The object of this study is the high level of errors of the first and second kind in the segmentation of images of urbanized areas acquired from space optoelectronic surveillance systems.

The method of image segmentation of urbanized areas implies two stages and, unlike known ones:

– takes into account each channel of brightness of the color space of the original image;

– at the first stage, an ant algorithm is used;

– image segmentation at the first stage is reduced to the calculation of the objective function, the areas of movement of ants, and the concentration of pheromone on the routes of ant movement;

– at the second stage, the brightness and geometric shape of the elements of objects are taken into account;

– contours and geometric primitives are defined in the Hough parameter space;

– the objects of interest of the urbanized area in the space of the original image are determined.

An experimental study into the segmentation of images of urbanized terrain acquired from space optoelectronic observation systems was carried out based on the ant algorithm and the Hough algorithm.

The quality of image segmentation of the urbanized area was assessed. It was found that the error of the first kind when using the improved method of segmentation is reduced by 2.75 %. The error of the second kind is reduced by 3.91 % when using the improved method of segmentation. This reduction became possible due to the use of an improved method of segmenting the image of an urbanized area by the ant algorithm at the first stage. Compared to Canny's algorithm, the error of the first kind decreased by 8.9 %, and the error of the second kind decreased by 11.0 %.

Methods for segmenting images of urbanized areas acquired from space optoelectronic surveillance systems can be implemented in software and hardware systems of image processing

Keywords: image segmentation, urbanized terrain, ant algorithm, Hough algorithm, space system

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DEVELOPMENT OF A TWO-STAGE METHOD FOR SEGMENTING THE COLOR IMAGES OF URBAN TERRAIN ACQUIRED FROM SPACE OPTIC-ELECTRONIC OBSERVATION SYSTEMS BASED ON THE ANT ALGORITHM AND THE HOUGH ALGORITHM

Hennadii Khudov
Corresponding author
Doctor of Technical Sciences, Professor, Head of Department*
E-mail: 2345kh_hg@ukr.net

Oleksandr Makoveichuk
Doctor of Technical Sciences, Associate Professor
Department of Computer Sciences and Software Engineering
Academician Yuriy Bugay International Scientific and Technical University
Mahnitohorskyi lane, 3, Kyiv, Ukraine, 02094

Vladyslav Khudov
PhD, Junior Researcher
Department of Information Technology Security
Kharkiv National University of Radio Electronics
Nauky ave., 14, Kharkiv, Ukraine, 61166

Irina Khizhnyak
PhD*

Rostyslav Khudov
Department of Theoretical and Applied Informatics
V. N. Karazin Kharkiv National University
Svobody sq., 4, Kharkiv, Ukraine, 61022

Volodymyr Maliuha
Doctor of Military Sciences, Associate Professor
Head of Department
Department of Anti-Aircraft Missile Forces Tactic **

Serhii Sukonko
PhD, Chief
Research Laboratory***

Oleksii Lunov
PhD
Deputy Dean of Faculty***

Mykhailo Buhera
PhD, Senior Researcher
Scientific and Organizational Department
Central Scientifically-Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine
Povitroflotsky ave., 28, Kyiv, Ukraine, 03049

Taras Kravets
Lecturer
Department of Artillery Facility Complexes and Devices
National Army Academy named after Hetman Petro Sahaidachnyi National Army Academy
Heroiv Maidanu str., 32, Lviv, Ukraine, 79026

*Department of Radar Troops Tactic**
**Ivan Kozhedub Kharkiv National Air Force University
Sumska str., 77/79, Kharkiv, Ukraine, 61023
***National Academy of the National Guard of Ukraine
Zakhysnykiv Ukrainy sq., 3, Kharkiv, Ukraine, 61001

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1. Introduction

Images from space optoelectronic surveillance systems are one of the main sources of operational information on assessing the state of urbanized areas [1].

Assessment of the state of urbanized areas is used to solve the problems of cartography, urban planning, architecture, land use, military affairs, design and construction, etc. [2, 3].

Under modern conditions, it is also becoming relevant to assess the destruction of objects in urbanized areas (for example, the consequences of earthquakes [4] and hostilities in urbanized areas [5]). This applies to both residential buildings and critical infrastructure in cities and suburbs [6]. This information is widely used in management decision-making systems by state authorities [7].

Processing images acquired from space optoelectronic surveillance systems is carried out automatically using specialized hardware and software [7]. The quality of image processing and the efficiency of management decision-making significantly depend on the quality of image segmentation [7].

Most known methods for segmenting images of urbanized areas from space systems of optoelectronic observation are reduced to determining the boundaries and contours of objects of interest. This uses the brightness difference of pixels in the images. Such known segmentation methods work quite well on tone images acquired from space surveillance systems. The quality of the methods improves in the case of segmentation of objects of interest with blurred and clear boundaries.

When segmenting color images, known methods do not take into account the color space of the image representation. The original image is converted to a tone image without taking into account its representation space, and segmentation is performed using known methods for tone images. Failure to take into account the color space of image representation can lead to the loss of some decryptive features of objects of interest. Known segmentation methods lead to blurring and breaking of the boundaries of objects of interest, which, in turn, leads to an increase in errors of the first and second kind of segmentation of color images. Taking into account the size of images acquired from space systems of optoelectronic observation, the value of errors of the first and second kind per unit of percent significantly affects the quality of segmentation and subsequent decryption of objects of interest.

Therefore, the development of methods for segmenting images of urbanized areas acquired from space optoelectronic surveillance systems with reduced error values of the first and second kind is an urgent task.

2. Literature review and problem statement

In [8], an integrated method for road identification on high-resolution images of remote sensing of earth is proposed. The essence of the methods [8] is to combine the method of segmentation and the method of classification with the analysis of related components to obtain extended objects of the road class. Based on geometric, textural, and spectral information, the k-nearest neighbors method is used, the reference vector machine method and the decision tree method are consistently applied. The result is to divide the image into two classes – the road class and the class of everything else. At the final stage, the marking of related components and a morphological operation are performed to remove what is not included in the class of roads. The advantage of [8] is the ability to highlight roads in images of remote sensing of the earth, even if there are obstacles with the same color and spectrum values as the road class (for example, vehicles, trees, shadows, etc.). The disadvantage of [8] is the selection of only one class of elements of urbanized terrain (roads).

Paper [9] proposed a method for road identification in images acquired from space surveillance systems. The proposed approach [9] is to select the boundaries in the image using the Canny edge detection algorithm, further combine adjacent segments, classify using the method of reference vectors, and improve the quality of selected roads using mathematical morphology methods. The advantage of [9] is the high accuracy of the selection of various types of roads in images acquired from space surveillance systems. The disadvantage of [9] is the selection of only one class of elements of urbanized terrain (roads).

Study [10] proposed a method of normalized section for the automatic detection of roads on satellite images of urban areas. It involves preliminary processing of the image to remove unwanted objects in the first stage and highlight road segments using progressive analysis of the image texture and graph-based method in the second stage of the method [10]. The advantage of [10] is the speed of work. The disadvantage of [10] is the identification of only one class of objects of interest (roads).

Work [11] demonstrates the method of segmenting images acquired from space surveillance systems to identify extended elements of urbanized terrain. The essence of [11] is the application of adaptive global threshold value and the subsequent use of morphological operators. The advantage of [11] is to take into account the average values of the intensity of pixels in the image. The disadvantage of [11] is the possibility of its use only for tone images.

Paper [12] proposed an object-oriented method for the identification of extended objects on satellite images. The method [12] implies the following sequence of actions:

– segmentation;
– the application of object-oriented Frangi filters;
– the determination of signs of objects of interest;
– the application of reference vectors and integration of tensor voting, active contour, and geometric information.

The advantage of [12] is an automated approach to the identification of extended objects on satellite images and high accuracy. The disadvantage of [12] is the large values of errors of the first kind when identifying even only asphalt roads.

Paper [13] proposed a method of automatic identification of buildings and roads on satellite images of suburban areas. This identification algorithm is based on the method of uncontrolled segmentation, based on the Markov model of a random field. The advantage of [13] is to obtain a large amount of data to determine the appropriate features for solving the problem of classifying objects of interest and high speed of the classification operation. The disadvantage of [13] is the identification of objects of interest without taking into account the color space of the image presentation.

In [14], convolutional neural networks are used to solve the problem of highlighting objects of interest in images of remote sensing of the earth. In [14], the application of three algorithms of convolutional neural networks with transfer training to a publicly available dataset of images of remote sensing of the Earth of different resolutions is considered. The advantage of [14] is a high indicator of the accuracy of the identification of objects of interest from the set of training. The main disadvantage of [14] is the omission of unknowns objects that were not part of the training set and, as a result, the need to retrain the convolutional neural network. In addition, the identification of objects of urbanized area is not considered in [14].

In [15], for semantic image segmentation of remote sensing of the earth, it is proposed to use attention modules that collect contextual information when processing all pixels in the image. In such a module, a map of attention is formulated and modeled by rows and columns based on the analysis of the covariance matrix. The advantages of [15] are to process the value of each pixel in the image, regardless of its location to the existing boundary. And as a result, high accuracy of identification of borders in images. The main disadvantage of [15] is that elements of urbanized areas are not considered as objects of interest.

In [16], to highlight the boundaries of objects of interest in satellite images, a through deep convolutional neural network is proposed. The advantage of [16] is the ability of the neural network to accumulate contextual information, combining the obtained semantic segmentation with semantically informed boundary detection. The advantage of [16] is the efficient use of memory and obtaining explicit and clear boundaries of objects. The disadvantage of [14] is the need to constantly add the selected boundaries to the architecture of the encoder-decoder and the impossibility of using [16] to determine the elements of an urbanized area.

In [17], to identify informal settlements, it is proposed to use an algorithm for detecting lines on satellite images, the result of which is a set of binary data for further analysis of lacunarity. The advantage of the proposed approach in [17] is less sensitivity to spectral variability in the images inherent in the terrain for settlement. The disadvantage of [17] is the processing of not the entire image at the same time, but sequentially with a grid of a certain size, which significantly increases errors of the first and second kind in determining the elements of settlements.

Work [18] demonstrates the use of a vector model using graph theory to segment images of urban areas. The essence of [18] is to use geometric primitives in the vector model to designate spatial objects in the image and apply the Dijkstra algorithm for further division into regions. The advantage of [18] is the possibility of thematic image segmentation of urban areas. The disadvantage of [18] is the transition from a raster format for storing data to vector and subsequent storage of vector data in the graph. This leads to an increase in errors of the first and second kind by 19 % and 23 %, respectively.

In [19], to perform the first stage of semantic image segmentation of urban infrastructure, an interactive segmentation algorithm ScribbleNet is proposed. The essence of [19] implies the conditional output of annotations and uses correlations in a deep neural network. The advantage of [19] is the ability to annotate new classes of objects that are not in the training population and process images in the presence of shadows. The disadvantage of [19] is its use only as a preliminary stage in terms of image segmentation, which does not lead to a decrease in errors of the first and second kind of segmentation of urban infrastructure elements.

In [20], for the automatic classification of urban areas in the images, it is proposed to use classifier training simultaneously with the features obtained from the satellite image database. The advantage of [20] is the consideration of color histograms to obtain the features of the image of urban areas. The disadvantage of [20] is the identification of only large planar objects such as an urban area, without objects of interest in the area.

In [21], to identify buildings on satellite images, a method based on the U-net deep learning architecture is proposed. The advantage of [21] is a good identification of buildings on satellite images of urban villages with a high population density. The disadvantage of [21] is the need for training and testing on the plots of the urban settlement and the presence of a vector file of the boundaries of buildings. This leads to a significant increase in errors of the first and second kind in the segmentation of unfamiliar urbanized areas.

In [22], to highlight objects of interest in multispectral aerial photographs, the use of textural information is proposed. The essence of the method in [22] is to apply both spectral characteristics and object-oriented textural features of Haralik to create classes for thematic segmentation and classification of urban land use. The advantage of [22] is the use of Haralik textural characteristics, which gives a higher accuracy of the identification of objects than when using only spectral information. The disadvantage of [22] is the possibility of confusion of spectra between several types of urban infrastructure objects, which leads to a significant increase in errors of the first and second kind.

In [23], the method of segmenting images acquired from space observation systems of color space Red-Green-Blue (RGB) using the particle swarm algorithm is considered. The advantage of [23] is the identification on space images of even objects of interest that are completely or partially covered with snow. The disadvantage of work [23] is an impossibility of applying the method to segment images of urban infrastructure from space surveillance systems.

In [24], it is proposed in order to increase the efficiency of processing materials of space survey by providing the results of the identification of information zones on space images for further semantic segmentation. The advantage of [24] is the reduction of time for the further stage of semantic segmentation. The disadvantage of [24] is the possibility of using the method only for the definition of large planar objects (information zones).

In [25], it is proposed to segment images of remote sensing of the earth by the method of k-mean and genetic algorithm. The advantage of [25] is good segmentation results for images acquired from space surveillance systems. The disadvantage of [25] is the failure to take into account the peculiarities of the elements of urbanized terrain, which leads to an increase in errors of the first and second kind.

Paper [26], for image segmentation from space observation systems, proposed the use of a genetic algorithm. The advantage of [26] is the good results of segmenting both simple objects of interest and disguised ones. The disadvantage of [26] is the resegmentation of the image of urban infrastructure, that is, the presence as a result of segmentation of a large number of unnecessary contours that are not of interest, the so-called "garbage" objects. This significantly increases the level of errors of the first and second kind (on average up to 30–35 %).

In [27], a method of re-segmentation is proposed, where the previous one already overly segmented is used as an input image to obtain a new set of objects of interest. The essence of [27] is to generate rectangular forms of urban infrastructure objects by merging in a balanced column of contiguity of regions. The advantage of [27] is the cleaning of re-segmentation on images of urban infrastructure. The disadvantage of [27] is the possibility of its application only for small objects of interest only of rectangular shape.

Study [28] proposed a method of re-segmentation to identify buildings on space images. In the method from [28], the shadow segments in the input image are first identified, and then such shadow segments belonging to one object are combined. The advantage of [28] is the execution of post-processing of the image in order to eliminate some false segments of the object. The disadvantage of [28] is the presence of an error in the assignment of shadow segments to the object, which negatively affects the level of errors of the first and second kind.

Paper [29] proposed a method of selecting objects of interest in images of urban areas. The essence of the method from [29] is the application of the improved Canny edge detection algorithm and the subsequent re-segmentation using the Hough transform. The advantage of [29] is the qualitative segmentation of rural roads and the boundaries of planar objects (fields, forests, hydrographic objects, etc.). The disadvantage of [29] is the high level of errors of the first and second kind in the segmentation of elements of urbanized terrain.

In [30], an improved method of selecting objects of interest on images of urban areas obtained from optoelectronic surveillance systems is proposed. The advantage of [30] is to take into account the complex structure of images acquired from space surveillance systems and the good results of image segmentation from both unmanned aerial vehicles and space surveillance systems. The main disadvantage of [30] is the identification of only the boundaries of objects of interest, having the form of only the type of straight line. When segmenting elements of urbanized areas, the method [30] has high values of errors of the first and second kind.

In [31], an ant algorithm is proposed to identify the contours on images acquired from space observation systems. The advantage of [31] is the speed of the process of segmenting complexly structured images of large size. In addition, an advantage of [31] is the visually qualitative definition of objects that can be represented by a set of geometric primitives (for example, a set of straight lines). The main disadvantage of [31] is the re-segmentation of the image, which certainly increases the error rate of the first and second kind.

Thus, known methods for segmenting images acquired from space systems of optoelectronic observation have certain disadvantages in segmenting images of urbanized areas. The main disadvantage of known methods is the high level of errors of the first and second kind of segmentation of objects of urbanized areas.

A feature of the images of urbanized areas is the presence of heterogeneous objects of interest. The deciphering feature of objects of interest in the images of urbanized areas is a geometrically defined form that characterizes anthropogenic structures [32]. Buildings in images are a set of rectangular objects that are located in parallel or at right angles to street lines. During reconstruction on the images, the shape of the object changes. The buildings under construction, in the images, are objects of rectangular shape, limited by a clear straight line (fence) [32].

Destroyed or damaged buildings have a rectangular shape but fuzzy contour. The type of change in the image is either the disappearance of the object of interest in the general group of objects or the appearance of a clear form (during reconstruction).

Industrial buildings (industrial enterprises, factories, plants, etc.) are a set of rectangular objects of larger sizes, which are arranged in rows. There must be access roads, pipes, and shadows from them. Such objects have a significant area and clear boundaries.

Streets and driveways in the images are lanes and/or lines restricting land. The type of change in the image is the appearance of new lanes and/or lines and their possible intersection [32, 33].

The railway track is narrow lanes and/or lines of considerable length. The absence in close proximity to such lanes of any buildings, but the presence of trees or gardens along them [32, 33].

A bridge, a crossing is a lane that crosses a river. It is divided along the lines (roadway) and with possible available transport. The type of change in the image is the change in the width of the lane, location, etc. [32, 33].

Objects of hydrography are the winding shape of the line/lane for a stream or river, a straight shape for a canal, a shape like a triangle for a pond or reservoir, a spot of various shapes for a lake, a rounded or rectangular shape for a water play [32, 33].

Parks, gardens, squares, reserves, etc. are areas of considerable plane with a point pattern and with clear lines/lanes (paths and paths) [32, 33].

An undeveloped area is spots of large dimensions of fuzzy contour and indefinite shape. The type of change in the image is the appearance of lanes and/or lines (construction of access roads and fences) [32, 33].

So, the objects of interest in the images of urbanized areas consist of elementary geometric primitives. This fact should be used as an additional decryptive feature of objects of interest in images of urbanized areas.

Therefore, taking into account the peculiarities of objects of interest in the images of urbanized areas, it is advisable to choose ant algorithms and Hough algorithms for further study of image segmentation acquired from space optoelectronic observation systems. The combination of the advantages of each of these algorithms will reduce the shortcomings of each algorithm individually and improve the quality of image segmentation as a whole.

The development of a method for segmenting images of urbanized areas acquired from space optoelectronic surveillance systems based on the ant algorithm and Hough algorithm can solve the problem associated with the limited known segmentation methods and the high level of errors of the first and second kind in such methods.

3. The aim and objectives of the study

The aim of our study is to reduce errors of the first and second kind of image segmentation of urbanized areas acquired from space optoelectronic surveillance systems. This will improve the quality of segmentation and further decryption of images of urbanized areas.

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

– to determine the main stages of the method for segmenting images of urbanized areas acquired from space optoelectronic surveillance systems based on the ant algorithm and Hough algorithm;

– to segment the image of an urbanized area from a space optoelectronic observation system using a two-stage method based on the ant algorithm and the Hough algorithm;

– to evaluate errors of the first and second kind of image segmentation of urbanized terrain acquired from space optoelectronic observation systems using a method based on the ant algorithm and Hough algorithm.

4. The study materials and methods

The object of the study is the high level of errors of the first and second kind of image segmentation of urbanized areas acquired from space optoelectronic surveillance systems.

The main hypothesis of the study assumed that the use of the ant algorithm and Hough algorithm would reduce segmentation errors of the first and second kind.

During the study, the following research methods were used: methods of image processing theory, evolutionary methods, mathematical apparatus of matrix theory, iterative methods, methods of system analysis, methods of probability theory and mathematical statistics, methods of mathematical modeling. When validating the proposed solutions, analytical and empirical methods of comparative research were used.

When conducting the study, the following restrictions and assumptions were adopted:

– the image of the urbanized area from the space system of optoelectronic observation is considered as the starting one;

– color representation space of the original image – RGB;

– it is accepted that in the brightness channels R, G, B the number of gradations of brightness is 256;

– the image shows an urbanized area with relevant objects of interest;

– the size of objects of interest is much smaller than the size of background objects;

– the influence of distorting factors on the original image is not taken into account.

5. Results of investigating the segmentation of images of urbanized areas

5. 1. Main stages of the method for segmenting images of urbanized areas based on the ant algorithm and the Hough algorithm

To formalize the segmentation of images of urbanized terrain acquired from space optoelectronic observation systems based on the ant algorithm and the Hough algorithm, we use expression (1) [30, 34]:

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

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

Segmentation of the original image of an urbanized area $f(x, y)$ implies the partitioning of $f(x, y)$ into segments B_i (expression (2)) [30, 34]:

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

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

LP can be represented by expression (3) [30, 34]:

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

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

The result of image segmentation of urbanized areas $f(x, y)$ is clustering into objects of interest and background objects.

The main stages of the method for the segmentation of images of urbanized areas based on the ant algorithm and Hough algorithm are shown in Fig. 1.

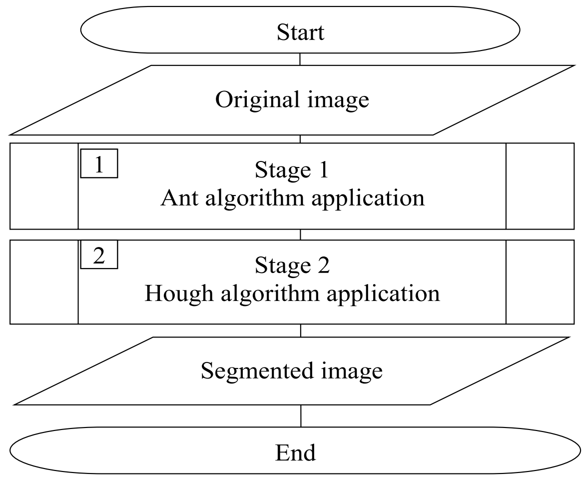

Fig. 1. Main stages of the method for segmenting images of urbanized areas based on the ant algorithm and the Hough algorithm

The first stage of the method for the segmentation of images of urbanized areas implies the use of an ant algorithm [35]. We represent the ant algorithm in the form of (4) [31, 35]:

$$ACO=\{S, M1, A, P, In, Out\}, \tag{4}$$

where ACO – ant colony optimization;

– S – number of ants (agents);

– $M1$ – a parameter that determines the experience of ants (agents) and the exchange of such experience between them;

– A – parameter that defines the stages and rules of the ant algorithm;

– P – parameters characterizing the rules of the stages of the ant algorithm;

– In, Out – a parameter that determines the interaction of the ant algorithm with the external environment (input and output).

Segmentation of the image of an urbanized area based on an ant algorithm implies the representation of an image in the form of a graph. Each pixel in the image of an urbanized area is a vertex with coordinates (x, y) and a corresponding brightness value.

Segmentation of the image of an urbanized area based on an ant algorithm (first stage) includes the following sequence of actions (Fig. 2).

1. Entering input data:

– input image – $f(\boldsymbol{X})$;

– the volume of pheromone on sections of the route – F_0;

– pheromone evaporation rate – ρ;

– parameter that sets the weight of the pheromone – α;

– parameter that sets the “greed” of the algorithm – β.

2. Randomly distributing agents throughout the image (expression (5)):

$$\mathbf{X}_{i1} = rand(f(\mathbf{X})), \tag{5}$$

where $\mathbf{X}_{i1}=(x_{i1}, y_{i1})$ is the vector of the positions of the agents on the first iteration of the ant algorithm. The total number of agents is equal to the total number of pixels in the image. This step is performed only on the first iteration of the ant algorithm.

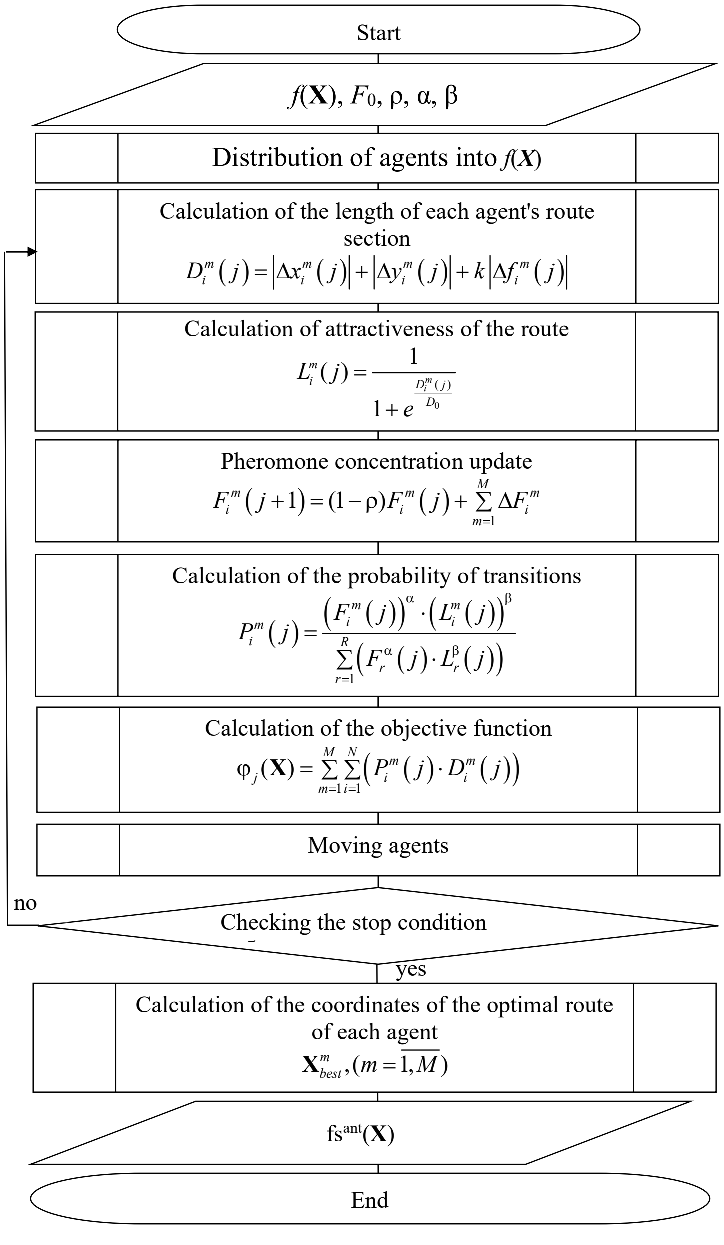

Fig. 2. The sequence of actions of the first stage of the method of segmenting images of urbanized areas based on an ant algorithm

3. Calculation of the length of the agent route section. To calculate, the difference in the brightness values of neighboring pixels is taken into account by expression (6):

$$D_i^m(j)=\left|\Delta x_i^m(j)\right|+\left|\Delta y_i^m(j)\right|+k\left|\Delta f_i^m(j)\right|, \qquad (6)$$

where m is the agent number; j – iteration number of the ant algorithm; i – pixel of the image; $\left|\Delta x_i^m(j)\right|$, $\left|\Delta y_i^m(j)\right|$ – moving the agent to another pixel of the image along the x and y axes, respectively; k – coefficient that takes into account the differences in brightness of pixels, scales, units of measurement, etc.; $\left|\Delta f_i^m(j)\right|$ – difference in pixel brightness. Calculated by expression (7):

$$\left|\Delta f_i^m(j)\right|=\left|f\left(x_i^m(j),y_i^m(j)\right)-f\left(x_{i-1}^m(j),y_{i-1}^m(j)\right)\right|. \qquad (7)$$

4. Calculation for each agent at the turning point of the route of attractiveness of the route section (expressions (8) to (10)):

$$L_i^m(j)=\frac{1}{D_i^m(j)}, \qquad (8)$$

$$L_i^m(j)=\frac{1}{1+\frac{D_i^m(j)}{D_0}}, \qquad (9)$$

$$L_i^m(j)=\frac{1}{1+e^{\frac{D_i^m(j)}{D_0}}}, \qquad (10)$$

where D_0 is a coeficient that takes into account the scale of the image.

5. Calculation of the concentration of pheromone values of agents. At the beginning of the algorithm, the amount of pheromone is assumed to be the same for all and is equal to the defined F_0. On subsequent iterations, the concentration of pheromone agents in the areas is updated by expression (11):

$$F_i^m(j+1)=(1-\rho)F_i^m(j)+\sum_{m=1}^{M}\Delta F_i^m, \qquad (11)$$

where ρ∈[0; 1] is the rate of evaporation of the pheromone value; ΔF_i^m – concentration of pheromone from the agent on the route after its passage.

6. Calculation of the probability of transition of the agent to the turning point on the route (expression (12)):

$$P_i^m(j)=\frac{\left(F_i^m(j)\right)^{\alpha}\cdot\left(L_i^m(j)\right)^{\beta}}{\sum_{r=1}^{R}\left(F_r^{\alpha}(j)\cdot L_r^{\beta}(j)\right)}, \qquad (12)$$

where R – number of turning points on the route; $F_i^m(j)$ – concentration of the agent's pheromone at the point of the image.

7. Calculation of the objective function (expression (13)):

$$\varphi_j(\mathbf{X})=\sum_{m=1}^{M}\sum_{i=1}^{N}\left(P_i^m(j)\cdot D_i^m(j)\right), \qquad (13)$$

where N is the size of the input image.

8. Moving agents.

Each agent in the image begins its route from the starting point, passes the turning points selected according to expression (12), and completes the route at one of the endpoints.

Such a movement of agents in the image is carried out according to the criterion of the minimum objective function (13). The objective function taking into account the four-coherence of the possible movement of agents (expression (14)):

$$\left|\Delta x_i^m(j)\right|+\left|\Delta y_i^m(j)\right|=1 \tag{14}$$

takes the form (expression (15)):

$$\varphi_j(\mathbf{X})= =\sum_{m=1}^{M}\sum_{i=1}^{N}\left(P_i^m(j)\cdot\left(1+k\left|\begin{array}{l}f\left(x_i^m(j),y_i^m(j)\right)-\\-f\left(x_{i-1}^m(j),y_{i-1}^m(j)\right)\end{array}\right|\right)\right)\to \to\min. \tag{15}$$

The routes on which the concentration of pheromone is the highest become the most attractive. On non-sexy routes, the pheromone “evaporates”, and they gradually disappear.

9. Checking the fulfillment of the stop condition. If the condition is met, proceed to the next stage. In the case of non-fulfillment – transition to step 3 of the next iteration of work.

10. Calculation of the best route found for each agent (expression (16)):

$$X_{best}^m,\left(m=\overline{1,M}\right). \tag{16}$$

11. Image output after the first stage $fs^{ant}(\mathbf{X})$.

The above steps of the method are carried out for each brightness channel of the RGB color space representation of the original image of the urbanized area.

The first stage of the method of segmenting images of urbanized areas acquired from space systems of optoelectronic observation, in contrast to known ones:

– takes into account each brightness channel of the RGB color space of the original image;

– an ant algorithm is used for segmentation;

– image segmentation at the first stage is reduced to the calculation of the objective function, the areas of ant movement, and the concentration of pheromone on the routes of ant movement.

At the second stage of the method of segmenting images of urbanized areas, we shall use the Hough algorithm for straight lines [29, 36, 37]. The essence of Hough algorithm is to use the voting procedure to the parameter space of each of the figures, from which such simple figures in an accumulative space can be obtained at local maxima. Accumulated space is created and accumulated during the calculation of the Hough transformation.

From the normal equation of the straight line (expression (17):

$$x\cos\alpha+y\sin\alpha=\rho, \tag{17}$$

where ρ is the length of the perpendicular made from the beginning of the coordinates (0; 0) on the straight line; α is the angle between ρ and the x axis a straight line is set on the plane [29, 36, 37].

Many straight lines can be drawn through one point of the Cartesian plane. If such a point in the image has coordinates (x_i; y_i), then all straight lines passing through a given point are written according to equation (18) [29, 36, 37]:

$$x_i\cos\alpha+y_i\sin\alpha=\rho. \tag{18}$$

Such a set of lines on the Cartesian plane corresponds to a sinusoidal curve in the parameter space (ρ; α). Each point in the parameter space corresponds to a set of points (x_i; y_i), forming a straight line in the image. If the sinusoidal curves corresponding to two points on the Cartesian plane are superimposed on each other in the parameter space, then the value of the point of their intersection is the parameters of the line that passes through these points. That is, the set of points in the Cartesian plane lying on a straight line determine the sinusoidal curves in the space of parameters that intersect at a point (ρ_i; α_i) for this straight line. Therefore, the problem of determining collinear points in the Cartesian plane is reduced to the problem of identifying intersecting sinusoidal curves in the parameter space [29, 36, 37].

For each point (ρ_i; α_i) a counter is placed in the parameter space in an accumulative space corresponding to a set of points (x_i; y_i) lying on a straight line (expression (19)) [29, 36, 37]:

$$x_i\cos\alpha_i+y_i\sin\alpha_i=\rho_i. \tag{19}$$

Thus, having selected the maximum values in the counter in the accumulative space, we obtain the parameters of the corresponding straight line in the parameter space. Fig. 3 shows the second stage of the method for the segmentation of images of urbanized areas based on the Hough algorithm:

1. Input the original image (image after the first stage $fs^{ant}(\mathbf{X})$)).

2. Determination of the input parameters of the algorithm: the minimum line length, the gap between pixels to combine them into one line, the threshold for the accumulator.

3. Select the sampling step for each parameter of the curve. The efficiency of the algorithm and the amount of calculations depend on the value of this parameter.

4. Fill the accumulator.

5. Accumulator analysis – search in the accumulative space of the counter with the maximum value.

6. Identification of the sinusoidal curve in the parameter space. Each counter of the accumulator space is the value of the parameter space, and accordingly, it sets a certain curve.

7. Subtraction from the accumulator space counter. For points of the selected sinusoidal curve, a temporary accumulator is used, which is then subtracted from the main one.

8. If the maximum counter in the accumulator space is empty, then the transition to step 5 of the algorithm is performed.

9. Formation of data to select straight lines in the image according to the input parameters of the algorithm.

10. Output the resulting image with straight lines highlighted.

The above steps of the method are carried out for each brightness channel of the RGB color space representation of the original image of the urbanized area. The second stage of the method of segmenting images of urbanized terrain acquired from space systems of optoelectronic observation, in contrast to known ones:

– takes into account each brightness channel of the RGB color space of the original image;

– the brightness and geometric shape of the elements of objects are taken into account;

– defines contours and geometric primitives in the parametric space of Hough;

– the objects of interest of the urbanized area in the space of the original image are determined.

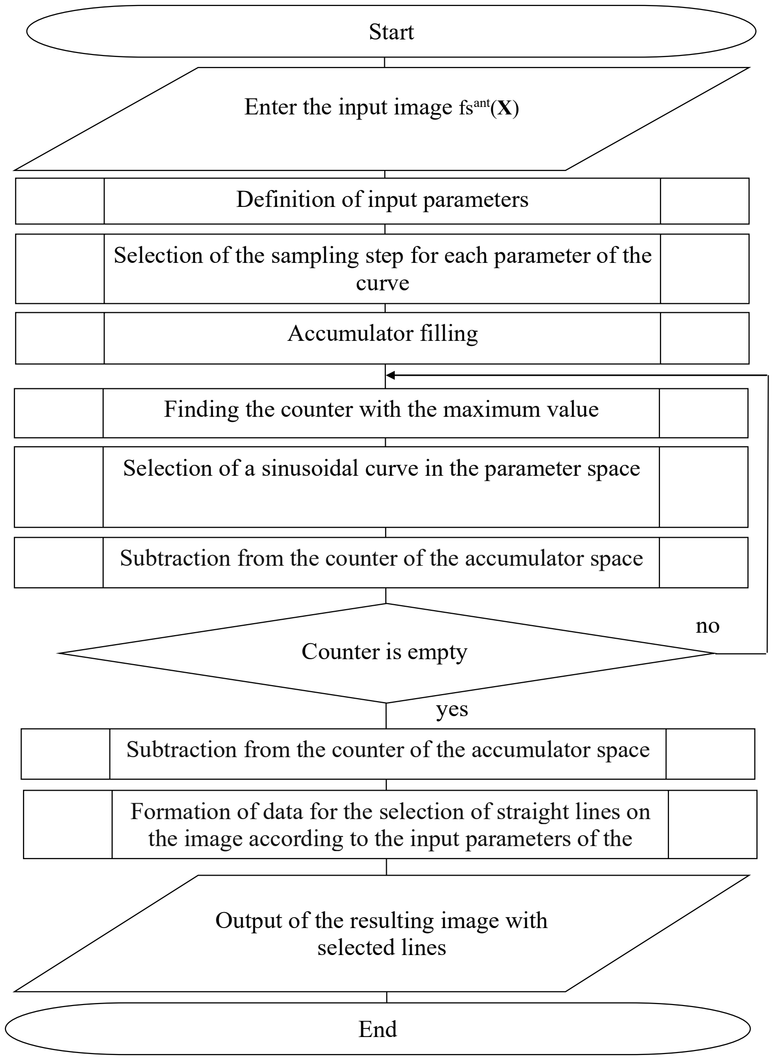

Fig. 3. The sequence of actions of the second stage of the method for the segmentation of images of urbanized areas based on the Hough algorithm

Thus, the method of segmenting images of urbanized terrain acquired from space optoelectronic surveillance systems implies two stages and, in contrast to known ones:

– takes into account each brightness channel of the RGB color space of the original image;

– an ant algorithm is used for segmentation;

– image segmentation at the first stage is reduced to the calculation of the objective function, the areas of ant movement, and the concentration of pheromone on the routes of ant movement;

– at the second stage, the brightness and geometric shape of the elements of objects are taken into account;

– defines contours and geometric primitives in the parametric space of Hough;

– the objects of interest of the urbanized area in the space of the original image are determined.

5. 2. Image segmentation using an ant algorithm and a Hough algorithm

Fig. 4 shows the original color image (RGB color space) of an urbanized area from the space optoelectronic surveillance system Ikonos ((USA) [29, 38]. The original image has a size of (3000×4000) pixels.

Fig. 4. Original color image (RGB color space) of an urbanized area acquired from the space optoelectronic surveillance system Ikonos (USA) [29, 38]

To implement the first stage of the segmentation method, the following parameters of the ant algorithm were adopted (Table 1). The number of iterations of the ant algorithm is 50.

Table 1

Parameters of the ant algorithm in the implementation of the first stage of the method of segmentation of an image of an urbanized area

Parameter name	S, pcs.	α	β	ρ	F_0
Parameter value	12000000 (equals the number of pixels in images)	2	1	10^{-3}	10^{-2}

Fig. 5 shows an image of an urbanized area after the first stage of the segmentation method based on an ant algorithm.

Fig. 5. An image of the urbanized area after the first stage of the segmentation method based on the ant algorithm

To implement the second stage of the segmentation method, the following parameters of Hough transform are adopted:

– $\Delta\rho$=15 pixels – step at the coordinate ρ in pixels;

– $[-\phi;\ \phi]=[-90°;90°]$ – range of change of coordinate ϕ in degrees;

– $\Delta\phi$=1 – step at the coordinate ϕ in degrees;

– Δl=5 pixels – the minimum length of elements of urban infrastructure objects in pixels;

– Δn=2 pixels – the number of missing pixels, the absence of which was ignored when determining urban infrastructure.

Fig. 6 shows an image of an urbanized area after the second stage of the segmentation method based on the ant algorithm and the Hough algorithm.

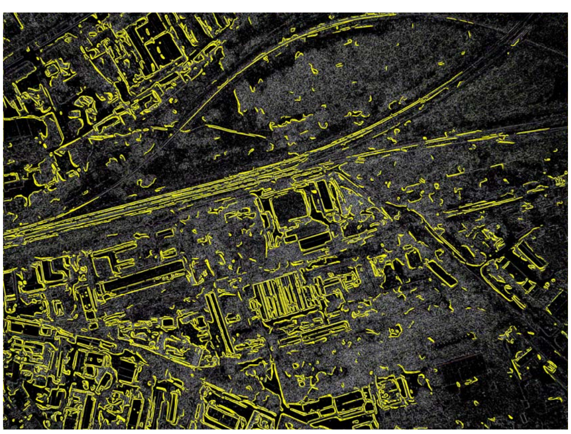

Fig. 6. An image of the urbanized terrain after the second stage of the segmentation method based on the ant algorithm and the Hough algorithm

Yellow color in Fig. 6 identified elements of the urbanized terrain.

Decryption, thematic classification, and recognition of certain elements of urbanized areas are the subject of further research.

The analysis of Fig. 6 shows that the improved method of segmenting images of urbanized terrain acquired from space optoelectronic surveillance systems based on the ant algorithm and the Hough algorithm allows for image segmentation.

5. 3. Evaluation of errors of the first and second kind of segmentation of the image of urbanized areas by a method based on the ant algorithm and the Hough algorithm

To assess the quality of image segmentation of urbanized areas by a method based on the ant algorithm and Hough algorithm from the list of quality indicators [39, 40] we select segmentation errors of the I and II kind.

In general, errors of the I and II kind are determined by the criterion of maximum plausibility [40, 41]. The criterion of maximum plausibility follows from the generalized criterion of the minimum average risk [40, 42].

Taking into account the generalized criterion of minimum average risk, the criterion of maximum plausibility of the error of segmentation of the I and II kind will be determined by expressions (20), (21), respectively [40, 41]:

$$\alpha_1=\frac{S_1\left(fs(\mathbf{X})\right)}{S_2\left(f(\mathbf{X})\right)}, \quad (20)$$

$$\beta_2=1-\frac{S_3\left(fs(\mathbf{X})\right)}{S_4\left(f(\mathbf{X})\right)}, \quad (21)$$

where $S_1(fs(\boldsymbol{X}))$ is the background plane erroneously attributed to the objects of interest in a segmented image of an urbanized area $fs(\boldsymbol{X})$; $S_2(f(\boldsymbol{X}))$ – the background plane of the original image $f(\boldsymbol{X})$; $S_3(\mathrm{fs}(\boldsymbol{X}))$ – plane of properly segmented objects of interest in a segmented image of an urbanized area $fs(\boldsymbol{X})$; $S_4(f(\boldsymbol{X}))$ is the plane of objects of interest in the original image of the urbanized area $f(\boldsymbol{X})$.

We shall assess the quality of image segmentation of urbanized areas using a method based on the ant algorithm and Hough algorithm and a known method. A known method to be considered is the method of image segmentation [29]. The method [29] implies the use of the Canny edge detector algorithm at the first stage, and the Hough algorithm at the second. Images after the first and second stages of the known method of segmentation of urbanized areas are shown in Fig. 7, 8, respectively [29].

The calculation of errors of the I and II kind by expressions (20) and (21) will be carried out by determining the $S_1(fs(\boldsymbol{X}))$, $S_2(f(\boldsymbol{X}))$, $S_3(fs(\boldsymbol{X}))$, $S_4(f(\boldsymbol{X}))$ values on the images of Fig. 5–8. The calculations were carried out using a high-level programming language and an interactive environment for programming, numerical calculations, and visualization of the results by MATLAB R2017b. To confirm the reliability of calculations, Fig. 9 shows a fragment of the program code for calculating errors of type I and II.

Table 2 gives comparative calculations of I and type II errors for each of the stages of the known and improved method of segmentation of urbanized areas.

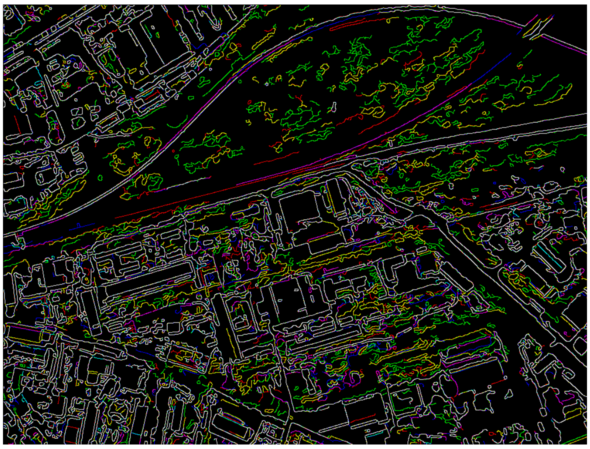

Fig. 7. Image after the first stage of the known method of segmentation of urbanized areas [29]

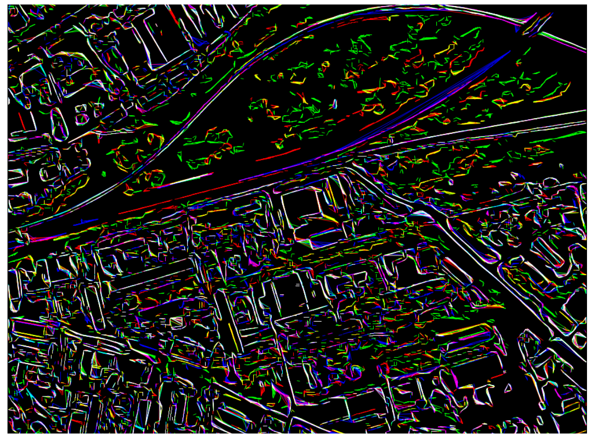

Fig. 8. Image after the second stage of the known method of segmentation of urbanized areas [29]

```
close all
clear all
clc

srcPath = 'src\';
files = dir([srcPath 'vl*.png']);

k0 = 2.5;
n = 1;
src = single(imread([srcPath files(n).name]))/255;
g0 = rgb2gray(src);
th = mean2(g0)+k0*std2(g0);
bw0 = g0>th;

method = { 'ACO', 'Hough_ACO', Canny', Hough_Canny'};

for n=1:length(files)

  srcName = [srcPath 'res\' files(n).name(1:end-4)];

  for m=1:length(method)
   fileName = sprintf('%s\\%s-%04d-u.png', srcName, method{m}, 8);
   res = imread(fileName);
   res = double(res)/255;
   g1 = rgb2gray(res);
   th = mean2(g1)+k0*std2(g1);
   bw1 = g1>th;
   s{m,n}(1,1) = mean2(double(bw0==0 & bw1==0));
   s{m,n}(2,1) = mean2(double(bw0==1 & bw1==0));
   s{m,n}(1,2) = mean2(double(bw0==0 & bw1==1));
   s{m,n}(2,2) = mean2(double(bw0==1 & bw1==1));

   fileName = sprintf('%s\\%s-%04d-bw.png', srcName, method{m}, 8);
   imwrite(bw1, fileName);
  end

end
fileName = sprintf('%s\\bw0.png', srcName);
imwrite(bw0, fileName);
```

Fig. 9. Fragment of the program code for calculating errors of type I and II

This reduction became possible due to the use at the first stage of an improved method of segmenting the image of an urbanized area based on an ant algorithm. Compared to Canny's algorithm, the error of the first kind decreased by 8.9 %, and the error of the second kind decreased by 11.0 %.

Table 2

Evaluation of errors of type I (α_1) and type II (β_2) in the segmentation of the image of an urbanized area by known and improved methods

Methods for segmenting the image of an urbanized area	The first stage of the known method (Canny's algorithm)	The first stage of the advanced method (ant algorithm)	The second stage of the known method (Hough's algorithm)	The second stage of the advanced method (Hough's algorithm)
α_1, %	22.19	13.29	9.30	6.55
β_2, %	26.71	15.71	13.22	9.31

The analysis of Table 2 reveals that the error of the first kind when using the improved method of segmentation is reduced by 2.75 %. The error of the second kind when using the improved method of segmentation is reduced by 3.91 %.

6. Discussion of results of the study on improving the method of segmentation

The method of segmenting images of urbanized terrain acquired from space optoelectronic surveillance systems, unlike known ones, involves two stages. At the first stage, an ant algorithm is used, at the second stage the Hough transform is used. Defined operations are performed for each brightness channel (Red, Green, Blue) representation of the original image.

The first stage of the method for the segmentation of images of urbanized areas implies the use of an ant algorithm (Fig. 2). In this case, the image is represented in the form of a graph, the vertices of which are pixels having coordinates and brightness values.

The ant algorithm implies:

– randomly distribution of agents throughout the image (expression (5));

– calculation of the length of the agent's route section (expression (6));

– calculation for each agent at the turning point of the route of attractiveness of the route section (expressions (8) to (10));

– calculation of the concentration of pheromone values of agents (expression (11));

– calculation of the probability of transition of the agent to the turning point on the route (expression (12));

– calculation of the objective function (expression (13));

– moving agents and checking the fulfillment of the stopping condition.

The second stage of the method of segmenting images of urbanized areas implies the use of the Hough algorithm for straight lines (Fig. 3). The essence of Hough algorithm is to use the voting procedure to the parameter space of each of the figures, from which such simple figures in an accumulative space can be obtained at local maxima. Accumulator space is created and accumulated during the calculation of the Hough transformation.

An experimental study of image segmentation of urbanized terrain acquired from space optoelectronic observation systems based on the ant algorithm and the Hough algorithm was carried out. Fig. 5 shows an image of an urbanized area after the first stage of the segmentation method based on an ant algorithm. Figure 6 shows an image of an urbanized area after the second stage of the segmentation method based on the ant algorithm and Hough algorithm. From the analysis of Fig. 6 it can be seen that the improved method of segmenting images of urbanized areas acquired from space optoelectronic surveillance systems based on the ant algorithm and the Hough algorithm allows for image segmentation of urbanized areas.

The quality of image segmentation of urbanized areas was assessed using a method based on the ant algorithm and Hough algorithm. From the analysis of Table 1 one can see that the error of the first kind when using the improved method of segmentation is reduced by 2.75 %. The error of the second kind when using the improved method of segmentation is reduced by 3.91 %. This reduction became possible due to the use at the first stage of an improved method of segmenting the image of an urbanized area based on an ant algorithm. Compared to Canny's algorithm, the error of the first kind decreased by 8.9 %, and the error of the second kind decreased by 11.0 %. This becomes possible due to the use of an ant algorithm and a Hough algorithm when segmenting the image.

When conducting the study, the following restrictions and assumptions were adopted:

– the image of the urbanized area from the space system of optoelectronic observation is considered as the starting point;

– color representation space of the original image – RGB;

– it is accepted that in the brightness channels R, G, B the number of gradations of brightness is 256;

– the image shows an urbanized area with relevant objects of interest;

– the size of objects of interest is much smaller than the size of background objects;

– the influence of distorting factors on the original image is not taken into account.

Methods for segmenting images of urbanized areas acquired from space optoelectronic surveillance systems can be implemented in software and hardware systems of image processing.

The disadvantage of the improved method of segmentation is its high-quality work mainly for images of urbanized terrain acquired from space optoelectronic surveillance systems.

Further research can be aimed at selecting the optimal number of agents at the first stage of the improved method and comparing the quality of the improved methol with segmentation methods based on genetic algorithms.

7. Conclusions

1. The method of segmenting images of urbanized terrain acquired from space optoelectronic surveillance systems implies two stages and, in contrast to known ones:

– takes into account each brightness channel of the RGB color space of the original image;

– an ant algorithm is used for segmentation;

– image segmentation at the first stage is reduced to the calculation of the objective function, the areas of ant movement, and the concentration of pheromone on the routes of ant movement.

– at the second stage, the brightness and geometric shape of the elements of objects are taken into account;

– defines contours and geometric primitives in the parametric space of Hough;

– the objects of interest of the urbanized area in the space of the original image are determined.

2. An experimental study of image segmentation of urbanized terrain acquired from space optoelectronic observation systems based on the ant algorithm and the Hough algorithm was carried out. It was found that the improved method of segmenting images of urbanized areas acquired from space optoelectronic observation systems based on the ant algorithm and the Hough algorithm allows image segmentation of urbanized areas.

3. The quality of image segmentation of urbanized areas was assessed using a method based on the ant algorithm and Hough algorithm. It was found that the error of the first kind when using the improved method of segmentation is reduced by 2.75 %. The error of the second kind when using the improved method of segmentation is reduced by 3.91 %. This reduction became possible due to the use at the first stage of an improved method of segmenting the image of an urbanized area based on an ant algorithm. Compared to the Canny algorithm, the error of the first kind decreased by 8.9 %, and the error of the second kind decreased by 11.0 %.

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 and the results reported in this paper.

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Data availability

All data are available in the main text of the manuscript.

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