This work examines the process that determines a phantom area in an image acquired from a space radar observation system. The principal hypothesis of the study assumed that improving a method for defining the phantom area could reduce image processing errors of the first and second kind.

The operational method for determining the phantom area in an image acquired from a space radar observation system has been improved; in it, in contrast to known ones,

– a radar image is represented as a two-dimensional array of pixels whose intensity is determined by the amplitude of the radar signal in grayscale;

– the influence of speckle noise is minimized using convolution with a Gaussian filter;

– the image histogram is aligned to increase contrast;

– the boundaries in the image are selected using a gradient operator;

– the area with the selected boundaries with objects of interest is defined as the phantom area in the image acquired from a space radar observation system.

An experimental study was conducted on the operational determination of the phantom area in an image from a space radar surveillance system. Phantom areas on which objects of interest are located are highlighted in an image from a space radar surveillance system. At the final stage of the improved method for boundary selection, the Sobel, Prewitt, and Roberts operators are considered. The choice of the Roberts operator at the final stage for boundary selection allowed for the following:

– a decrease in processing errors of the first kind: by 2.64% compared to the Sobel operator; by 5.66% compared to the Prewitt operator;

– a reduction of processing errors of the second kind: by 2.4% compared to the Sobel operator; by 4.26% compared to the Prewitt operator

Keywords: space radar surveillance system, phantom area, errors of the first and second kind

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IMPROVING A METHOD THAT RAPIDLY DETERMINES THE PHANTOMIZATION AREAS IN AN IMAGE ACQUIRED FROM A SPACE-BASED RADAR OBSERVATION SYSTEM

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1. Introduction

When solving certain tasks using space radar surveillance systems, there is a need to prevent acquiring reliable information from such systems (for example, [1, 2]). This may include information about some objects of interest (military objects, critical infrastructure, military and other equipment, etc.) [3]. Therefore, there is a need to change certain information regarding some areas of the terrain. This process is commonly called phantomization [2].

Known phantomization methods (for example, [1, 2]) are based on the principles of receiving and processing a radar signal as a source of observation information. However, such methods have certain disadvantages. First of all, such disadvantages are associated with the complexity of processing radar information, uncertainty regarding the parameters of radar signals, etc. In [2], only the basics of the theory of phantomization of images from space radar surveillance systems are outlined. At the same time, certain examples of processing such images for the purpose of their further phantomization are not considered. In [2], some requirements are also set for the size of the phantomization area of a radar image for certain observation conditions. However, the calculation of the size and orientation of such areas is not considered in [2]. In addition, in [2] it is noted that one of the requirements for image processing for the purpose of its further phantomization is rapidity.

Therefore, it is a relevant task to improve the method that rapidly determines the phantomization area in an image acquired from a space radar observation system.

2. Literature review and problem statement

It was established in [1, 2] that during radar observation of the Earth's surface, the amplitude of the radar signal can be used for operational processing of radar information. In this case, the amplitude can be considered as the intensity of brightness, and the set of amplitudes of the radar signal can be represented in the form of a two-dimensional array (image). In this case, the value of the amplitude of the radar signal can be considered as the brightness of a pixel of the radar image. With this representation, to determine the areas of phantomization, the radar image can be processed by known methods for processing optoelectronic images.

In [4], a detailed analysis of threshold segmentation methods, which are also used in the processing of radar images, is given. The paper compares the results of image segmentation by both classical and modified global thresholding methods. In this case, the radar image was selected with the presence of speckle noise. The main advantages of the approach considered in [4] are the simplicity of implementation and high quality of segmentation only when selecting segments in the amount of no more than three. However, the issues of segmentation efficiency remained unresolved. A likely reason is the presence of speckle noise in the image. An option to overcome it is the use of local thresholding. This is the approach used in [5].

In [5], the use of a local thresholding approach is proposed, where the threshold is determined locally in the blocks into which the entire radar image is divided. The main advantages of [5] are the absence of the need for training and adaptability to the conditions of radar imaging. However, the issues of the need for computational operations, which reduces the efficiency of processing, remained unresolved. A likely reason is the dependence on the size of the block into which the image is divided. An option to overcome this is the use of a texture approach. This is the approach applied in [6].

In [6], the use of a radar image processing method based on a texture approach based on a co-occurrence matrix is proposed, with the help of which changes in shooting scenes are studied over time. The advantages of [6] are the ability to display the structure of all objects shown in the original image and the ability to adapt to different scenes and shooting scales. However, the issues of computational complexity and sensitivity remain unresolved. This leads to distortion of the co-occurrence matrix. An option to overcome this is to extract texture characteristics from the segmented image. This is the approach employed in [7].

In [7], a method for automatic extraction of texture characteristics from segmented radar images is proposed. The advantages of [7] are the universality of this approach, i.e., there is no binding to a specific type of objects of interest and automation. The disadvantages of [4] are the complete dependence of the result of the method on the quality of the segmentation result of the input image and the resource-intensive nature of this image processing method. An option to overcome this is to use a hybrid approach to automatic object extraction. This is the approach reported in [8].

In [8], a hybrid approach to automatic object extraction of interest in radar images is proposed, which is based on the k-means clustering method and the data augmentation strategy. The advantages of [8] are the simplicity of the method implementation and the flexibility of operation under conditions of limited a priori information about the types of objects of interest in the images. The main disadvantage of [8] is the need for training at the stage of using the data augmentation strategy and the dependence on the volume of the data set of "input" samples.

For processing complex agricultural areas, the Organization Evolution Algorithm ISODATA method was proposed in [9] for processing radar images, which is a modification of the classical clustering algorithm. The essence of the method is to cluster not individual pixels by their intensity value but rather groups of pixels. The advantage of [9] is good segmentation results on complex agricultural landscapes even in the presence of noise in the images. The disadvantages are the direct dependence of the increase in time, computational costs, and resource intensity on the division of the image into groups of pixels. An option to overcome this is to use combined features. This is the approach chosen in [10].

In [10] it was proposed to use a method that combines physically based features, statistical modeling, and comparison of the template and test image when processing radar images. The main advantage is to increase the robustness of the system for processing radar images. The main disadvantages are computational complexity, the need for a template library, and the need to select the parameters of the method.

In [11], in order to improve the quality of segmentation, a method combining super pixels and structural modeling is used. The advantage is a higher quality of image processing compared to classical methods. The main disadvantage is the dependence of the segmentation result on the size and compactness of super pixels, when either details are lost in the resulting image when the super pixel size is too large or the computational costs increase when it is too small.

For the classification of polarimetric radar images, an approach was proposed in [12] that takes into account both the probabilistic data distribution model and the neighborhood of pixels or segments. The main advantages are adaptability to the structure of the survey area due to the ability of the system to adjust to the geometry of the terrain and the versatility of the method in terms of processing both homogeneous and heterogeneous areas, both urbanized and agricultural areas. The main disadvantages of the approach in [12] are high computational complexity and dependence on the settings of the input parameters of the method. An option to overcome this is to use simplified processing and reduce the number of input parameters. This is the approach proposed in [13].

In [13] it was proposed to take into account the shortcomings of the approach from [12] and in the improved method of processing polarimetric radar images, simplified mathematical processing is already used and the number of input parameters is reduced. Other advantages are the stability of operation in the presence of noise in the input image. The main disadvantage is the high probability of the end of the iterative process of the algorithm with the problem of several "local minima".

In [14] it was proposed to use a method from the "regional" family, the essence of which is the growth of regions around the starting points using a statistical homogeneity criterion. The advantage of the method is the absence of the need for preliminary filtering of radar images, the peculiarity of which is the presence of speckle noise. The main disadvantages of [14] are the dependence of the processing result on the choice of starting points and computational complexity.

In [15], when performing the segmentation task, it is proposed to consider the radar image as a topographic surface where "watersheds" form the boundaries between the segments. However, this approach is most often used as one of the stages of image processing; it is not an independent processing method, which is the main drawback of [15]. Another drawback is re-segmentation, i.e., the appearance of an excessive number of false segments. The main advantages are its use as an auxiliary stage of radar image processing and high quality of processing when segmenting water surface images.

In [16], a graph method was proposed for water surface separation in radar images, in which segmentation is performed by minimizing the energy of the graph. In [16], the similarity of the main pixel and neighboring pixels to the water and/or land model was taken into account. The main advantage is the high quality of dividing the radar image into two segments – land and water – under an automatic mode. The main disadvantages are the possibility of using this approach only for water surface separation and the high computational complexity of constructing the graph.

In [17], the use of specialized super pixel generation in the processing of polarimetric radar images was proposed. Unlike the classical approach of the super pixel algorithm, the improved method [17] eliminates the problems of working with the presence of speckle noise in the image and high textural heterogeneity of the input image. The main disadvantages are the need for preprocessing the input image and, with a fixed super pixel size, the problem of resegmentation arises in the case of images with a water surface and under-segmentation when processing urbanized images.

In [18], a method is proposed that combines the advantages of the transformer and the advantages of CNN in order to distinguish ships on radar images under conditions of a complex background and the presence of noise in the images. The advantages are the operational separation of ships of different sizes on the water surface even under conditions of a complex background, for example, large waves, proximity to the shore, etc. The disadvantages are the need to train on a sufficiently large data set and the availability of resources for training. Another disadvantage is the limitation to the only type of object that can be distinguished, namely ships. An option to overcome this is to use artificial intelligence methods. This is the approach suggested in [19].

In [19], a hybrid method was proposed for the separation of ships on a complex background of radar images with noise, which combines the advantages of the transformer and YOLO. This method quickly solved the problem of separation of ships of different sizes, even when they are crowded, but has high computational costs and training on a large data set. An option to overcome this is to use several neural networks. This is the approach described in [20].

For the selection of water areas on satellite radar images, in [20] it is proposed to use two neural networks: U-Net and DeepLabv3+. The results of the study showed that the U-Net network is better at selecting narrow rivers or water streams, and the DeepLabv3+ network, on the contrary, is better at selecting wide rivers and reservoirs. Therefore, the main advantage of the method is its versatility and flexibility in selecting water streams of different widths. The main disadvantages are the division of the input image into only two classes, i.e., the resulting image is a binary image, and the need for training and further testing on a large amount of data.

In [21] a method for selecting the contours of urban infrastructure objects on remote sensing images of the Earth is proposed. The essence of the method is its two-stage nature where at the first stage of the method, the boundaries are selected using the classical Canny boundary detector, and at the second stage, geometric primitives are selected using the classical Hough transform. The main advantage of the method is good results of contour extraction on the input image. The disadvantages are that the experimental studies were conducted only on optoelectronic images and required high computational costs.

In [22], the use of a genetic algorithm for processing images from both unmanned aerial vehicles and space observation systems is proposed. The results of the method showed high quality segmentation of optoelectronic images, which is an advantage of this approach. However, the main disadvantage is the failure to take into account possible artifacts that are relevant for real images from space observation systems. An option to overcome this is to use simplified methods of boundary extraction. This is the approach chosen in [23].

In [23], an improved boundary selection method was proposed to be used to select information zones in images from airborne reconnaissance and surveillance systems. The main advantage is the reduction of time for searching for objects of interest in complexly structured space images. The disadvantage is the computational complexity of the proposed method.

Thus, our analysis of known image processing methods revealed certain disadvantages, the main ones of which are:

– computational complexity;
– long processing time;
– significant processing errors of the first and second kind;
– lack of processing efficiency, etc.

This indicates the feasibility of a study aimed at improving a method that rapidly determines the phantomization area in an image acquired from a space radar surveillance system.

3. The aim and objectives of the study

The aim of our research is to reduce the processing errors of the first and second kind by using a method that rapidly determines the phantom area in the image from the space radar observation system. This will make it possible to increase the efficiency of defining a phantom area in the image acquired from a space radar observation system.

To achieve the goal, the following tasks were set:

– to list the main stages of the method that rapidly determines the phantom area in the image acquired from a space radar observation system;

– to conduct an experimental study on the operational determination of the phantom area in the image acquired from a space radar observation system.

4. The study materials and methods

The object of our study is the process of determining the phantom area in an image acquired from a space radar surveillance system.

The principal hypothesis assumes that improving the method for determining the phantom area could reduce image processing errors of the first and second kind.

The following assumptions were adopted in the study:

– an image acquired from a space radar surveillance system is considered;

– the image is represented in grayscale from 0 to 255.

The following simplifications were accepted for the study:

– in the experimental study, there is one object of interest in the image;

– the influence of distorting factors is not considered.

During the experimental study, we used the following:

– hardware: DELL Intel(R) Core(TM) i7-8650U CPU @ 1.90GHz (2.11 GHz) laptop (USA);

– software: object-oriented programming language Python 3.14 (The Netherlands).

The following general methods were used in the research:

– system analysis;

– mathematical apparatus of matrix theory;

– spectral analysis;

– digital processing of radar signals;

– digital image processing;

– probability theory and mathematical statistics;

– mathematical modeling;

– analytical and empirical methods of comparative research.

5. Results of investigating the method that rapidly determines a phantom area

5. 1. Main stages of the method that rapidly determines a phantom area

When defining the main stages of the method that rapidly determines a phantom area in the image acquired from a space radar observation system, the results reported in [24] were used. However, unlike [24], the features of the radar image were taken into account.

The main stages of the method that rapidly determines a phantom area in the image acquired from a space radar observation system are shown in Fig. 1.

The main stages of the method for operationally determining the phantom area in an image acquired from a space radar observation system are:

1) inputting the source image acquired from a space radar observation system;

2) representing the source image as a data array with brightness values from 0 to 255 in grayscale;

3) minimizing the impact of speckle noise using convolution with a Gaussian filter.

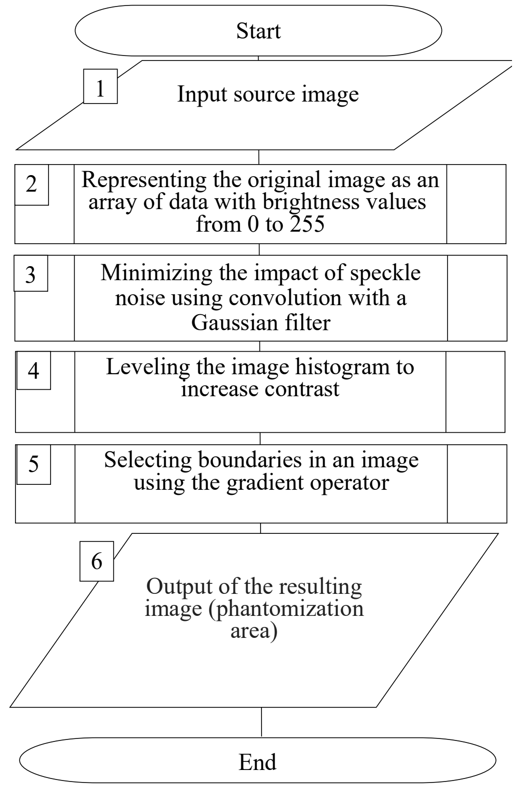

Fig. 1. Main stages of the method for operationally determining the phantomization area in an image acquired from a space radar surveillance system

The main noise that distorts the image acquired from a space radar observation system is speckle noise [1]. Therefore, it is necessary to reduce the impact of speckle noise. For this purpose, a simple Gaussian filter is used. That is, the input image data array is smoothed in the grayscale color model using convolution with a Gaussian filter [25], which is represented by the following expression (1)

$$G(x,y)=\frac{1}{2\pi\sigma^2}\cdot e^{-\frac{x^2+y^2}{2\sigma^2}}, \qquad (1)$$

where x, y – coordinates of the image pixel (element of the data array);

σ – mean square deviation of the normal distribution.

4. Image histogram equalization to increase contrast.

At this stage, the image histogram equalization operation is applied to the result of filtering with a Gaussian filter. This operation is performed by redistributing the intensity of pixels on the histogram. This is done in order to maximize detail and overall brightness and, as a result, increase contrast.

5. Selection of boundaries in the image using a gradient operator.

The area with highlighted boundaries with objects of interest is defined as the phantomization area in the image acquired from a space radar observation system.

The use of spatial filtering is proposed to highlight the boundaries. Some of the most known discrete differentiation operators are considered, namely by Sobel, Roberts, and Prewitt. The use of such simple operators is due to the requirement of efficiency in determining the phantomization area.

The values of the image gradients in the vertical and horizontal directions are formed using the classical Sobel gradient operator [24].

Square matrices of size (3 × 3) for calculation using the convolution operation of the values of the derivatives in the horizontal and vertical directions for the Sobel operator are represented by expressions (2) and (3), respectively:

$$\begin{bmatrix} 1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}, \tag{2}$$

$$\begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}. \tag{3}$$

And the components of gradients G_x and G_y, respectively, by expressions (4) and (5):

$$G_x = \begin{bmatrix} 1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * I, \tag{4}$$

$$G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * I, \tag{5}$$

where I is the result of image histogram equalization after processing the original image acquired from a space radar observation system with a Gaussian filter;

* is the convolution operation.

To calculate the gradient value G in each pixel, expression (6) is used

$$G = \sqrt{G_x^2 + G_y^2}. \tag{6}$$

The direction of gradient G is calculated from the following expression (7)

$$\Theta = \arctan\left(\frac{G_y}{G_x}\right). \tag{7}$$

The work of the Prewitt operator for highlighting the boundaries in the image after histogram equalization is considered. Square matrices of the same size as in the Sobel operator (3 × 3) for calculating the values of the derivatives in the horizontal and vertical directions are represented by expressions (8) and (9), respectively:

$$\begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix}, \tag{8}$$

$$\begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}, \tag{9}$$

and the components of gradients G_x and G_y, respectively, by expressions (10) and (11):

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} * I, \tag{10}$$

$$G_y = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * I. \tag{11}$$

Unlike the Sobel operator, this discrete operator uses only those weight kernels that are equal to 0 and 1, that is, this operator is simpler in calculations.

The value and direction of gradient G in each pixel are calculated similarly using expressions (6) and (7).

Another gradient operator is considered – the Roberts operator for highlighting the boundaries in the image after histogram equalization. Unlike the Sobel and Prewitt operators, this discrete operator uses square matrices of size (2 × 2), which are represented by expressions (12) and (13):

$$\begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix}, \tag{12}$$

$$\begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix}, \tag{13}$$

and the components of gradients G_x and G_y, respectively, by expressions (14) and (15):

$$G_x = \begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix} * I, \tag{14}$$

$$G_y = \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix} * I. \tag{15}$$

The value and direction of gradient G in each pixel are calculated similarly using expressions (6) and (7).

6. Output of the resulting image (phantomization area).

Thus, the method of operational determination of the phantomization area in the image acquired from a space radar observation system has been improved; in it, in contrast to known ones,

– the radar image is represented as a two-dimensional array of pixels, the intensity of which is determined by the amplitude of the radar signal in grayscale;

– the influence of speckle noise is minimized using convolution with a Gaussian filter;

– the image histogram is aligned to increase contrast;

– the boundaries in the image are selected by the gradient operator;

– the area with the selected boundaries with objects of interest is determined as the phantomization area in the image acquired from a space radar observation system.

5. 2. Experimental study on the operational determination of a phantomization area

To conduct an experimental study on the operational determination of the phantomization area in an image acquired from a space radar observation system, an image (Fig. 2 [26]) was selected as the source.

This image was obtained from the Sentinel-1 space-based radar system (European Space Agency) [26]. The original image (Fig. 2) was acquired from the website (https://surl.li/kjfphq) of the European Earth Observation Program Sentinel [26]. The Sentinel program provides free and open data (images) from space-based radar systems for scientific and applied purposes. The original image (Fig. 2) is represented as an array of data where each element of the array is a pixel intensity value in the range [0; 255] in grayscale. The histogram of the original image is shown in Fig. 3.

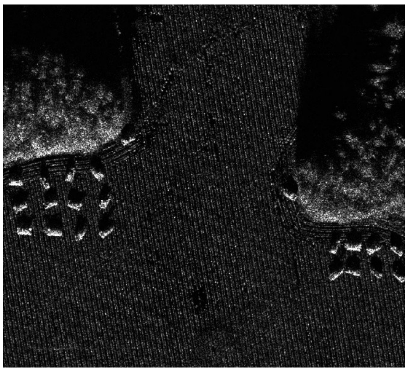

Fig. 2. Output image from the space-based radar surveillance system [26]

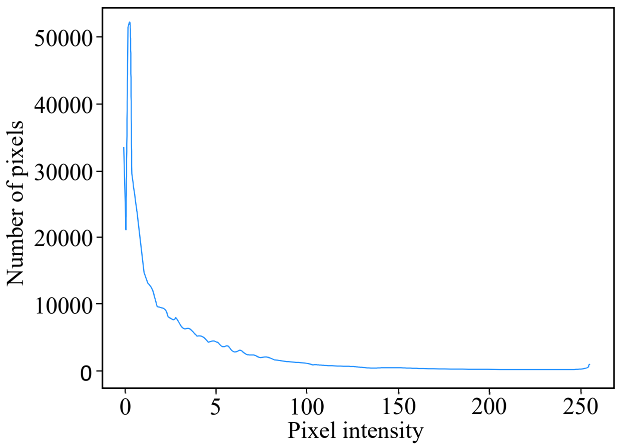

Fig. 3. Histogram of the original image from the space-based radar surveillance system

One can see that the histogram has a certain peak in a narrow range of pixel intensities.

To reduce the effect of speckle noise, a Gaussian filter is used. Fig. 4 shows the result of convolution of the input radar image in the grayscale color model (Fig. 1) with a Gaussian filter.

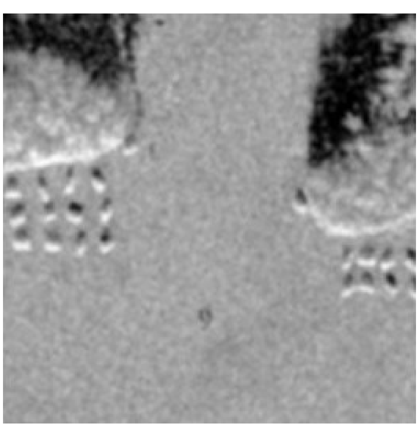

Fig. 4. The result of convolution of the input radar image in the grayscale color model (Fig. 1) with a Gaussian filter

At the next stage, the image histogram equalization operation is applied to the result of Gaussian filtering (Fig. 4). All these stages are intended for preliminary preparation of the input radar image for further boundary selection on it in order to determine the phantomization area.

Fig. 5 shows the result of the improved method for operational determination of the phantomization area on an image acquired from a space radar observation system when using the Sobel operator for boundary selection.

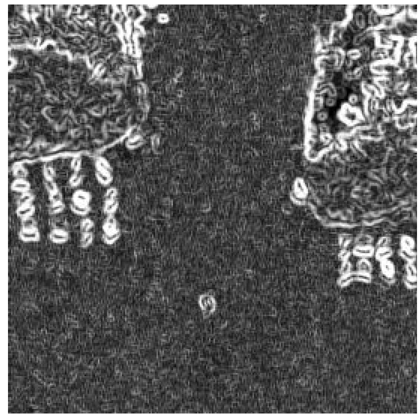

Fig. 5. Result of the improved method when applied to extract the borders of the Sobel operator

The work of the Prewitt operator for highlighting boundaries in the image after histogram equalization has been considered. The result of the work of the improved method for operational determination of the phantomization area in the image acquired from a space radar observation system when using the Prewitt operator for highlighting boundaries is shown in Fig. 6.

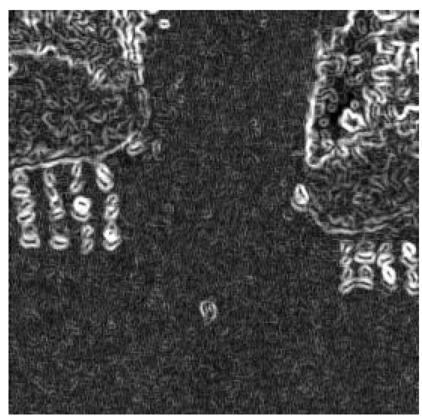

Fig. 6. Result from the improved method when applied to extract the borders of the Prewitt operator

The work of another gradient operator, the Roberts operator, for edge detection in an image after histogram equalization has been considered. The result of the improved method when using the Roberts operator for edge detection is shown in Fig. 7.

Based on the results from the improved method of operational determination of the phantomization area in the image from the space radar observation and analysis system, phantomization areas are highlighted in Fig. 5–8. These are areas where objects of interest are located – objects of technology.

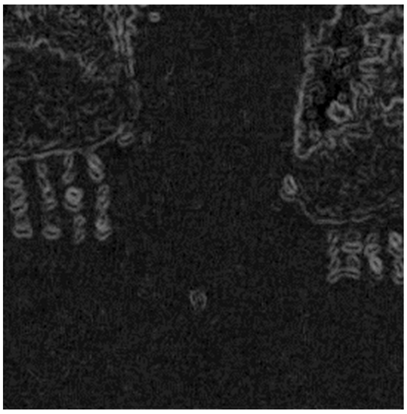

Fig. 7. Result from the improved method when applied at the last stage to highlight the borders of the Roberts operator

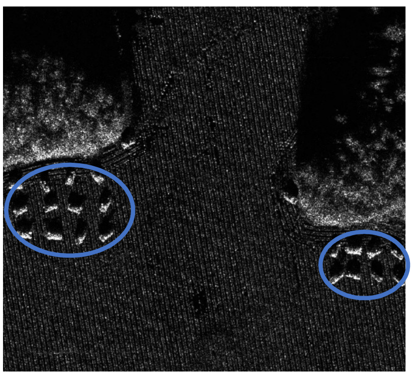

Fig. 8. Image from a space-based radar surveillance system with highlighted phantomized areas

To select a boundary selection method at the final stage of the improved method, the image processing errors of the first and second kind were calculated. The image processing errors of the first (α_1) and second (β_2) kind were calculated using expressions (15), (16) [21, 22]:

$$\alpha_1 = \frac{S_1\left(fs\left(\mathbf{X}\right)\right)}{S_2\left(f\left(\mathbf{X}\right)\right)}, \tag{15}$$

$$\beta_2 = 1 - \frac{S_3\left(fs\left(\mathbf{X}\right)\right)}{S_4\left(f\left(\mathbf{X}\right)\right)}, \tag{16}$$

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

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

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

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

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

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

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

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

Analysis of Table 1 reveals the feasibility of using the Roberts operator at the final stage for boundary selection. This allowed us to reduce the processing errors of the first kind:

– by 2.64% compared to the use of the Sobel operator;

– by 5.66% compared to the Prewitt operator.

Table 1

Processing errors of the first (α_1) and second (β_2) kind

Segmentation method	Processing error of the first kind (α_1), %	Processing error of the second kind (β_2), %
Application of the Sobel operator for boundary selection	19.76	18.29
Application of the Prewitt operator for boundary selection	22.78	20.17
Application of the Roberts operator for boundary selection	17.12	15.89

This also allowed us to reduce the processing errors of the second kind:

– by 2.4% compared to the Sobel operator;

– by 4.26% compared to the Prewitt operator.

So, in general, all three boundary selection operators can be used at the final stage of the improved method. As for a specific radar image, then, taking into account Table 1, it is advisable to use the Roberts operator for boundary selection.

The considered operators are simple; therefore, they ensure the efficiency of their use, taking into account the automation of radar image processing.

6. Improving the method that rapidly determines the phantom area: results and summary

A method for operational determination of the phantomization area in the image acquired from a space radar observation system (Fig. 1) has been improved; in it, in contrast to known ones:

– the radar image is represented as a two-dimensional array of pixels, the intensity of which is determined by the amplitude of the radar signal in grayscale;

– the influence of speckle noise is minimized using convolution with a Gaussian filter;

– the image histogram is aligned to increase contrast;

– the boundaries in the image are selected by the gradient operator;

– the area with the selected boundaries with objects of interest is determined as the phantomization area in the image acquired from a space radar observation system.

An experimental study was conducted on the operational determination of the phantom area in an image from a space-based radar observation system. Fig. 4 shows the result of convolution of the input radar image in a grayscale color model with a Gaussian filter. Fig. 5 shows the result of the improved method that rapidly determines the phantom area in an image from a space-based radar observation system when using the Sobel operator to select the boundaries. The result of the improved method that rapidly determines the phantom area in an image from a space-based radar observation system when using the Prewitt operator to select the boundaries is depicted in Fig. 6. The result of the improved method when using the Roberts operator to select the boundaries is given in Fig. 7.

According to the results of the improved method that rapidly determines the phantom area in an image from a space-based radar observation system and the analysis of Fig. 5–8, phantom areas were selected. These are areas on which objects of interest are located – objects of technology.

To select a method for boundary selection at the final stage of the improved method, the first and second kind image processing errors were calculated (Table 1). Analysis of Table 1 reveals the feasibility of using the Roberts operator at the final stage for boundary selection. This allowed us to reduce the first kind processing errors:

– by 2.64% compared to the Sobel operator;

– by 5.66% compared to the Prewitt operator.

That also reduced the processing errors of the second kind:

– by 2.4% compared to the Sobel operator;

– by 4.26% compared to the Prewitt operator.

This all became possible owing to the use of several stages of the improved method of operational determination of the phantomization area. The efficiency of the phantomization area selection is ensured by using a simple Roberts operator for boundary selection at the final stage.

So, in general, all three boundary selection operators can be used at the final stage of the improved method. As for a specific radar image, then, taking into account Table 1, it is advisable to use the Roberts operator for boundary selection. The considered operators are simple; therefore, they ensure efficiency of their use, taking into account the automation of radar image processing.

The improved method of operational determination of the phantomization area in an image acquired from a space radar observation system allowed us to solve the problem part, namely:

– to reduce computational complexity – by using simple operations at the component stages of the method;

– to reduce processing time – by using the speed of methods to minimize the effect of speckle noise, image histogram equalization, and boundary selection;

– to reduce processing errors of the first and second kind.

Our research limitations are:

– the results are given for an image acquired from a space radar observation system;

– the phase of the radar signal when probing the earth's surface is not taken into account.

The disadvantages of the study are:

– the complexity of implementing the improved method when other noises affect the radar image (Gaussian, salt and pepper);

– a decrease in the quality and efficiency of image processing when rotating and resizing the radar image.

Further studies imply improving the methods of preprocessing the radar image to compensate for speckle noise.

7. Conclusions

1. The main stages of the method for quickly determining the phantom area in an image acquired from a space radar observation system are:

– input of the source image acquired from a space radar observation system;

– representation of the source image as a data array with brightness values from 0 to 255 in grayscale;

– minimization of the effect of speckle noise using convolution with a Gaussian filter;

– image histogram equalization to increase contrast;

– selection of boundaries in the image by a gradient operator;

– output of the resulting image (phantom area).

2. An experimental study was conducted on quickly determining the phantom area in an image acquired from a space radar observation system. Phantom areas on which objects of interest are located were highlighted in the image acquired from a space radar observation system. The choice of the Roberts operator at the final stage for boundary selection allowed for the following:

– a decrease in the processing errors of the first kind: by 2.64% compared to the application of the Sobel operator; by 5.66% compared to the Prewitt operator;

– a reduction in the processing errors of the second kind: by 2.4% compared to the Sobel operator; by 4.26% compared to the Prewitt operator.

Conflicts of interest

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

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

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

Authors' contributions

Hennadii Khudov: Conceptualization, Methodology, Software, Investigation, Writing – review & editing, Supervision, Project administration; **Oleksandr Makoveichuk:** Validation, Data curation, Investigation, Software; **Irina Khizhnyak:** Validation, Data curation, Writing-original draft, Visualization; **Dmytro Huriev:** Data curation, Writing-original draft, Visualization; **Anatoliy Popov:** Methodology, Investigation, Resources, Writing-review & editing, Supervision, Project administration, Funding Acquisition; **Serhii Oliynick:** Methodology, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition; **Pavlo Malashta:** Formal analysis, Data curation, Resources, Writing – original draft, Visualization; **Yaroslav Sydorov:** Formal analysis, Data curation, Resources, Writing-original draft, Visualization; *Olexandr Rohulia***:** Formal analysis, Data curation, Visualization; ***Maksym Adamchuk*****:** Formal analysis, Data curation, Visualization.

References

1. Amitrano, D., Di Martino, G., Di Simone, A., Imperatore, P. (2024). Flood Detection with SAR: A Review of Techniques and Datasets. Remote Sensing, 16 (4), 656. https://doi.org/10.3390/rs16040656
2. Pavlikov, V., Zhyla, S., Pozdniakov, P., Kolesnikov, D., Cherepnin, H., Shmatko, O. et al. (2024). Foundations of radar synthesis theory of phantom objects formation in SAR images. Radioelectronic and Computer Systems, 2024 (4), 123–140. https://doi.org/10.32620/reks.2024.4.11
3. Hrushko, O., Zhytar, D., Ilkiv, E., Hrynishak, M., Kukhtar, D. (2025). Geospatial Analysis of War-Affected Areas in Ukraine Based on SAR and GIS Technologies. 18th International Conference Monitoring of Geological Processes and Ecological Condition of the Environment, 1–5. https://doi.org/10.3997/2214-4609.2025510159
4. Al-Bayati, M., El-Zaart, A. (2013). Automatic Thresholding Techniques for SAR Images. Computer Science & Information Technology (CS & IT), 75–84. https://doi.org/10.5121/csit.2013.3308
5. Tan, J., Tang, Y., Liu, B., Zhao, G., Mu, Y., Sun, M., Wang, B. (2023). A Self-Adaptive Thresholding Approach for Automatic Water Extraction Using Sentinel-1 SAR Imagery Based on OTSU Algorithm and Distance Block. Remote Sensing, 15 (10), 2690. https://doi.org/10.3390/rs15102690
6. Hillebrand, F. L., Prieto, J. D., Mendes Júnior, C. W., Arigony-Neto, J., Simões, J. C. (2024). Gray Level Co-occurrence Matrix textural analysis for temporal mapping of sea ice in Sentinel-1A SAR images. Anais Da Academia Brasileira de Ciências, 96 (2). https://doi.org/10.1590/0001-3765202420240554
7. Anusha, N., Vasanth, K., Masurkar, S. P. (2024). Automated Extraction of Textural Features From Segmented Sentinel-1ASynthetic Aperture Radar Satellite Image Using Grey Level Co-Occurrence Matrix. Procedia Computer Science, 235, 2124–2134. https://doi.org/10.1016/j.procs.2024.04.201
8. Zhai, Y., Liu, K., Piuri, V., Ying, Z., Xu, Y. (2016). SAR automatic target recognition based on K-means and data augmentation. Proceedings of the 2016 International Conference on Intelligent Information Processing, 1–6. https://doi.org/10.1145/3028842.3028894
9. Chen, Z., Cong, B., Hua, Z., Cengiz, K., Shabaz, M. (2021). Application of clustering algorithm in complex landscape farmland synthetic aperture radar image segmentation. Journal of Intelligent Systems, 30 (1), 1014–1025. https://doi.org/10.1515/jisys-2021-0096
10. Qin, J., Liu, Z., Ran, L., Xie, R., Tang, J., Zhu, H. (2023). An SAR Image Automatic Target Recognition Method Based on the Scattering Parameter Gaussian Mixture Model. Remote Sensing, 15 (15), 3800. https://doi.org/10.3390/rs15153800
11. Ma, F., Gao, F., Sun, J., Zhou, H., Hussain, A. (2019). Weakly Supervised Segmentation of SAR Imagery Using Superpixel and Hierarchically Adversarial CRF. Remote Sensing, 11 (5), 512. https://doi.org/10.3390/rs11050512
12. Yin, J., Liu, X., Yang, J., Chu, C.-Y., Chang, Y.-L. (2020). PolSAR Image Classification Based on Statistical Distribution and MRF. Remote Sensing, 12 (6), 1027. https://doi.org/10.3390/rs12061027
13. Hu, G. C., Zhao, Q. H. (2017). G0-WISHART distribution based classification from polarimetric sar images. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, IV-2/W4, 451–455. https://doi.org/10.5194/isprs-annals-iv-2-w4-451-2017
14. Carvalho, E. A., Ushizima, D. M., Medeiros, F. N. S., Martins, C. I. O., Marques, R. C. P., Oliveira, I. N. S. (2010). SAR imagery segmentation by statistical region growing and hierarchical merging. Digital Signal Processing, 20 (5), 1365–1378. https://doi.org/10.1016/j.dsp.2009.10.014
15. Guo, Z., Wu, L., Huang, Y., Guo, Z., Zhao, J., Li, N. (2022). Water-Body Segmentation for SAR Images: Past, Current, and Future. Remote Sensing, 14 (7), 1752. https://doi.org/10.3390/rs14071752
16. Bao, L., Lv, X., Yao, J. (2021). Water Extraction in SAR Images Using Features Analysis and Dual-Threshold Graph Cut Model. Remote Sensing, 13 (17), 3465. https://doi.org/10.3390/rs13173465
17. Li, M., Zou, H., Qin, X., Dong, Z., Sun, L., Wei, J. (2023). Superpixel Generation for Polarimetric SAR Images with Adaptive Size Estimation and Determinant Ratio Test Distance. Remote Sensing, 15 (4), 1123. https://doi.org/10.3390/rs15041123
18. Li, K., Zhang, M., Xu, M., Tang, R., Wang, L., Wang, H. (2022). Ship Detection in SAR Images Based on Feature Enhancement Swin Transformer and Adjacent Feature Fusion. Remote Sensing, 14 (13), 3186. https://doi.org/10.3390/rs14133186
19. Zhao, K., Lu, R., Wang, S., Yang, X., Li, Q., Fan, J. (2023). ST-YOLOA: a Swin-transformer-based YOLO model with an attention mechanism for SAR ship detection under complex background. Frontiers in Neurorobotics, 17. https://doi.org/10.3389/fnbot.2023.1170163
20. Dewi, N. P. K., Suputra, P. H., Paramartha, A. A. G. Y., Dewi, L. J. E., Varnakovida, P., Aryanto, K. Y. E. (2025). River Area Segmentation Using Sentinel-1 SAR Imagery with Deep-Learning Approach. Geomatics and Environmental Engineering, 19 (4), 39–63. https://doi.org/10.7494/geom.2025.19.4.39
21. Ruban, I., Makoveichuk, O., Khudov, V., Khudov, H., Khizhnyak, I., Yuzova, I., Drob, Y. (2019). The Method for Selecting the Urban Infrastructure Objects Contours. 2019 IEEE International Scientific-Practical Conference Problems of Infocommunications, Science and Technology (PIC S&T), 689–693. https://doi.org/10.1109/picst47496.2019.9061267
22. Ruban, I., Khudov, H., Makoveichuk, O., Khudov, V., Kalimulin, T., Glukhov, S. et al. (2022). Methods of UAVs images segmentation based on k-means and a genetic algorithm. Eastern-European Journal of Enterprise Technologies, 4 (9 (118)), 30–40. https://doi.org/10.15587/1729-4061.2022.263387

23. Khudov, H., Makoveichuk, O., Khizhnyak, I., Shamrai, B., Glukhov, S., Lunov, O. et al. (2022). The Method for Determining Informative Zones on Images from On-Board Surveillance Systems. International Journal of Emerging Technology and Advanced Engineering, 12 (8), 61–69. https://doi.org/10.46338/ijetae0822_08
24. Khudov, H., Khudov, R., Khizhnyak, I., Hridasov, I., Hlushchenko, P. (2025). The small aerial objects segmentation method on optical-electronic images based on the sobel edge detector. Advanced Information Systems, 9 (2), 5–10. https://doi.org/10.20998/2522-9052.2025.2.01
25. Rafael, C., Gonzalez, R. E. W. (2002). Digital Image Processing. Prentice Hall, 793. Available at: https://www.amazon.com/Digital-Image-Processing-Rafael-Gonzalez/dp/0201180758
26. Sentinel-1. Available at: https://sentinels.copernicus.eu/copernicus/sentinel-1