Problems of identification in information systems

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THE METHOD FOR APPROXIMATING THE EDGE DETECTION CONVOLUTIONAL OPERATOR USING A GENETIC ALGORITHM FOR SEGMENTATION OF COMPLEX-STRUCTURED IMAGES

Abstract. The **subject matter** of the study in the article is the method for approximating the convolutional operator for edge detection using a genetic algorithm for segmentation of complex-structured images. The **goal** is to develop a method for approximating the convolutional operator for edge detection using a genetic algorithm for the segmentation of complex-structured images. The **tasks** are: analysis of known methods of segmentation of optoelectronic images, development of a method for approximating the edge detection convolutional operator using a genetic algorithm for segmenting complex-structured images, practical validation of the method for approximating the edge detection convolutional operator using a genetic algorithm for segmenting complex-structured images. The **methods** used are: digital image processing methods, data clustering techniques, matrix theory mathematics, swarm intelligence methods, the genetic algorithm, mathematical modelling techniques, optimization theory methods, as well as analytical and empirical methods for image comparison. The following **results** are obtained. The advantages and disadvantages of the main known methods for segmenting optoelectronic images have been identified. It has been established that the most effective segmentation methods for images from space-based optoelectronic observation systems (complex-structured images) are those based on swarm intelligence and genetic algorithms. An important case of segmentation – binarization (segmentation into two classes), has been considered. The task of binarization has been formalized, and the concepts of structural and amplitude predicates have been introduced. The method for segmenting complex-structured images has been improved, in which, unlike existing methods, a genetic algorithm is used for approximating the edge detection convolutional operator, facilitating segmentation of images at various scales with later integration of the results. A visual assessment of the quality of the segmented image has been conducted using the improved method. **Conclusions**. The method for segmenting complex-structured images has been improved, in which, unlike existing methods, a genetic algorithm is employed to approximate the edge detection convolutional operator, easing segmentation of images at various scales with later integration of the results. A visual assessment of the quality of the segmented image using the improved method shows a significant reduction in the number of noise objects present in the segmented image.

Keywords: complex-structured image; segmentation; convolutional kernel; genetic algorithm; ant algorithm; multiscale processing.

Introduction

Formulation of the problem. Currently, space-based optoelectronic observation systems are used to address a wide range of tasks. For example, based on the analysis (decoding) of optoelectronic images, various tasks are being solved [1–3]:

– monitoring environmental situation;
– agriculture and land management;
– urbanization of territories;
– monitoring of temporarily occupied territories;
– fighting with terrorism;
– at the interests of the State Border Guard service;
– making management decisions by governmental authorities;
– to ensure security and defence, etc.

The satisfaction of consumer requirements for the quality of decoding optoelectronic images is primarily determined by the quality of their segmentation [4, 5]. The quality of segmentation significantly affects the completeness, accuracy, and reliability of the information derived from the interpretation of optoelectronic images. Such requirements from information consumers necessitate the use of appropriate methods for the segmentation of optoelectronic images.

A distinctive feature of optoelectronic images from space observation systems is their complex structure. This means that [6, 7]:

– a large number of heterogeneous objects;
– objects in the image belong to various structural-spatial elements;
– own significant characteristics of each type of object;
– the morphologically complex structures of the objects;
– the objects are compact;
– the objects have low-contrast compared to the background.

The complexity of such images results in difficulties and, in some cases, complete ineffectiveness in applying known segmentation methods. Therefore, research focused on the development of segmentation methods for complex-structured images from space optoelectronic observation systems is of significant relevance.

Analysis of recent research and publications. In [8], methods for segmentation based on the statistical description of textures are proposed. A texture characterizes the distribution of brightness values in the image. A drawback of [8] is the ineffectiveness of segmentation when the objects of interest are obscured by background objects.

In [9], the use of Laws' texture energy for image segmentation is proposed. The method is two-stage. The first stage involves calculating the local mean value for each pixel in the image. The second stage entails the parallel application of sixteen masks of 5x5 size. These masks are used to isolate different texture components of the image (Laws' energy characteristics). A drawback of the method [9] is the dependence of mask size on the type of image and the complexity of parallel processing with all masks simultaneously.

In [10], the computation of a co-occurrence matrix is proposed for conducting segmentation. This matrix serves as a source of statistical information on the brightness of the neighbourhood of each pixel in the image. The drawbacks of method [10] include:

– the complexity of working with pixels of varying brightness;

– the necessity of having reference textures available.

In [11], a segmentation method based on the k-means algorithm is proposed. A significant drawback of [11] is the substantial dependence of the method's performance on the selection of the k parameter.

In [12], a segmentation method based on the C-means algorithm is discussed. In this case, fuzzy entropy is used to figure out the number of segments. A drawback of [12] is the method's sensitivity to additive noise, which, in turn, significantly deteriorates the quality of segmentation.

In [13], an improved segmentation method based on the fuzzy local binary pattern C-means algorithm is proposed. A drawback of [13] is also its sensitivity to additive noise.

In [14], a segmentation method using Voronoi tessellation is proposed. The method involves constructing a set of polygons, selecting polygons with common properties, and merging them into regions. A drawback of [14] is its low computational efficiency.

In [15], the use of a Haar mosaic is proposed. The Haar mosaic consists of a collection of primitives, which are assembled into a mosaic and analysed. Spatial filtering of the image is employed to obtain the primitives. A drawback of [15] is the method's complexity in scenarios involving a combination of textured and non-textured areas.

In [16], a segmentation method based on a fractal algorithm is proposed. A drawback of [16] is the difficulty in unifying structures in a way that ensures the delineation of fractal dimensions.

In [17], a segmentation method based on the use of spectral texture measures is proposed. The spectral texture measure of the image is calculated using the Fourier spectrum. A drawback of [17] is the complication of processing when fine-grained texture is present in the image.

In [18], segmentation methods based on convolutional neural networks are proposed. A drawback of [18] is the necessity of mandatory pre-training of the convolutional neural network.

In [19], the use of support vector machines for image segmentation is proposed. The essence of [19] lies in combining a supervised machine learning model with support vector machines. The classification of objects of interest is conducted using support vector methods, along with boundary segmentation and the complete lambda algorithm. A drawback of [19] is the multi-stage nature of the proposed approach.

In [20], the use of the Random Forest method for segmenting natural surfaces (grass, gravel, sand, water) in images is proposed. A drawback of [20] is the limited range of objects of interest available for segmentation.

In [21], a segmentation method based on the particle swarm algorithm is proposed. A drawback of [21] is the complexity involved in implementing the method.

In [22], an improved method for segmenting complex-structured colour images is proposed. The essence of [22] lies in the use of the ant colony optimization algorithm to highlight the contours of objects of interest in satellite imagery. An advantage of [22] is the increased accuracy of segmentation compared to known methods. A drawback of [22] is the emergence of a large number of small contours in the resulting image (over-segmentation).

In [23-24], a segmentation method for optoelectronic images based on a genetic algorithm is proposed. The method has proven its effectiveness. For instance, the application of the genetic algorithm reduces first and second type segmentation errors by approximately 10% to 17%, depending on the type of image. The drawbacks of [23-24] include the complexity of implementing the genetic algorithm and its lengthy processing time, particularly considering the size of the input image.

Thus, the analysis of known segmentation methods indicates that the most effective techniques for segmenting images from space optoelectronic observation systems are those based on swarm and genetic algorithms. Therefore, it is advisable to combine the advantages of the segmentation methods based on swarm and genetic algorithms for the segmentation of images from space optoelectronic systems.

Thus, the **goal** of the article is to improve the method of segmenting images from a space optoelectronic observation system using an operator whose elements are computed with the aid of a genetic algorithm.

Main results

The task of segmenting optoelectronic images can be considered a specific instance of the data clustering problem, which is carried out by minimizing pairwise mean squared deviations within each cluster.

Let $x = (x_1, x_2, \dots, x_n)$ be a set of observations, where each observation is a d-dimensional real vector. The goal of clustering is to partition n observations into $k \le n$ subsets $S = \{S_1, S_2, \dots, S_n\}$ such that the intracluster sum of squared distances (i.e., the variance) is minimized, which can be expressed in the form of equation:

$$S = \\ = \arg\min_S \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2 = \arg\min_S \sum_{i=1}^{k} |S_i| \operatorname{var}(S_i), \quad (1)$$

where μ_i – mean of the set S_i; $|S_i|$ – number of the elements in S_i; var (S_i) – the variance of the quantity S_i.

A practically important case of segmentation is binarization – segmentation into 2 classes, commonly referred to as foreground and background. In this case, the segmented image f can be represented as a binary matrix b, such that for each pixel with coordinates (i, j), the following expression holds:

$$b_{ij} = \begin{cases} 1, & \textit{if } f_{ij} \textit{ is foregound pixel;} \\ 0, & \textit{if } f_{ij} \textit{ is backgound pixel.} \end{cases} \quad (2)$$

It should be noted that selecting only the brightness of a pixel as a feature for binarization is not the optimal choice. In many cases, it is advisable to include other additional features for binarization. Formally, this can be represented as

$$b_{ij} = \bigcap_n \left(P_n \left(f_{ij} \right) \right), \quad (3)$$

where each predicate P_n is true if a certain condition is met.

For instance, in [21, 22], it is demonstrated that to highlight artificial objects on the Earth's surface, it is advisable to use the following two features: the artificial object has a high value of brightness contrast at the boundary with the background, and the object itself is generally brighter than the background. Thus, in this case, equation (3) can be represented as

$$b_{ij} = P_1\left(f_{ij} \right) \cap P_2\left(f_{ij} \right), \quad (4)$$

where $P_1(f_{ij})$ – a predicate, which we will henceforth refer to as the structural predicate, that is true if, at this point, the value of the brightness gradient magnitude is large (i.e., exceeds a specified threshold) (for example, in the terminology of [25] – an image-filter); $P_2(f_{ij})$ – a predicate that we will refer to as the amplitude predicate, which is true if, at this point, the brightness value exceeds a specified threshold.

As shown in [25], the values of the gradients need to be analysed across a scale pyramid (for example, [26]), meaning that the structural predicate $P_1(f_{ij})$ should be represented as

$$P_1\left(f_{ij} \right) = S_2^k \circ \left| \vec{\nabla} S_{1/2}^k f_{ij} \right| > \tau_1, \quad (5)$$

where symbol ($\circ$) denotes a composition of vectors, $S_{1/2}^k$ and S_2^k are defined by expressions (6) and (7), respectfully:

$$S_{1/2}^k = \overbrace{S_{1/2} \circ S_{1/2} \circ \ldots S_{1/2}}^{k}, \quad (6)$$

$$S_2^k = \overbrace{S_2 \circ S_2 \circ \ldots S_2}^{k}, \quad (7)$$

and denote k-fold compositions of $S_{1/2}$ operators (which scale down the image by a factor of 2) and S_2 operators (which scales the image up by a factor of 2) respectfully; $\vec{\nabla}$ – the Hamiltonian operator (nabla), which is used to denote the gradient of a function; τ_1 – the binarization threshold for the structural predicate.

The amplitude predicate $P_2(f_{ij})$, in its turn, can be represented as

$$P_2\left(f_{ij} \right) = f_{ij} > \tau_2, \quad (8)$$

where τ_2 – the binarization threshold for the amplitude predicate.

Equation (5) can be generalized by replacing the gradient magnitude with the general edge detection operator D [27]:

$$P_1\left(f_{ij} \right) = S_2^k \circ \left| D \circ S_{1/2}^k f_{ij} \right| > \tau_1. \quad (9)$$

Thus, expression (4) can be rewritten as

$$b_{ij} = \left(S_2^k \circ \left| D \circ S_{1/2}^k f_{ij} \right| > \tau_1 \right) \cap \left(f_{ij} > \tau_2 \right). \quad (10)$$

It should be noted that for practical applications, it is sometimes convenient to use fuzzy logic [28], where the logical variables are not binary but are instead real numbers in the interval [0, 1]. By analogy, we will also use the term fuzzy binarization. For performing fuzzy binarization, we will assume that the brightness values of each pixel f_{ij} are also normalized to the range [0, 1], thus, the logical operation ∩ can be represented simply as the multiplication of real numbers. In this case the equation (expression (10)) is simplified (as thresholds τ1, τ2 are not needed:

$$b_{ij} = \left(S_2^k \circ \left| D \circ S_{1/2}^k f_{ij} \right| \right) \cdot f_{ij}, \quad (11)$$

where dot (·) represents simple multiplication.

As shown in [26], a good choice for edge detection is the use of optimization algorithms based on Ant Colony Optimization (ACO) (see also [29]). A drawback of this approach is its high computational cost.

In this work, it is proposed to find an approximation of the edge detection operator using the ant colony method (denoted as D^{ACO}) with a convolution operator having a kernel size of ($w \times w$) (denoted as $D^{w \times w}$). The convolution operator will be determined using a genetic algorithm.

First, we will select a target function for optimization. Let us assume that, for the input image $\tilde{f}_{ij}$ the ant colony method has computed a set of edge images $\tilde{d}_{ij}$ for a scale pyramid of size k:

$$\tilde{d}_{ij} = \left(S_2^{k'} \circ \left| D^{ACO} \circ S_{1/2}^{k'} \right| \right) \tilde{f}_{ij}, \quad (12)$$

where $k' = 1 \ldots k$.

Then, the objective function $s(\mathbf{q})$ of the vector of unknown variables $\mathbf{q}$ (the number of which is obviously w^2) can be represented as (expression (13)):

$$s(\mathbf{q}) = \sum_{k'=1}^{k} \left\| S_2^{k'} \circ \left| D^{w\times w}(\mathbf{q}) * S_{1/2}^{k'} \tilde{f}_{ij} \right| - \tilde{d}_{ij}^{k'} \right\|_2, \quad (13)$$

where $D^{w\times w}(\mathbf{q})$ is simply a matrix of $w\times w$ size, symbol (*) denotes convolution, and the summation of differences in the L_2-norm (the choice of the L_2-norm is not fundamental, as similar results can be obtained using any image comparison metric) is carried out across all scales $k' = 1...k$.

Minimising $s(\mathbf{q})$ (value $\mathbf{q}$ is chosen from the interval [-1, +1]), we obtain an approximation for $D^{w\times w}(\mathbf{q})$. Comparing to (5), it can be understood that $D^{w\times w}(\mathbf{q})$ selected by analogy with operator $\vec{\nabla}$, so it is reasonable to expect that $D^{w\times w}(\mathbf{q})$ will be similar to the matrix approximation of the Sobel operators (or, possibly, since the magnitude of the convolution result is taken, it may resemble the Laplacian).

It should be noted that function (12) is significantly nonlinear (primarily due to the scaling operators $S_{1/2}^{k'}$, $S_2^{k'}$ and possibly when using a nonlinear image comparison metric instead of the L_2 norm) making it impossible to find its minimum using standard methods. For this type of problem, evolutionary optimization methods, including genetic algorithms, are most suitable. The slowness of the genetic algorithm in this case is insignificant, as $D^{w\times w}(\mathbf{q})$. (unlike D^{ACO}) is calculated only once for the input image (or for a set of input images—expression (12) can be easily generalized for this case). The application of $D^{w\times w}(\mathbf{q})$ is fast, as the convolution calculations can be easily parallelized and are optimized operations for modern computing systems.
We will illustrate the operation of the proposed algorithm for finding $D^{w\times w}(\mathbf{q})$ for w=5. The genetic algorithm was initiated with default parameters, Population Size set to 200, a Maximum Number of Generations equals 1000 (Listing 1). The expression chosen as the objective function is (12), with its realization in MATLAB as shown (Listing 2).

```
ga_opts = optimoptions('ga','display','iter',...
    'PopulationSize', 200, 'MaxGenerations', 1000,
    ...
    'PlotFcn','gaplotbestf');
```

Listing 1

```
function curr = fitness(x, win, metric, src,
    dst, scales)
kernel = reshape(x, [win win]);
curr = 0;
for n=1:numel(src)
     for s = 1:numel(scales)
         src2 = imresize(src{n},1/scales(s));
         dst2 = imfilter(src2, kernel,
    'symmetric');
         dst2 = abs(dst2);
         curr = curr + metric(dst{n}{s}, dst2);
     end
end
```

Listing 2

For accurate comparison of the results, we will use the input image (Fig. 1) [30].

Fig. 1. The input colour satellite image [30]

Fig. 2 presents the graphs of changes in Best fitness and Mean fitness as a function of Generation.

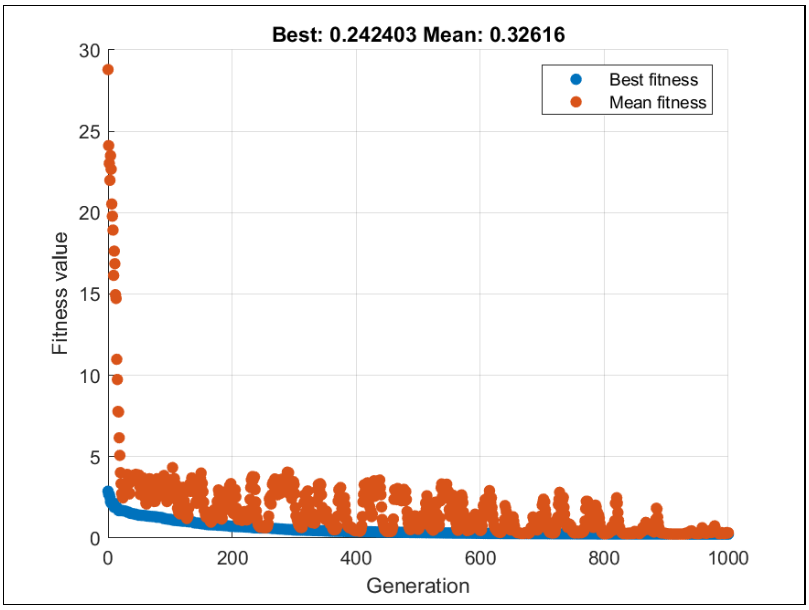

Fig. 2. Graphs of changes in Best fitness and Mean fitness as a function of Generation

As can be seen from the analysis of Fig. 2, the minimum value of the objective function $s(\mathbf{q})$ is 0,242403, while the mean value of the objective function $s(\mathbf{q})$ is 0,32616. Fig. 3 visualizes $D^{5\times5}(\mathbf{q})$ kernel, which was obtained as a result of the operation of the genetic algorithm.

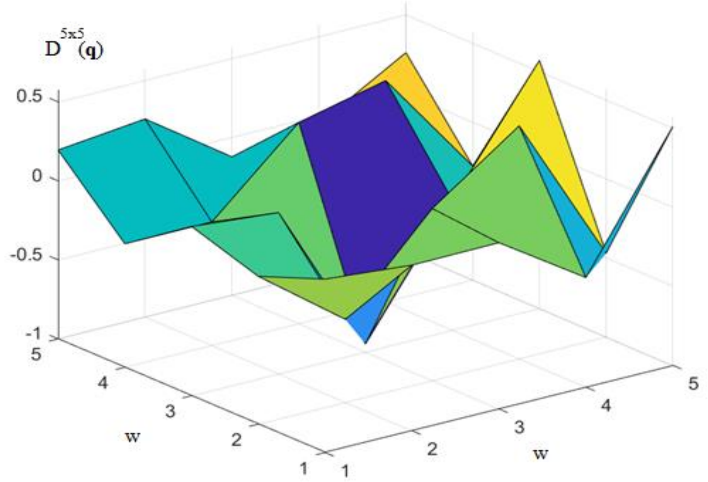

Fig. 3. Visualization of $D^{5\times5}(\mathbf{q})$ kernel, obtained as a result of the operation of the genetic algorithm

Fig. 4 represents a top view for a $D^{5\times5}(\mathbf{q})$ kernel, obtained as a result of the operation of the genetic algorithm. Further analysis of Fig. 4 allows us to assert the similarity of the convolution kernel $D^{5\times5}(\mathbf{q})$ to a Laplacian kernel.

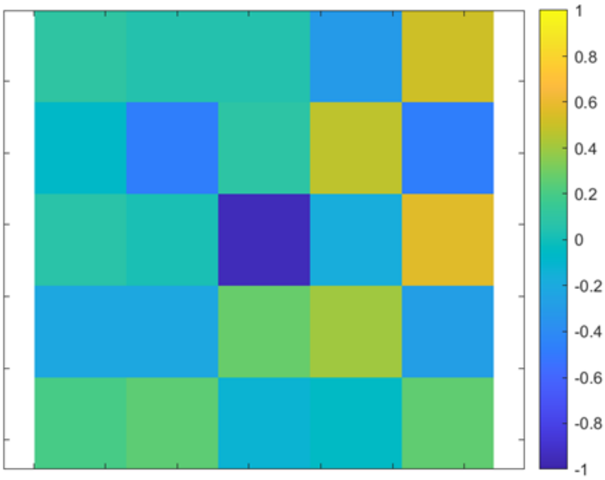

Fig. 4. Visualization of $D^{5\times5}(\mathbf{q})$ kernel, obtained as a result of the operation of the genetic algorithm (top view)

Fig. 5 shows the segmented image obtained through the approximation of the convolution operator $D^{5\times5}(\mathbf{q})$ using the genetic algorithm. The scaling factor is $k = 1$.

Fig. 6 presents the segmented image obtained using the convolution operator D^{ACO} based on the results of [25, 26], for comparative analysis. The scaling factor for the images in Fig. 6 is also $k = 1$.

Visual analysis of Fig. 5 and Fig. 6 indicates a reduction of noise objects in Fig. 5 compared to Fig. 6. It is worth noting that the presence of a certain number of noise objects is one of the main drawbacks of using the ant colony algorithm for segmenting complex-structured images.

Fig. 7 shows the results of segmenting the input image (Fig. 1) obtained through the approximation of the convolution operator $D^{5\times5}(\mathbf{q})$ using the genetic algorithm. However, unlike Fig. 5, images with varying scaling factors were applied (1/8, 1/4, 1/2, 1).

For comparative analysis, Fig. 8 presents the segmented image obtained using the convolution operator D^{ACO} based on the results of [25, 26]. The scaling factors for the images in Fig. 8 are (1/8, 1/4, 1/2, 1).

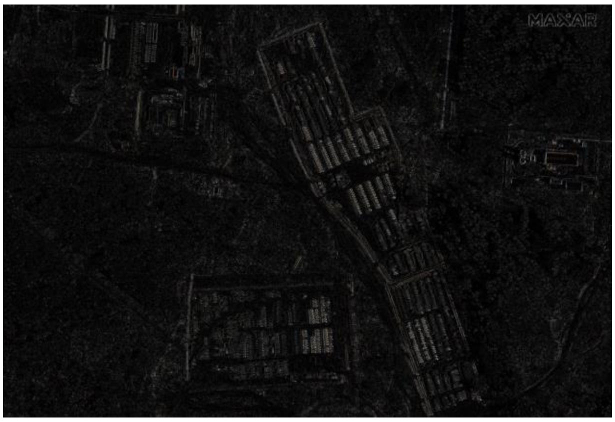

Fig. 5. Segmented image obtained through the approximation of the convolution operator $D^{5\times5}(\mathbf{q})$ (scaling factor $k = 1$)

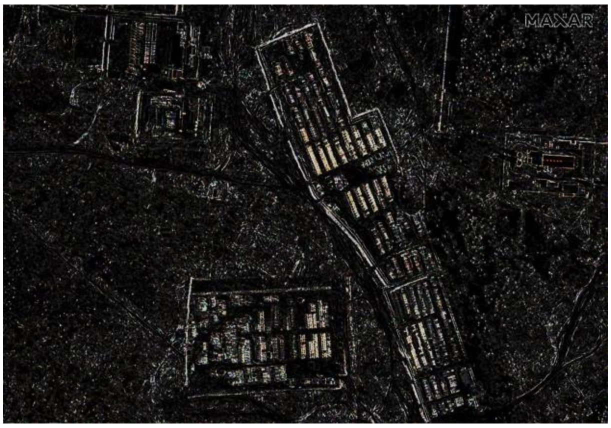

Fig. 6. The segmented image obtained using the convolution operator D^{ACO} [25, 26] (scaling factor $k = 1$)

Fig. 7. The segmented image obtained through the approximation of the convolution operator $D^{5\times5}(\mathbf{q})$ using the genetic algorithm (scaling factors 1/8, 1/4, 1/2, 1)

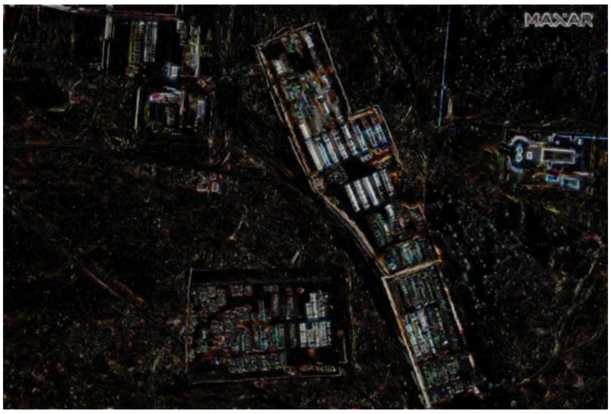

Fig. 8. The segmented image obtained using the convolution operator D^{ACO} [25, 26] (scaling factors 1/8, 1/4, 1/2, 1)

Visual analysis of Fig. 7 and Fig. 8 indicates a reduction of noise objects in Fig. 7 compared to Fig. 8. Lesser amount of noise objects in Fig. 7, Fig. 8, compared to Fig. 5, Fig. 6, is also attributed to the application of segmenting complex-structured images at different scales (scaling factors of 1/8, 1/4, 1/2, 1) with subsequent merging of the segmentation results for images at each scale. Thus, the method for segmenting complex-structured images has been improved, in which, unlike known methods, a genetic algorithm is used for the approximation of the edge detection convolution operator, allowing for segmentation of images at different scales followed by the merging of results.

Visual assessment of the quality of the segmented image using the improved method indicates a significant reduction in the number of noise objects in the segmented image.

Conclusions and the directions of further research

An analysis of known methods for segmenting optoelectronic images has been conducted.

It has been established that the most effective segmentation methods for images from space optoelectronic observation systems (complex-structured images) are those based on swarm and genetic algorithms.

Therefore, it is advisable to combine the advantages of these segmentation methods based on swarm and genetic algorithms for the segmentation of images from space optoelectronic systems.

A practically important case of segmentation— binarization (segmentation into 2 classes) – has been considered.

The binarization task has been formalized, and it has been concluded that for highlighting artificial objects on the Earth's surface, it is advisable to use the following two features:

– the artificial object has a high value of brightness contrast at the boundary with the background;

– the artificial object is generally brighter than the background.

The following concepts have been introduced:

– structural predicate, which is true if, at this point, the value of the brightness gradient magnitude is high (i.e., exceeds a specified threshold);

– amplitude predicate, which is true if, at this point, the brightness value exceeds a specified threshold.

The method for segmenting complex-structured images has been improved, in which, unlike known methods, a genetic algorithm is employed for the approximation of the edge detection convolution operator. This method facilitates segmentation of images at different scales followed by the merging of results.

Visual assessment of the quality of the segmented image using the improved method shows a significant reduction in the number of noise objects in the segmented image.

The directions for further research are:

– to ensure the robustness of the method, it is necessary to train the convolution operator on a specific set of images;

– conducting a quantitative assessment of the quality of segmentation when approximating the edge detection convolution operator using a genetic algorithm for segmenting complex-structured images.

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Метод апроксимації генетичним алгоритмом згорткового оператора визначення границь для сегментування складноструктурованих зображень

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Анотація. Предметом вивчення в статті є метод апроксимації генетичним алгоритмом згорткового оператора визначення границь для сегментування складноструктурованих зображень. **Метою** є розробка методу апроксимації генетичним алгоритмом згорткового оператора визначення границь для сегментування складноструктурованих зображень. **Завдання**: аналіз відомих методів сегментування оптико-електронних зображень, розробка методу апроксимації генетичним алгоритмом згорткового оператора визначення границь для сегментування складноструктурованих зображень, практична перевірка роботи методу апроксимації генетичним алгоритмом згорткового оператора визначення границь для сегментування складноструктурованих зображень. Використовуваними **методами** є: методи цифрової обробки зображень, методи кластеризації даних, математичний апарат теорії матриць, методи ройового інтелекту, генетичний алгоритм, методи математичного моделювання, методи теорії оптимізації, аналітичні та емпіричні методи порівняння зображень. Отримані такі **результати**. Визначені переваги та недоліки основних відомих методів сегментування оптико-електронних зображень. Встановлено, що найбільш якісними методами сегментування зображень з космічних систем оптико-електронного спостереження (складноструктурованих зображень) є методи на основі ройових та генетичного алгоритмів. Розглянуто практично важливий випадком сегментації – бінаризація (сегментація на 2 класи). Формалізовано завдання бінарізації та введені поняття структурного та амплітудного предикатів. Удосконалено метод сегментування складноструктурованого зображення, в якому, на відміну від відомих, для апроксимації згорткового оператора визначення границь використовується генетичний алгоритм, проводиться сегментування зображень різних масштабів з подальшим об'єднанням результатів. Проведена візуальна оцінка якості сегментованого зображення удосконаленим методом **Висновки**. Удосконалено метод сегментування складноструктурованого зображення, в якому, на відміну від відомих, для апроксимації згорткового оператора визначення границь використовується генетичний алгоритм, проводиться сегментування зображень різних масштабів з подальшим об'єднанням результатів. Візуальна оцінка якості сегментованого зображення удосконаленим методом дозволяє стверджувати про суттєве зменшення кількості "сміттєвих" об'єктів на сегментованому зображенні.

Ключові слова: складноструктуроване зображення; сегментування; ядро згортки; генетичний алгоритм; мурашиний алгоритм; багатомасштабна обробка.