant Colony Optimization algorithm; quality of segmentation; errors of the first and second kinds.

Introduction

Formulation of the problem. In the current context of rapid development of unmanned aerial vehicles (UAVs), the need for effective methods of processing the captured images is increasing to solve a wide range of tasks. Such tasks may include monitoring, mapping, agri-visualization, object detection, and others [1]. One of the key stages in the analysis of UAV-acquired images is the segmentation stage. This stage enables the identification of areas and/or objects of interest in UAV imagery [2]. However, the quality of segmentation largely depends on the presence of noise, which often arises during image acquisition in real-world conditions. Moreover, the specifics of UAV imaging introduce several additional factors that contribute to the occurrence of noise. Among these factors are [3, 4]:

– vibrations, which can cause micro-shifts in the image even in the presence of gyroscopic stabilization;

– weight and size limitations, which necessitate the use of small sensors with a lower signal-to-noise ratio;

– insufficient lighting, as sensors receive fewer photons in low-light conditions, increasing the noise-to-signal ratio;

– video or photo compression, which is often performed in real time, leading to the appearance of artifacts;

– radio interference, which can affect signal transmission and introduce digital noise;

– automatic image processing algorithms, which may apply excessive filtering or sharpening, also resulting in artifacts.

When capturing images with UAVs, several types of noise can be observed, such as [5, 6]: additive Gaussian noise, salt-and-pepper noise, impulse noise, quantization noise, color (chroma) noise, compression artifacts, motion blur noise, and dark current noise. Their occurrence is due both to the physical limitations of sensors and to the specific conditions of UAV operation [7]. The presence of such noise significantly complicates the accurate extraction of objects of interest from images, which necessitates the development and application of noise-resistant segmentation methods.

Analysis of recent research and publications. To date, the segmentation of images acquired from UAVs has become one of the key areas of modern research in the field of computer vision and image processing. Considerable attention is being paid to the development and improvement of algorithms capable of accurately identifying objects of interest in noisy imagery.

In [8], a new object detection algorithm is proposed, which is specially designed for noisy imagery obtained from UAVs. The algorithm includes a blurry image restoration auxiliary branch (BRAB) and a feature fusion module with attention, which allows for effective object detection even when the imagery is blurred. The advantages of [8] are the ability to compensate for the blurring characteristic of high-speed UAV imaging, thanks to the blurry image restoration auxiliary branch (BRAB), and improving the quality of the input signal even before the main object detection. A disadvantage of the proposed approach [8] is its increased complexity and computational cost. The inclusion of the restoration branch and complex fusion mechanisms significantly raises the computational load during training. Moreover, the training process requires a large volume of data: both the BRAB and MAGFF modules demand annotated images captured under diverse conditions, such as varying lighting, noise levels, and motion blur.

In study [9], a novel feature fusion architecture is presented, specifically designed for object detection tasks in UAV imagery. The advantages of [9] include the improved accuracy of object localization and classification (especially for small objects), even under challenging conditions with noise and occlusions. The disadvantages of [9] lie in the fact that the proposed method may not provide sufficient efficiency when processing ultra-high-resolution UAV images, which limits its applicability in real-time scenarios.

In study [10], a new object detector optimized for UAV imagery is presented. The proposed ChannelC2f and GatedFFN modules improve the detection of small objects and ensure low latency. This is an advantage of the approach in [10], as it enables efficient real-time performance even in the presence of noise. The main disadvantage of [10] is that despite the high efficiency and speed of the RemDet model, it shows reduced accuracy in detecting very small objects in complex scenes with significant clutter.

In [11], a lightweight semantic segmentation model for UAV imagery is proposed, which combines global and local information to improve accuracy and performance. The advantage of [11] is that the model effectively handles noise and complex backgrounds. The disadvantage of [11] is a decline in performance when operating on limited hardware resources, which may hinder its application on lightweight UAVs.

The study [12] analyzes the application of the U-Net algorithm for UAV image segmentation, focusing on its effectiveness in various fields such as agriculture and urban planning. The advantage of [12] lies in its high segmentation accuracy of UAV imagery due to the efficient Unet architecture, which performs well even with limited datasets. The main disadvantage of [12] is its high computational demand, which may hinder its use in real-time applications or on low-performance devices.

Thus, many studies [8–12] consider classical and deep learning methods, but recently, more and more attention has been paid to bioinspired approaches, in particular optimization algorithms.

The paper [13] presents an image segmentation method for UAV-acquired images based on one of the well-known swarm intelligence techniques – the Particle Swarm Optimization (PSO) algorithm. The proposed approach enables effective detection and separation of objects in aerial images by optimizing the positions of clusters during the segmentation process. The advantage of [13] lies in its high efficiency when segmenting complex images, achieved through PSO's ability to quickly locate global optimal solutions in a large search space. The main disadvantage of [13] is the method's sensitivity to initialization parameters and the possibility of converging to local minima, which may degrade segmentation quality under varying conditions or image types.

In the article [14], a method for detecting objects in images based on the Firefly Algorithm is proposed. The algorithm imitates the behavior of fireflies, which are attracted to brighter individuals, which allows optimizing the process of searching for objects in images using the mechanism of adaptive movement in the search space. The main advantage of [14] is that the method demonstrates high efficiency in object detection due to the ability of the Firefly algorithm to avoid local minima and find accurate results in complex scenes. The main disadvantage of [14] is the increased resource consumption and slow convergence with many fireflies, which makes it difficult to scale the method to process large satellite images.

In the article [15], methods for determining the contours of objects in complex-structured color space images using the Ant Colony Optimization (ACO) algorithm are developed. This method imitates the behavior of ants in nature to search for optimal paths. This allows finding clear contours of objects in images with complex texture. The main advantage of [15] is the ability of the method to accurately determine contours even in difficult conditions, thanks to the global search inherent in the ACO algorithm. The disadvantage of [15] is the significant computational time, which reduces the efficiency when processing large space imagery.

The analysis shows that the approach proposed in [15] is one of the promising directions for solving the problem of segmentation of images obtained from UAVs. As shown in a number of studies, in particular in [16, 17], this approach demonstrates efficiency in finding global extrema of image separation functions, which, according to the authors, makes it appropriate for use in conditions of noise.

At the same time, the issue of applying Ant Colony Optimization algorithms for segmenting UAV images containing additive Gaussian noise remains insufficiently studied. This necessitates the need for experimental studies aimed at assessing the stability and accuracy of the proposed algorithm in conditions of noise pollution.

Therefore, the **goal** of the article is to reduce the probability of first and second type errors in image segmentation by applying a segmentation method based on the Ant Colony Optimization algorithm under the influence of additive Gaussian noise.

Main results

The study proposes the application of the Ant Colony algorithm for solving image segmentation tasks based on data obtained from UAVs. The Ant Colony algorithm is based on modeling the natural behavior of ants that leave pheromone trails on their way to food sources, thereby forming optimal paths. This bio-inspired approach provides an effective mechanism for finding solutions to complex problems [16–18].

The algorithm is among the most well-known metaheuristic methods used for solving a wide range of combinatorial optimization problems, including the traveling salesman problem, transportation logistics tasks, and other discrete optimization problems. Its implementation involves the following key stages [16–18]:

Stage I. *Initialization*

At the initial stage of the algorithm, key parameters are set that determine the behavior of ants (agents) and affect the efficiency of finding the optimal solution.

The main steps of this stage include:

– setting the number of agents (ants) that will participate in the search process. Their number usually correlates with the size of the problem (for example, the number of pixels in the image);

– setting weighting coefficients: a coefficient that determines the degree of influence of pheromone information on the choice of the ant's next step (α) and a coefficient that characterizes the importance of heuristic information during decision-making (β);

– setting the pheromone evaporation coefficient (ρ), which models the process of decreasing the intensity of the pheromone trail over time, preventing excessive accumulation of pheromones and promoting a balance between research and exploitation;

– setting the initial level of pheromones on all edges of the graph, which provides equal conditions for starting the search from any vertex;

– forming a graph model of the problem, where nodes correspond to pixels, and edges to potential paths between them with appropriate weights.

This stage lays the foundation for the effective functioning of subsequent phases of the algorithm and provides control over the optimization process.

Stage II. *Ant placement*

After the initialization stage is completed, the initial placement of agents (ants) in the spatial structure of the problem, represented in the form of a graph, is performed. This stage includes the following key actions:

– random initial placement of each ant at one of the vertices of the graph. This provides an initial diversity of search paths, reducing the probability of premature convergence of the algorithm to a local extremum;

– assigning each ant the task of constructing its own solution. Each ant must form a complete route that passes through all the necessary nodes of the graph, adhering to the constraints of the problem;

– storing local information about already visited nodes, which is necessary to ensure the feasibility of the solution (for example, avoiding repeated visits to pixels).

This approach promotes the parallel generation of a set of independent solutions, which increases the efficiency of the global search and creates the basis for collective learning of the system through pheromone updates in subsequent stages.

Stage III. *Construction of solutions*

At this stage, each ant, starting from its starting vertex, gradually builds a complete route (solution to the problem) by gradually choosing the next vertex of the graph. The choice is based on a probabilistic approach that takes into account two key factors:

– the level of pheromone concentration τ_{ij} on the edge between the current vertex *i* and the potential vertex *j*. The higher the level of pheromone, the more attractive the transition is considered;

– heuristic information η_{ij}, which is usually the inverse of the distance between the vertices:

$$\eta_{ij} = 1/d_{ij}\,, \tag{1}$$

where d_{ij} is the distance between the vertices *i* and *j*. Thus, the closer vertices are more attractive for selection.

The process of selecting the next vertex is performed according to the probabilistic formula:

$$P_{ij} = \frac{\left[\tau_{ij}\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum_{k \in K} \left[\tau_{ik}\right]^{\alpha} \cdot \left[\eta_{ik}\right]^{\beta}}, \tag{2}$$

where K is the total sum of admissible vertices, i.e. the sum in the denominator is performed over all admissible (not yet visited) vertices.

Each ant repeats this process until the complete route is built or the conditions of the problem are met. This approach combines the exploitation of accumulated information (through pheromones) with the exploration of new solution options (through random selection), which allows for an effective balance between accuracy and breadth of search.

Stage IV. *Evaluation of solutions*

Once each ant has completed building its route, the stage of evaluating the quality of the obtained solutions is performed. This stage includes several key steps:

– calculating the quality of solutions. In minimization problems, the smaller the criterion value, the better the solution;

– storing the best solutions. These routes are saved in a special memory (sometimes as the global best route or the local best). The best solutions can be used to reinforce the pheromone trail in the next stage, helping to guide the search towards even better solutions in future iterations;

– using for algorithm adaptation. The evaluation of solutions allows the algorithm to learn – it identifies which routes are effective and which are not. This provides a foundation for pheromone updates (the next stage), which influence the behavior of ants in subsequent iterations.

Stage V. *Pheromone update*

This stage is key in the learning and adaptation mechanism of the algorithm. It regulates how information about good paths is stored and influences further decisions of the ants.

This stage includes two substages:

– pheromone evaporation simulates the natural decay of pheromone over time. It helps to avoid getting stuck in local minima according to expression:

$$\tau_{ij} \leftarrow (1-\rho) \cdot \tau_{ij}\,, \tag{3}$$

where $\rho \in (0,1)$ is pheromone evaporation coefficient; τ_{ij} is current amount of pheromone on the edge (i, j).

This allows less attractive paths to lose influence over future decisions.

– adding pheromones.

Each ant that has completed the construction of the solution contributes according to expression:

$$\Delta\tau_{ij} = \sum\nolimits_{k=1}^{K} \Delta\tau_{ij}^{(k)}, \tag{4}$$

where K is the number of ants, and the contribution of each ant k is defined as (5):

$$\Delta\tau_{ij}^{(k)} = \begin{cases} Q/L_k, \text{ if ant } k \text{ passed through the edge } (i, j); \\ 0, \quad \text{other}, \end{cases} \quad (5)$$

where Q is constant; L_k is the length of the k ant's route.

This means: shorter (better) routes leave more pheromone, thereby making these paths more attractive to future ants.

So, in general, the pheromone on an edge (i, j) is updated according to the formula:

$$\tau_{ij} \leftarrow (1-\rho)\cdot\tau_{ij} + \Delta\tau_{ij}. \quad (6)$$

Stage VI. *Repetition (iteration) of the algorithm*

This stage determines the cyclic nature of the algorithm, where at each iteration the search for the optimal solution is refined. The iteration continues until the stopping criterion is reached. As soon as the stopping condition is met, the algorithm stops the iterations, and the best solution found is returned.

Stage VII. *Derivation of the best solution*

This is the final stage of the Ant Colony Optimization algorithm, during which the best solution found during the entire execution time of the algorithm is determined and displayed (returned or stored).

The experimental studies conducted in [15] demonstrate that the proposed image segmentation method based on the Ant Colony Optimization algorithm is effective in identifying structural elements of a scene, owing to its ability to simulate the collective behavior of agents and adaptively respond to local image features. The formation of pheromone trails reinforces the edges between segments, contributing to a more precise separation of objects of interest.

However, the performance of the algorithm largely depends on the quality of the input UAV imagery. In practice, digital images often contain various types of noise, in particular additive Gaussian noise. This type of noise arises due to imperfections in reading sensors, lighting conditions, electronic interference, etc. [19, 20]

The analysis showed that additive Gaussian noise has the following impact on image processing [21]:

– distorts gradient transitions – makes it difficult to detect the edges of objects of interest;

– leads to the appearance of false contours or "graininess";

– reduces the effectiveness of heuristic estimates in the Ant Colony algorithm.

Such noise has a normal distribution and is superimposed on the real pixel intensity values, complicating the gradient analysis process and, accordingly, reducing the segmentation accuracy. Therefore, a preliminary analysis of the characteristics of additive Gaussian noise is a necessary step before applying the Ant Colony algorithm.

Additive Gaussian noise is random noise that is added to each pixel independently, has a normal (Gaussian) distribution with mathematical expectation μ and variance σ^2:

$$n(x, y) \sim N(\mu, \sigma^2), \quad (7)$$

where $n(x, y)$ – noise value at a point (pixel) with coordinates x and y in the image; μ is the mathematical expectation (mean value of noise), usually $\mu \approx 0$; σ is standard deviation, which determines the intensity of the noise. Depending on the value of the standard deviation σ, the visual impact of noise on the image varies significantly.

At low noise levels ($\sigma \le 10$), the distortion is almost imperceptible and has minimal effect on image quality. This level of noise is typical for high-quality cameras or images acquired under controlled conditions. In the case of a medium noise level ($\sigma \approx 15 \div 30$), visible graininess appears, affecting local image characteristics such as gradients, texture, and contours. This complicates accurate segmentation and object delineation.

At a high noise level ($\sigma \ge 40$), a significant amount of information becomes distorted: the image acquires a pronounced grainy appearance, and object edges become blurred. In such cases, applying image processing algorithms without prior filtering may prove ineffective. Therefore, a series of experimental studies will be conducted to evaluate the robustness and accuracy of the image segmentation method for UAV-acquired images based on the ant colony optimization algorithm under conditions of additive Gaussian noise. The study also compared the results of image segmentation obtained using the method presented in [22], which is based on the use of the Sobel filter to detect small aerial objects in optoelectronic images.

An aerial photograph obtained from a UAV was selected as the original image (Fig. 1).

Fig. 1. Original UAV image [23]

The image shows a vehicle with a trailer moving along the road. The trailer is partially masked by vegetation, which creates additional complexity for the segmentation task. The upper part of the scene contains background vegetation along the edge of the road, which forms natural textures and brightness transitions. This image is a typical example of the problem of detecting and isolating ground objects in real-world UAV applications. It was used as a baseline test image for experimental studies of the stability and accuracy of the segmentation algorithm based on Ant Colony Optimization under the influence of additive Gaussian noise.

We will conduct the study when the original UAV image (Fig. 1) is distorted by additive Gaussian noise with an intensity of 5 (Fig. 2) and 15 (Fig. 3).

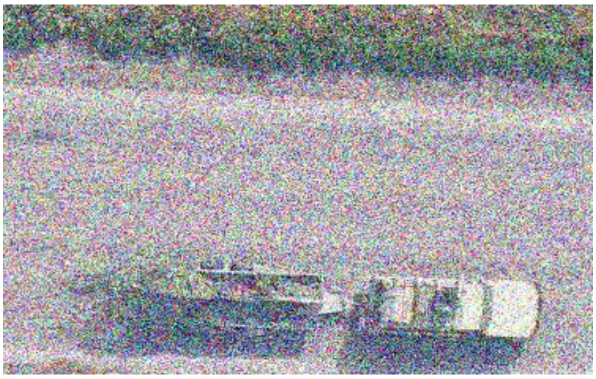

Fig. 2. The original UAV image affected by additive Gaussian noise (σ_{noise}=5)

Fig. 3. The original UAV image affected by additive Gaussian noise (σ_{noise}=15)

Fig. 4–6 illustrate the results of image segmentation using a method based on the Ant Colony Optimization algorithm at different levels of noise pollution: without noise (Fig. 4), at σ_{noise}=5 (Fig. 5), and at σ_{noise}=15 (Fig. 6).

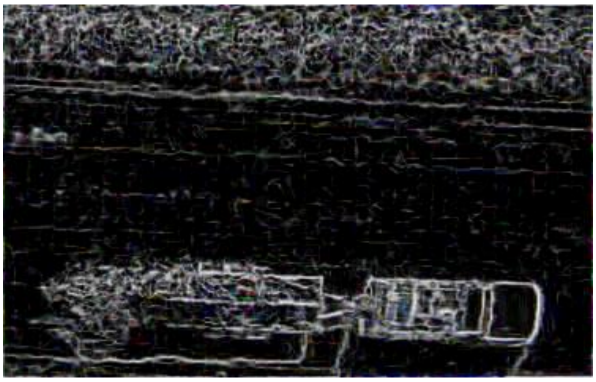

Fig. 4. The segmented original image without the influence of additive Gaussian noise (σ_{noise}=0) using a method based on the Ant Colony Optimization algorithm

For comparison purposes, Fig. 7–9 show the segmentation results of the same images, but using a method based on the Sobel filter. Accordingly, Fig. 7 shows the result without noise, Fig. 8 – σ_{noise}=5, and Fig. 9 – σ_{noise}=15.

This comparison allows for a visual analysis of the segmentation quality under different noise levels for two approaches – based on the Ant Colony Optimization algorithm and the Sobel filter.

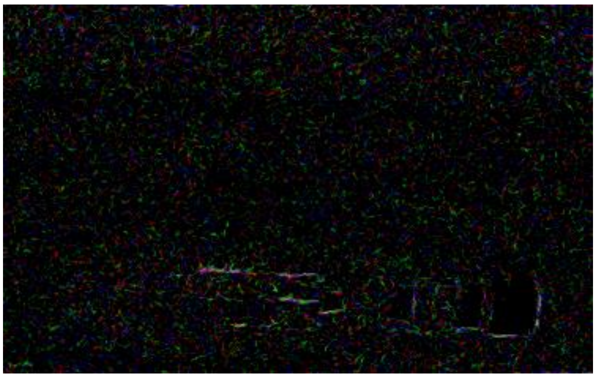

Fig. 5. The segmented original image with the influence of additive Gaussian noise (σ_{noise} = 5) using a method based on the Ant Colony Optimization algorithm

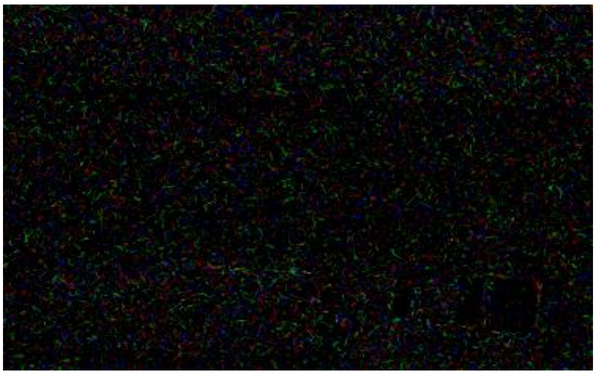

Fig. 6. The segmented original image with the influence of additive Gaussian noise (σ_{noise}=15) using a method based on the Ant Colony Optimization algorithm

Fig. 7. The segmented original image without the influence of additive Gaussian noise (σ_{noise}=0) using a method based on the Sobel filter

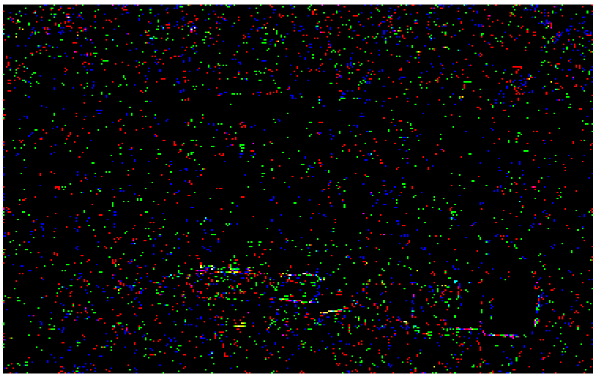

Fig. 8. The segmented original image with the influence of additive Gaussian noise (σ_{noise}=5) using a method based on the Sobel filter

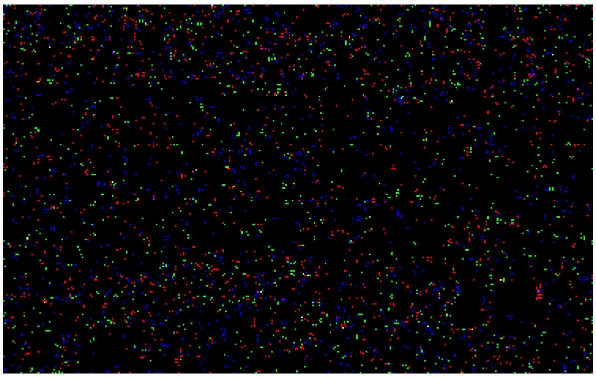

Fig. 9. The segmented original image with the influence of additive Gaussian noise (σ_{noise}=15) using a method based on the Sobel filter

Beyond visual inspection, the quality of image segmentation was evaluated using numerical metrics.

In particular, errors of the first and second kinds can be applied for this purpose, as suggested in prior studies [24–26].

The segmentation errors of the first kind (α_1) and second kind (β_2) are determined using formulas (8) and (9), respectively, in accordance with the methodology outlined in [26]:

$$\alpha_1 = \frac{S_1(fs(\boldsymbol{X}))}{S_2(f(\boldsymbol{X}))}, \quad (8)$$

where $S_1(fs(\boldsymbol{X}))$ denotes the background region that was incorrectly classified as part of the target objects in the segmented image $fs(\boldsymbol{X})$; $S_2(f(\boldsymbol{X}))$ represents the background region in the original image $f(\boldsymbol{X})$;

$$\beta_2 = 1 - \frac{S_3(fs(\boldsymbol{X}))}{S_4(f(\boldsymbol{X}))}, \quad (9)$$

where $S_3(fs(\boldsymbol{X}))$ refers to the area of correctly identified target objects in the segmented image $s(\boldsymbol{X})$; $S_4(f(\boldsymbol{X}))$ corresponds to the region of the actual target objects in the original image $f(\boldsymbol{X})$.

The errors of the first kind (false positive) and the second kind (false negative), presented in Table 1 and Table 2.

Table 1 – **Segmentation errors of the first kind, %**

Segmentation method name	The standard deviation of the amplitude of additive Gaussian noise		
	σ_{noise}= 0	σ_{noise}= 5	σ_{noise}= 15
Method based on the ACO algorithm	27	42	77
Method based on the Sobel filter	41	67	100

Table 2 – **Segmentation errors of the second kind, %**

Segmentation method name	The standard deviation of the amplitude of additive Gaussian noise		
	σ_{noise}= 0	σ_{noise}= 5	σ_{noise}= 15
Method based on the ACO algorithm	32	49	83
Method based on the Sobel filter	47	77	100

As can be seen from Table 1, in the absence of noise (σ_{noise}=0), the method based on the Ant Colony Optimization algorithm provides a lower percentage of errors of the first kind (27 %) compared to the Sobel method (41 %).

With increasing noise level (σ_{noise}=15), the number of errors for both methods increases, but the error increase is less rapid for the ACO method (up to 77 %) compared to the Sobel method (100 %).

A similar comparison for segmentation errors of the second kind is presented in Table 2. Again, at all noise levels, the ACO algorithm demonstrates better accuracy: at σ_{noise}=0 – 32 % versus 47 %, at σ_{noise}=15 – 83 % versus 100 %.

An examination of the data presented in Table 1 and Table 2 reveals that the enhanced segmentation approach based on the Ant Colony Optimization algorithm results in a decrease in first-kind segmentation errors by approximately 14 % to 23 %, and a reduction in second-kind errors by about 15 % to 17 % (with a minimum reduction of 9 %), depending on the level of additive noise.

Thus, the results of quantitative analysis confirm the superiority of the method based on the ant colony algorithm in the presence of additive Gaussian noise, both in terms of object detection accuracy and resistance to increasing noise load.

Conclusions and the directions of further research

In this study, the segmentation quality of UAV-acquired images under the influence of additive Gaussian noise was experimentally investigated using a method based on the Ant Colony Optimization algorithm.

The conducted analysis confirmed the relevance of developing noise-resistant segmentation approaches due to the presence of various types of distortions in UAV imagery, which significantly complicate the identification of objects of interest.

The review of existing research showed that while deep learning and classical methods dominate the field, bioinspired algorithms, particularly swarm intelligence approaches such as the Ant Colony Optimization algorithm, offer promising advantages in terms of global optimization and segmentation precision in complex scenes.

Experimental results demonstrated that the proposed ACO-based method provides improved segmentation performance compared to traditional edge-detection techniques, such as the Sobel filter, especially in noisy conditions.

Quantitative evaluation revealed a reduction in both segmentation errors of the first and second kind by an average of 14–23 % and 9–17 %, respectively, depending on the noise level.

Therefore, the use of the Ant Colony Optimization algorithm in image segmentation tasks under noisy conditions proves to be a robust and effective solution, particularly for UAV applications where real-time noise interference is common.

Future work may focus on improving

computational efficiency and adapting the method for onboard processing in UAV systems.

Acknowledgements

The research was funded by the grant support from the National Research Fund of Ukraine within the frame-work of the competition "Science for Strengthening the Defense Capability of Ukraine", project title "Information technology of automated segmentation of object images in the targeting systems of strike FPV drones based on swarm intelligence algorithms", registration number 2023.04/0153.

References

1. Mohsan, S. A. H., Oth Man, N. Q. H., Li, Y., Alsharif, M. H., and Khan, M. A. (2023), "Unmanned aerial vehicles (UAVs): practical aspects, applications, open challenges, security issues, and future trends", *Intelligent Service Robotics*, vol. 16 (1), pp. 109–137, doi: https://doi.org/10.1007/s11370-022-00452-4
2. Ahmed, S. A., Desa, H., Easa, H. K., Hussain, A.-S. T., Taha, T. A., Salih, S. Q., Hasan, R. A., Ahmed, O. K. and Ng, P. S. J. (2024), "Advancements in UAV image semantic segmentation: A comprehensive literature review", *Multidisciplinary Reviews*, vol. 7 (6), e2024118, doi: https://doi.org/10.31893/multirev.2024118
3. Liu, Z., An, P., Yang, Y., Qiu, S., Liu, Q., and Xu, X. (2024), "Vision-Based Drone Detection in Complex Environments: A Survey", *Drones*, vol. 8(11), 643, doi: https://doi.org/10.3390/drones8110643
4. Motlagh, N. H., Kortoci, P., Su, X., Loven, L., Hoel, H. K., Haugsvaer, S. B., Srivastava, V., Gulbrandsen, C., and Tarkoma, S. (2023), "Unmanned Aerial Vehicles for Air Pollution Monitoring: A Survey", *IEEE Internet of Things Journal*, vol. 10(24), pp. 21687–21704, doi: https://doi.org/10.1109/JIOT.2023.3290508
5. Rascon, C., and Martinez-Carranza, J. (2024), "A Review of Noise Production and Mitigation in UAVs", *Machine Learning for Complex and Unmanned Systems*, pp. 220–235, CRC Press, doi: https://doi.org/10.1201/9781003385615-12
6. Kryvenko S., Lukin V., Bondzulic B., and Stojanovic N. (2025), "Compression of noisygrayscaleimageswith compression ratio analysis", *Advanced Information Systems*, vol. 9. no 2, pp. 68–74, doi: https://doi.org/10.20998/2522-9052.2025.2.09
7. Zhang, Z., and Zhu, L.-X. (2023), "A Review on Unmanned Aerial Vehicle Remote Sensing: Platforms, Sensors, Data Processing Methods, and Applications", *Drones*, vol. 7(6), 398, doi: https://doi.org/10.3390/drones7060398
8. Li, Q., Zhang, Y., Fang, L., Kang, Y., Li, S., and Zhu, X. X. (2024), "DREB-Net: Dual-stream Restoration Embedding Blur-feature Fusion Network for High-mobility UAV Object Detection", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 63, doi: https://doi.org/10.1109/TGRS.2025.3543270
9. Wang, X., Peng, Y., and Shen, C. (2025), "Efficient feature fusion for UAV object detection", *IEEE Transactions on Image Processing*, vol. 34, pp. 123–135, doi: https://doi.org/10.1109/TIP.2025.1234567
10. Li, C., Zhao, R., Wang, Z., Xu, H., and Zhu, X. (2024), "RemDet: Rethinking Efficient Model Design for UAV Object Detection", *arXiv preprint arXiv:2412.10040*, doi: https://doi.org/10.48550/arXiv.2412.10040
11. Zhang, Z., and Li, G. (2025), "UAV imagery real-time semantic segmentation with global–local information attention", *Sensors*, vol. 25(6), pp. 1786, doi: https://doi.org/10.3390/s25061786
12. Ding, R. (2024), "Segmentation analysis of UAV images based on Unet deep learning algorithm", *Applied and Computational Engineering*, vol. 54, pp. 248–253, doi: https://doi.org/10.54254/2755-2721/54/20241644
13. Khudov, H., Khudov, V., Makoveichuk, O., Khizhnyak, I., Hridasov, I., Butko, I., Khudov, R., Glukhov, S., Shamrai, N., and Lisohorskyi, B. (2025), "Development of an image segmentation method from unmanned aerial vehicles based on the particle swarm optimization algorithm", *Technology Audit and Production Reserves*, № 3/2(83), pp. 88–95, doi: https://doi.org/10.15587/2706-5448.2025.330973
14. Khudov, H., Khizhnyak, I., Glukhov, S., Shamrai, N., and Pavlii, V. (2024), "The method for objects detection on satellite imagery based on the firefly algorithm", *Advanced Information Systems*, vol. 8, no. 1, pp. 5–11, doi: https://doi.org/10.20998/2522-9052.2023.4.01
15. Khudov, H., Hridasov, I., Khizhnyak, I., Yuzova, I., and Solomonenko, Y. (2024), "Segmentation of image from a first-person-view unmanned aerial vehicle based on a simple ant algorithm", *Eastern-European Journal of Enterprise Technologies*, vol. 4(9 (130)), pp, 44–55, doi: https://doi.org/10.15587/1729-4061.2024.310372
16. Khudov, H., Koval, V., Khizhnyak, I., Bridnia, Y., Chepurnyi, V., Prykhodko, S., Oleksenko, O., Glukhov, S. and Savran, V. (2022), "The method of transport logistics problem solving by the MAX-MIN ACO algorithm", *International Journal of Emerging Technology and Advanced Engineering*, vol. 12 (07), pp.108–119, doi: https://doi.org/10.46338/ijetae0722_12
17. Zhao, H.-Y., Wang, J.-C., Guan, X., Wang, Z.-H., He, Y.-H. and Xie, H.-L. (2020), "Ant Colony System for Energy Consumption Optimization in Mobile IoT Networks", *Journal of Circuits Systems and Computers*, vol. 29(9), 2050150, doi: https://doi.org/10.1142/S0218126620501509
18. Dorigo, M., Maniezzo, V., and Colorni, A. (1996), "Ant system: Optimization by a colony of cooperating agents", *IEEE Trans. on Systems, Man, and Cybernetics – Part B*, vol. 26(1), pp. 29–41. doi: https://doi.org/10.1109/3477.484436
19. Kuchuk, H., Mozhaiev, O., Tiulieniev, S., Mozhaiev, M., Kuchuk, N., Tymoshchyk, L., Lubentsov, A., Onishchenko, Y., Gnusov, Y. and Tsuranov, M. (2025), "Devising a method for increasing data transmission speed in monitoring systems based on the mobile high-density Internet of Things", *Eastern-European Journal of Enterprise Technologies*, vol. 3(4 (135)), pp. 52–61, doi: https://doi.org/10.15587/1729-4061.2025.330644
20. Petrovska, I., Kuchuk, H., Kuchuk, N., Mozhaiev, O., Pochebut, M. and Onishchenko, Yu. (2023), "Sequential Series-Based Prediction Model in Adaptive Cloud Resource Allocation for Data Processing and Security", *2023 13th International Conference on Dependable Systems, Services and Technologies*, DESSERT 2023, 13–15 October, Athens, Greece, code 197136, doi: https://doi.org/10.1109/DESSERT61349.2023.10416496
21. Svyrydov, A., Kuchuk, H. and Tsiapa, O. (2018), "Improving efficiency of image recognition process: Approach and case study", *Proceedings of 2018 IEEE 9th International Conference on Dependable Systems, Services and Technologies*, DESSERT 2018, pp. 593–597, doi: https://doi.org/10.1109/DESSERT.2018.8409201
22. Khudov, H., Khudov, R., Khizhnyak, I., Hridasov, I., and Hlushchenko, P. (2025), "The small aerial objects segmentation method on optical-electronic images based on the Sobel Edge Detector", *Advanced Information Systems*, vol. 9, no. 2, pp. 5–10, doi: https://doi.org/10.20998/2522-9052.2025.2.01

23. (2026), *Portalgis.pro – industry information resource*, available at: https://portalgis.pro/bpla/bezkoshtovni-resursy-bpla
24. Khudov, H., Makoveichuk, O., Khizhnyak, I., Glukhov, S.,, Shamrai, N., Rudnichenko, S., Husak, M., and Khudov, R, (2022), "The Choice of Quality Indicator for the Image Segmentation Evaluation", *International Journal of Emerging Technology and Advanced Engineering*, vol. 12 (10), pp. 95–103, doi: https://doi.org/10.46338/ijetae1022_11
25. Khudov, H., Makoveichuk, O., Kalimulin, T., Khudov, V., and Shamrai, N. (2024), "The method for approximating the edge detection convolutional operator using a genetic algorithm for segmentation of complex-structured images", *Advanced Information Systems*, vol. 8, no. 4, pp. 5–12, doi: https://doi.org/10.20998/2522-9052.2024.4.01
26. Hurin, A., Khudov, H., Kostyria, O., Maslenko, O. and Siadrystyi, S. (2024), "Comparative analysis of spectral anomalies detection methods on images from on-board remote sensing systems", *Advanced Information Systems*, vol. 8, no. 2, pp. 48–57, doi: https://doi.org/10.20998/2522-9052.2024.2.06

Received (Надійшла) 12.03.2025
Accepted for publication (Прийнята до друку) 18.06.2025

ABOUT THE AUTHORS / ВІДОМОСТІ ПРО АВТОРІВ

Худов Геннадій Володимирович – доктор технічних наук, професор, начальник кафедри тактики радіотехнічних військ, Харківський національний університет Повітряних Сил імені Івана Кожедуба, Харків, Україна;
Hennadii Khudov – Doctor of Technical Sciences, Professor, Head of Department of Radar Troops Tactic, Ivan Kozhedub Kharkiv National Air Force University, Kharkiv, Ukraine;
e-mail: 2345kh_hg@ukr.net; ORCID Author ID: https://orcid.org/0000-0002-3311-2848;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=57196079841.

Маковейчук Олександр Миколайович – доктор технічних наук, доцент, доцент кафедри комп'ютерних наук та інженерії програмного забезпечення, Міжнародний науково-технічний університет ім. ак. Ю. Бугая, Київ, Україна;
Oleksandr Makoveichuk – Doctor of Technical Sciences, Associate Professor, Associate Professor of Department of Computer Sciences and Software Engineering, Academician Yuri Bugay International Scientific and Technical University, Kyiv, Ukraine;
e-mail: omakoveychuk@gmail.com; ORCID Author ID: https://orcid.org/0000-0003-4425-016X;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=57196074907.

Хижняк Ірина Анатоліївна – доктор технічних наук, начальник НМВ забезпечення якості освітньої діяльності та вищої освіти, Харківський національний університет Повітряних Сил імені Івана Кожедуба, Харків, Україна;
Irina Khizhnyak – Doctor of Technical Sciences, Head of Scientific and Methodological Department for Quality Assurance of Educational Process and Higher Education, Ivan Kozhedub Kharkiv National Air Force University, Kharkiv, Ukraine;
e-mail: khizh_ia@ukr.net; ORCID Author ID: https://orcid.org/0000-0003-3431-7631;
Scopus ID: https://www.scopus.com/authid/detail.uri?authorId=57196075236.

Варваров Валерій Володимирович – кандидат технічних наук, провідний науковий співробітник науково-дослідної лабораторії, Харківський національний університет Повітряних Сил імені Івана Кожедуба, Харків, Україна;
Valerii Varvarov – Candidate of Technical Sciences, Leading Researcher of the Research Laboratory, Ivan Kozhedub Kharkiv National Air Force University, Kharkiv, Ukraine;
e-mail: varvarovv@ukr.net; ORCID Author ID: https://orcid.org/0000-0003-1273-5605.

Зоц Федір Федорович – кандидат технічних наук, доцент, доцент кафедри озброєння радіотехнічних військ, Харківський національний університет Повітряних Сил імені Івана Кожедуба, Харків, Україна;
Fedir Zots – Candidate of Technical Sciences, Associate Professor, Associate Professor of the Department of Radio Engineering Troops Armaments, Ivan Kozhedub Kharkiv National Air Force University, Kharkiv, Ukraine;
e-mail: fedorzots@gmail.com; ORCID Author ID: https://orcid.org/0000-0001-6070-2862.

Експериментальні дослідження якості методу сегментування зображень з безпілотних літальних апаратів на основі алгоритму оптимізації мурашиної колонії під впливом адитивного гаусового шуму

Г. В. Худов, О. М. Маковейчук, І. А. Хижняк, В. В. Варваров, Ф. Ф. Зоц

Анотація. Предметом статті є експериментальні дослідження якості методу сегментування зображень з БпЛА на основі алгоритму оптимізації мурашиної колонії під впливом адитивного гаусового шуму. **Метою статті** є зниження ймовірності виникнення помилок першого та другого роду при сегментуванні зображень шляхом застосування методу сегментування на основі алгоритму оптимізації мурашиної колонії в умовах дії адитивного гаусового шуму**. Завдання дослідження** полягають у тому, щоб оцінити стійкість і точність запропонованого методу сегментування при різних рівнях адитивного гаусового шуму, а також порівняти його ефективність із класичним методом сегментування на основі фільтра Собеля. Використані **методи** включають: методи цифрової обробки зображень, статистичний аналіз якості сегментування, реалізацію алгоритму оптимізації мурашиної колонії, моделювання умов зашумлення та порівняння помилок сегментування першого і другого роду. Отримані **результати**: метод на основі алгоритму мурашиної колонії демонструє вищу стійкість до шуму та забезпечує кращу точність сегментування порівняно з методом Собеля. Зокрема, кількість помилок першого роду знижується на 14–23 %, а другого роду – на 9–17 % залежно від рівня шуму. Візуальний та кількісний аналіз підтверджують ефективність запропонованого підходу для обробки зображень з БпЛА, заздалегідь спотворених адитивним гаусовим шумом. **Висновки.** Результати експериментальних досліджень підтвердили, що метод сегментування на основі алгоритму оптимізації мурашиної колонії демонструє перевагу над традиційними методами виявлення контурів, особливо в умовах зашумлення, забезпечуючи вищу точність і надійність у широкому діапазоні рівнів шумового впливу.

Ключові слова: зображення з БпЛА; сегментування зображення; адитивний гаусів шум; мурашиний алгоритм; якість сегментування; помилки першого та другого роду.