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USING THE SET OF INFORMATIVE FEATURES OF A BINDING OBJECT TO CONSTRUCT A DECISION FUNCTION BY THE SYSTEM OF TECHNICAL VISION WHEN LOCALIZING MOBILE ROBOTS

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The object of this study is the process of constructing a decision function by the optical-electronic system of technical vision under the conditions of the influence of obstacles on the current image, which is formed in the process of localization of a mobile robot. The paper reports the results of solving the problem of constructing a decision function when reducing the signal-to-noise ratio of the current image by using a set of informative features for the selection of the binding object, namely, brightness, contrast, and its area. The selection of the binding object is proposed to be carried out by choosing the appropriate values of the quantization thresholds of the current image for the selected informative features, taking into account the signal-to-noise ratio, which provides the necessary probability of object selection. The dependence of the object selection probability on the selected values of the quantization thresholds was established. The use of the results could enable the construction of a unimodal decision function when localizing mobile robots on imaging surfaces with weakly pronounced brightness and contrast characteristics of objects, as well as with their small geometric dimensions. By modeling, the probability of forming a decision function was estimated depending on the degree of noise of the current images. It is shown that the application of the proposed approach allows selection of objects with a probability ranging from 0.78 to 0.99 for the values of the signal-to-noise ratio of images formed by the technical vision system under real conditions. The method to construct a decision function under the influence of interference could be implemented in information processing algorithms used in optical-electronic technical vision systems for the navigation of unmanned aerial vehicles

Keywords: mobile robot, decision function, informative features, quantization thresholds, signal-to-noise ratio

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1. Introduction

Mobile robots (MRs) equipped with technical vision systems (TVS) are widely used for monitoring the viewing surface (VS), assessing the state of critical infrastructure objects (CIO), performing search and rescue operations, etc. [1]. The effectiveness of solving these tasks is determined by many factors, first of all, the quality of information support, which depends on the completeness and stability of information features (IF). They are measured by TVS sensors and are used in the construction of current images (CI) [1], which must clearly correspond to the previously formed reference information about the state of VS [2]. It is the correspondence of the reference (RI) and current images that is the main condition for the construction of a unimodal decision function (DF), i.e., the accuracy of the assessment of the coordinates and state of the imaging objects and the probability of place determination of MR [2].

One of the possible ways of providing information to TVS about the state of VS objects under the conditions of noise pollution is the selection of objects using a set of relevant information features, which must also be used for the construction of RI. Therefore, the formation of TVS DF is determined by the chosen method of object selection in the images.

Many studies [3–7] tackle the development of methods to form the DF of TVS. Most often, the construction of unimodal DF is studied under the conditions of the influence of geometric distortions on CI [8], the appearance of false objects on the CI, and perspective distortions of the images of VS [9]. At the same time, the problem is solved by using, as a rule, one information feature – signal intensity. And the use of a set of IFs for the selection of objects on images for the purpose of forming DF has not been properly developed.

A significant body of research [10–13] consider the development of methods and algorithms for the selection of objects in images, which are related to image segmentation methods. However, the analysis revealed that the results of these works are not related to the place determination of MR or the assessment of the condition of imaging objects, which limits their use in TVS. At the same time, in the works that address the local determination of MR using TVS, the problem is solved under the conditions of a limited number of operations during the construction of DF, especially for high-speed aircraft. In this case, time constraints require using only contours or brightness of objects as information features. In work [9], it is proposed to use fractal dimension as an information feature of objects. But the developed infrastructure with existing small-sized, low-contrast, and similar objects with brighter characteristics reduce the signal-to-noise ratio and lead to a decrease in the effectiveness of the MR TVS operation. Interference also has a negative effect on the operation of TVS.

Therefore, devising a method for the construction of DF under difficult conditions based on the selection of objects on CI using the totality of IF is an urgent task.

2. Literature review and problem statement

In paper [1], the method of forming a set of RIs to ensure reliable monitoring of CIO with the help of mobile robots has been improved. The approach to the formation of the totality of RI CIO using the brightness of objects as an invariant is substantiated. The degree of image correlation was determined within the range of 0.6...0.7. The advantage is increasing the speed of the secondary processing system. The disadvantage is the use of only one type of invariant for the formation of a set of reference images, which limits the use of a set of RIs in the formation of DFs under the influence of interference that leads to distortion of CI.

Study [2] proposed a method of construction of DF for localization of an unmanned aerial vehicle (UAV) using radiometric and optical-electronic information acquisition channels. It is proposed to use the brightest stationary imaging objects for the formation of CI and RI. The advantage is to increase the accuracy of UAV localization by adapting them to perspective and large-scale image distortions. The disadvantage is the impossibility of using the method for localizing UAVs under conditions of developed infrastructure in the presence of small-sized and low-contrast objects.

In work [3], it is proposed to highlight long small objects on intense and non-stationary backgrounds. The advantage is an increase in the probability of highlighting small-scale objects in real images. The disadvantage is that errors of the first and second kind are not taken into account when evaluating the effectiveness of object selection and the complexity of the image processing process.

Study [4] proposed a method of dynamic setting and adjustment of the threshold level, which is based on the analysis of isolated fragments selected in the image during the segmentation process. Digital processing consists of pre-filtering, thresholding, and logic filtering. The advantage of the method is the optimal solution to the task of object selection on digital images against the background of Gaussian noise. The disadvantage is that it can only be used to highlight long objects.

In work [5], the localization of objects on CI, when the scale of the object on it is slightly different from the scale of the object on RI, was studied. The advantage of the technology is the speed and reliability of detecting objects, and the disadvantage is the impossibility of using the technology at long distances.

Work [6] investigated the effectiveness of road selection in images even in the presence of obstacles with the same color and spectrum values as the road class. The disadvantage is multistage and the selection of only one class of objects of interest.

Paper [7] discusses the method of highlighting roads on images, which uses vectors and methods of mathematical morphology. The advantage of the method is to ensure high accuracy. The disadvantage is the effectiveness of the application for only one class of objects.

In work [8], a method of forming RI using three-dimensional stationary objects with the highest radio luminosity temperature by contouring and determining the average radio luminosity temperature was developed. The advantage of the method is taking into account the three-dimensional shape of VS objects. The disadvantage is the use of one IF – the radioluminescence temperature and the impossibility of selecting small-sized objects.

In [9], the possibility of forming a unimodal DF under the conditions of the appearance of false objects on CI was considered. The advantage of the method is the consideration of perspective distortions of CI, the disadvantage is the low speed of the construction of DF and the use of one IF for the localization of the object on CI.

In [10], a method of image preprocessing for various shooting conditions for machine vision systems was developed. The study of the method showed that when preprocessing images of the same scene based on entropy analysis, obtained under different conditions, have a more stable correlation coefficient than the original images, which is an advantage. The disadvantage of the method is the implementation of processing without determining the type of IF.

Paper [11] proposed the use of a normalized section for automatic road detection. The advantage of the method is the effective selection of road segments using progressive image texture analysis and the graph method in emergency situations. The disadvantage is the low efficiency of application for the selection of small, non-extending objects.

The authors of [12] proposed a lightweight asymmetric network that uses an asymmetric encoder-decoder architecture. The encoder uses an asymmetric bottleneck module for joint extraction of local and contextual information. The decoder uses an advanced pyramid merging module and an upsampling module, which are used to aggregate multi-scale contextual information and combine functions from different levels, respectively. The advantage of the network is to achieve an optimal compromise between segmentation accuracy, inference speed, and model size. But the accuracy is 73.6 % at 95.8 frames per second, which is a disadvantage of the network.

In [13], a two-way cascading network is proposed for the fusion of the functions of preserving information about the target and providing the possibility of segmentation for multi-scale targets due to the requirements for the light weight of the model. In particular, a feature enhancement module is presented at the stage of feature extraction, including two-dimensional attention in the convolutional layer. This module effectively reduces redundant information and greatly improves network feature extraction capabilities. In addition, the network output uses cross-aggregation to fuse the output characteristics of different branches to solve the problem of missing pixels during the fusion process. The advantage of the method is the balance of segmentation accuracy and processing speed for ground robots. The disadvantage of the method is the impossibility of application on objects moving at high speed, namely on aircraft.

In [14], a method of forming a reference image based on the constructed field of fractal analysis is proposed, which makes it possible to quickly evaluate the informativeness of the image using the fractal dimension. The advantage of the method is high accuracy. The disadvantage is a significant dependence on the background-object composition of the imaging surface.

Study [15] proposed a multi-objective clustering algorithm. The efficiency of the algorithm depends on the maximization of the intercluster distance or the minimization of intraclass compactness. The advantage of the algorithm is the generation of a set of solutions that are not considered. The disadvantage is that the efficiency of its work depends on the choice of the objective function, namely on the maximization of the intercluster distance or on the minimization of intraclass compactness.

Paper [16] proposed a method for automatic selection of buildings and roads in images, which is based on a random field model. The advantage of the method is high speed. The disadvantage is the selection of objects of interest only on color images.

In study [17], it is proposed to use convolutional neural networks to highlight objects in images. The advantage of the method is the high accuracy of selection of objects from the training set. The disadvantage is the omission of objects that were not part of the training set.

In [18], it is proposed to use the ScribbleNet interactive segmentation algorithm to form images of urban infrastructure. The algorithm uses correlations in a deep neural network. The advantage of the algorithm is the ability to annotate new classes of objects that were not included in the training sample and image processing in the presence of shadows. The disadvantage of the algorithm is that it is used only at the preliminary stage of image formation.

Work [19] proposed the use of a genetic algorithm. The advantage is the ability to highlight masked objects. The disadvantage is the appearance of a large number of redundant contours that do not reach the objects of interest and leads to noisy images.

Paper [20] proposed a segmentation method using a previously excessively segmented input image by generating rectangular shapes of urban infrastructure objects and merging them in a weighted adjacency graph of regions. The advantage is the elimination of redundant information that appeared in the images of urban infrastructure. The disadvantage is the possibility of further analysis of unmerged objects.

In [21], a method for selecting objects of interest on images of developed infrastructure is proposed. The method consists in the application of the Canni method and in the further segmentation of the image using the Hough transform. The advantage of the method is the high efficiency of image segmentation at small distances. The disadvantage is that small objects are not taken into account.

Study [22] devised a method for selecting objects on images of optical-electronic systems. The advantage of the method is the possibility of forming images from different heights. The disadvantage is the selection of only the boundaries of objects of interest that have a straight-line type.

In [23], an ant algorithm was developed for highlighting the contours of objects in images. The advantage is the speed of the segmentation process of large images. The disadvantage is the appearance of excess information, which leads to image noise.

Paper [24] reports the results of research on the two-stage procedure for selecting the binding object on CI, which is formed by the correlation-extreme navigation system. The disadvantage of the proposed approach is the possibility of unreliable determination of the object on low-contrast CIs.

Our review revealed that despite a significant number of methods for forming DF and selecting objects on images, they have limited suitability and cannot be applied in TVS of MR without further refinement.

Thus, there is a need to solve the problem of DF construction under conditions of noisy CI of developed infrastructure in the presence of small-sized, low-contrast and similar objects with brighter characteristics. The development of the method of DF construction based on the selection of the binding object using a set of informational features will allow solving the identified problem.

3. The aim and objectives of the study

The purpose of our research is to devise an approach to DF construction using imaging surfaces with weakly pronounced brightness and contrast characteristics of objects, as well as with their small geometric dimensions. This will make it possible to select an object on CI with a high probability and to construct a unimodal DF.

To achieve the goal, it is necessary to solve the following tasks:

– to devise a method of DF construction based on the use of the totality of IF of VS objects;

– to evaluate the probability of the construction of unimodal DF under the conditions of noise of CI on VS with weakly pronounced brightness and contrast characteristics of the objects, as well as with their small geometric dimensions.

4. The study materials and methods

The object of our study is the process of DF construction by optical-electronic (OE) TVS under the influence of interference on CI, which is formed in the process of MR localization. The main hypothesis of the study assumed that the use of a set of IFs of VS objects could enable the construction of a unimodal DF under the conditions of a decrease in the signal-to-noise ratio of CI.

The following research methods were used during our study: methods of correlation-extremal processing, methods of image processing, methods of probability theory and mathematical statistics, methods of statistical modeling, MATLAB programming environment.

The following limitations and assumptions were adopted during the research:

– the VS image is binary, the values of 1 correspond to the elements of the object, and 0 to the background;

– the object is uniform in brightness, the background around the object is uniform;

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

– the image contains several small objects that are slightly different;

– the height of the objects is insignificant, which does not lead to the need to take into account shadows;

– the contrast of VS objects at the sensitivity limit of the TVS sensor;

– the value of the signal-to-noise ratio of the TVS sensor is minimally acceptable.

5. Results of the study on the construction of a decision function by the system of technical vision

5. 1. Devising a method for constructing a decision function

DF, which is constructed by TVS, involves comparing the current and reference images of VS. VS is a collection of small-sized objects characterized by the corresponding values of brightness B_b, contrast ΔB_c, and area D.

TVS forms CI frames $\psi_0, ..., \psi_\rho$:

$$\psi_0 = \psi\left(\mathbf{r}(t), t_0\right), \ldots, \psi_\rho = \psi\left(\mathbf{r}(t), t_\rho\right), \tag{1}$$

where $t_\rho = t_0 + \Delta t_\rho$; t_0, t_ρ – moments of time of construction of CI frames ψ_0, ψ_ρ;

$\mathbf{r}(t) = (x(t), y(t))$ is the displacement vector in the coordinate system of the image plane;

Δt_ρ is the time interval between frames ψ_0 and ψ_ρ.

At the same time, CI is formed in each frame, respectively:

$$\mathbf{S}_{CI_0} = \psi_0 \cap \mathbf{S}\left(\mathbf{r}, t_0\right),\ \ \mathbf{S}_{CI_\rho} = \psi_\rho \cap \mathbf{S}\left(\mathbf{r}, t_\rho\right). \tag{2}$$

CI model.

CI that is formed by TVS is a set of elements:

$$\mathbf{S}_{CI}\left(\mathbf{r}, \mathrm{t}_k\right) = \left\| S_{CI_{i,j}} \right\|_{\substack{i=\overline{1...M} \\ j=\overline{1...N}}}, \tag{3}$$

where $\mathbf{S}_{CI}(i,j) = f(B_b, \Delta B_c, D, t_k)$; M, N – dimensions of CI; t_k is the k-th moment of CI construction.

Limitations and assumptions adopted in the CI model:

– there are no or minimal changes in the parameters that describe the state of VS during the construction of CI;

– part of CI is distorted;

– obstacles that lead to a change in the structure of PE are described as the objects of PE;

– images formed by OE sensors are represented by M_1*M_2 separation elements;

– multiplicative obstacles caused by the influence of the distribution environment on CI are not taken into account;

– models of VS images correspond to the measured totality of IF;

– IFs, on the basis of which CI is formed, have an established functional connection with the electrophysical properties of VS.

RI model. The RI is formed in advance with the help of a set of IFs used in the construction of CI. RI is noiseless and represents a set of elements:

$$\mathbf{S}_{RI} = \left\| S_{RI_{i,j}} \right\|_{\substack{i=\overline{1...M_2} \\ j=\overline{1...N_2}}}, \tag{4}$$

where $\mathbf{S}_{RI}(i,j) = f(B_b, \Delta B_c, D)$; M_2, N_2 are the dimensions of RI.

The construction of RI is carried out for the selected geometric conditions of viewing: height and angles – h, α, β, and the corresponding resolution of OE – $2\theta_{0,5}$.

Statement of the problem.

For the selected conditions and image models, it is necessary to devise a method to construct DF under the influence of interference on CI based on the selection of OP using a defined set of IFs, namely, brightness, contrast, and its area.

Thus, it is required to solve the problem of forming a unimodal DF taking into account the conditions and image models (3), (4) defined above, ensuring the maximum probability of DF construction P_c:

$$\mathbf{R}(\mathbf{r}, t) = \mathbf{F}_{SP}\left(\mathbf{S}_{CI}\left(\mathbf{r}, t_k\right),\ \mathbf{S}_{RI}\left(2\theta_{0,5}, h, \alpha, \beta, t_\rho\right)\right) \to \max,$$

$$P_c = f(q) \to \max, \tag{5}$$

where $\mathbf{F}_{SP}$ is the operator describing the algorithm for comparing CI and RI;

q is the signal-to-noise ratio.

The assumption of the selection of the object on CI by using the set of IFs allows us to propose one of the possible ways to solve the problem of DF construction under specified conditions in the form of a four-stage procedure.

At the first stage, the task of selecting the object from the existing population by area is set, completely ignoring the energy relations between the elements of the images. This approach will simplify the process of CI construction since the area of objects does not depend on the geometric conditions of visualization, and only the shape of objects changes. At the second stage, taking into account the peculiarities of the operation of TVS, it is necessary to convert CI into binary. The transformation is carried out by quantization relative to the determined average value of the background brightness. This approach requires determination of the quantization threshold. At the third stage, taking into account the results of the first stage, the object is selected from interference signals. At the fourth stage, the result of the third stage is refined by quantizing CI relative to the average contrast value, taking into account the sensitivity of the OE TVS sensor.

The structure of the object selection algorithm using a set of IFs is shown in Fig. 1.

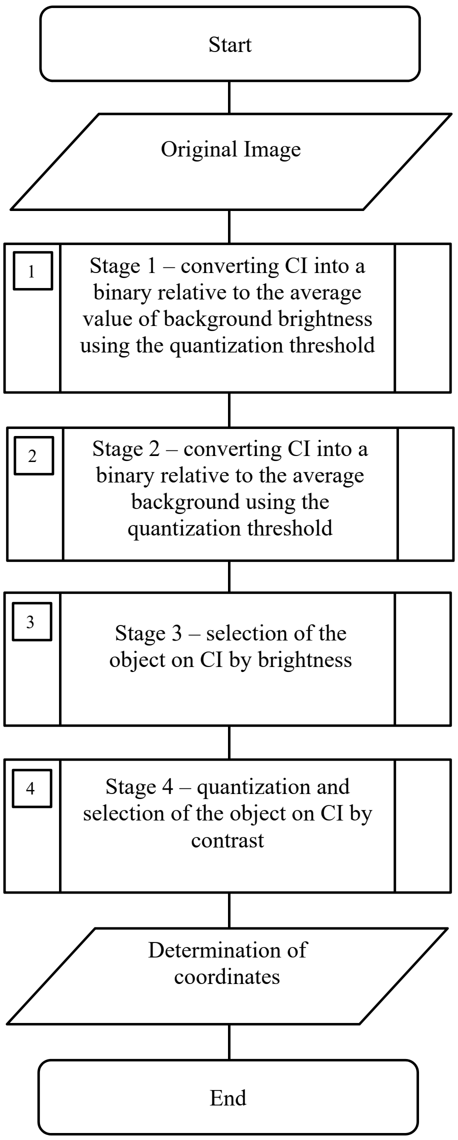

Fig. 1. Main stages of object selection in the current image

At the first stage, a step-by-step process of selecting objects by area was introduced. To this end, in accordance with the selected thresholds, we shall perform quantization of CI. The threshold values will be chosen taking into account the discrimination of objects close in size to the selection object and the discriminating ability of the OE TVS sensor. Errors of the first α and second β kind at this stage are taken into account according to the following formulas [19]:

$$\alpha = \frac{D_1\left(S_D(x,y)\right)}{D_2\left(S(x,y)\right)}, \tag{6}$$

$$\beta = 1 - \frac{D_3\left(S_D(x,y)\right)}{D_4\left(S(x,y)\right)}, \tag{7}$$

where $D_1(S_D(x, y))$ is the area of the object that is mistakenly attributed to the selection object on the quantized image $S_D(x, y)$;

$D_2(S_D(x, y))$ is the background area of the original image $S(x, y)$;

$D_3(S_D(x, y))$ is the area of correctly selected objects on the quantized image $S_D(x, y)$;

$D_4 S(x, y)$ is the area of the object in the original image $S(x, y)$.

CI processing was carried out using selected quantization thresholds L_m, $m=\overline{1,M}$. Threshold values are selected taking into account the size of objects D_k, $k=\overline{1,K}$. As a result, a set of image fragments with objects that stand out better according to the threshold value is formed. In fact, each fragment of the image is a matrix with the corresponding pixel value. An object whose area has the required number of pixels represents the desired selection object.

As a criterion for the selection of the object, we shall choose the total indicator of the relative area. The final matrix D_Σ, obtained by combining the matrices $D_{i,j}$, represents the values of independent readings in the form of integral indicators of the area. The $D_{i,j\Sigma}$ element, which will contain the required number of pixels, enters the D_Σ matrix with the selected object.

The probability of selection of an object on CI is independent of processing for different threshold values. Based on this, the probability of object selection during step-by-step processing based on the area of the object $P_C(D)$ can be determined using the following formula:

$$P_c(D) = 1 - \left(1 - P_{c_i}(D)\right)^K, \tag{8}$$

where $P_{Ci}(D)$ is the probability of object selection at the i-th step.

The second and subsequent stages of selection of the object on CI are carried out using the energy characteristics of the object. They are based on the application of CI quantization thresholds based on brightness and contrast indicators.

Determination of the value of quantization thresholds was also carried out using the measure of coincidence of the compared images. As such measure, the coefficient of mutual correlation (CMC) was used [2]. The determination of the CMC value in accordance with the classical correlation algorithm for informative signs of brightness $K_b(k, l)$ and contrast $K_K(k, l)$ is carried out according to the following expressions [2]:

$$K_B(k,l) = \\ = \frac{1}{M_2 N_2} \sum_{m=1}^{M_2} \sum_{n=1}^{N_2} S_{RI}(m,n) \cdot S_{CI}(m+k-1, n+l-1), \tag{9}$$

$$K_K(k,l) = \\ = \frac{1}{M_2 N_2} \sum_{m=1}^{M_2} \sum_{n=1}^{N_2} \begin{matrix} \left[S_{RI}(m,n) - \bar{S}_{RI}\right] \times \\ \times \left[S_{CI}(m+k-1, n+l-1) - \bar{S}_{CI_{kl}}\right] \end{matrix}, \tag{10}$$

where:

$$i = 1 \ldots M_1 - M_2, \quad j = 1 \ldots \mathrm{N}_1 - N_2;$$

$$\bar{S}_{RI} = \frac{1}{M_2 N_2} \sum_{m=1}^{M_2} \sum_{n=1}^{N_2} S_{RI}(m,n);$$

$$\bar{S}_{CI_{kl}} = \frac{1}{M_1 N_1} \sum_{i=1}^{M_1} \sum_{j=1}^{N_1} S_{CI}(m+k-1, n+l-1).$$

The use of quantization thresholds for the purpose of determining the fragment of the binary CI that most closely corresponds to RI predetermines the application of L threshold levels:

$$K_2 < K_{\mathrm{B(K)}} < K_3,\ \ K_L < K_{\mathrm{B(K)}} \le 1, \tag{11}$$

where K_L=K_t.

It is clear that the value of the threshold level K_L=K_t=1 corresponds to the greatest coincidence of images.

For energy IFs, the minimum value of the signal-to-noise ratio of the image $q_{\min}$, taking into account errors of the first and second kind, is determined from the following formula [24]:

$$q_{\min} = \Phi^{-1}(1-l-p_{01}) + \Phi^{-1}(1-l-p_{02}), \tag{12}$$

where $\Phi(x)$ is the Laplace integral.

The probability of selecting an object on CI at the third and fourth stages using the brightness $P_c(B)$ and the contrast $P_c(\Delta B)$ can be determined according to the following expression [24]:

$$P_{c_{\Sigma(B,\Delta B)}}(q) = \sum_{j=1}^{K} C_K^j (1-\alpha)^j \alpha^{K-j} \left[\sum_{k=0}^{j-1} C_K^k \beta^k (1-\beta)^{K-k} \right]^K, \tag{13}$$

where C_n^k – binomial coefficients;

$$\alpha = \alpha(l') = 1 - \Phi(q - l');$$

$$\beta = \beta(l') = \frac{1}{1+B}\left[\Phi(-l') + Be^{-\lambda' l'}\right];$$

l'=$l/\sigma|$ – relative quantization threshold for the corresponding IF;

σ – noise dispersion in the measurement channel;

λ›=$\lambda\sigma$ is a relative parameter that determines the distribution of small objects in the image.

Thus, the use of a set of IF enables the selection of an object on CI with a probability, the final expression for which can be written in the form:

$$P_c(D,B,\Delta B) =$$
$$= 1 - \left[\left(1 - P_{c_\Sigma}(D)\right)\left(1 - P_{c_\Sigma}(B)\right)\left(1 - P_{c_\Sigma}(\Delta B)\right) \right]. \tag{14}$$

Expression (14) makes it possible to estimate the probability of object selection by choosing the appropriate values of CI quantization thresholds for selected informative features, taking into account the signal-to-noise ratio in the IF measurement channel. During the selection of the necessary object on CI by comparing the CI with RI, DF is formed (5). It is clear that the construction of the unimodal DF corresponds to the maximally achieved probability of selection of the object on CI. The presence of multi-extreme DF indicates an insufficiently high probability of selection of the object, which will lead to a large error in the MR localization MR.

5. 2. Estimating the probability of construction of a unimodal decision function

In order to evaluate the effectiveness of the DF construction method using a set of IFs, a simulation of the object selection process using a set of IFs was carried out. To this end, we used a fragment of VS image from Google Earth Pro, which is shown in Fig. 2.

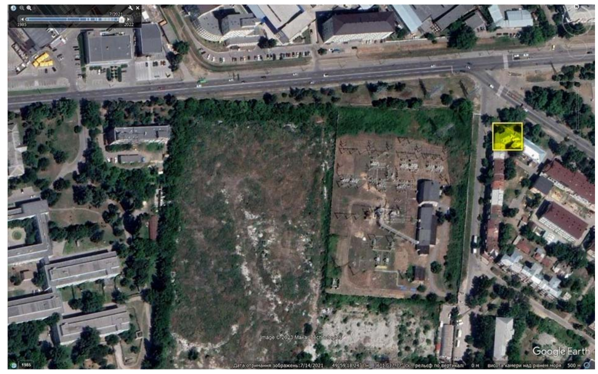

Fig. 2. Image of the viewing surface from Google Earth Pro (1732x1080 pixels)

The transformed original image in shades of gray is shown in Fig. 3.

Fig. 3. The original image of the viewing surface

Using the original image shown in Fig. 2, segmented images were constructed for different values of the cross-correlation coefficient and IF. In accordance with the stages defined above, the selection of the object on CI was carried out by area for CMC 0.7. For selection of the object according to other IFs, the value of CMC above 0.8 was chosen. The selection of CMC values in this case is performed to demonstrate the selection process. The results of constructing segmented images are shown in Fig. 4–9.

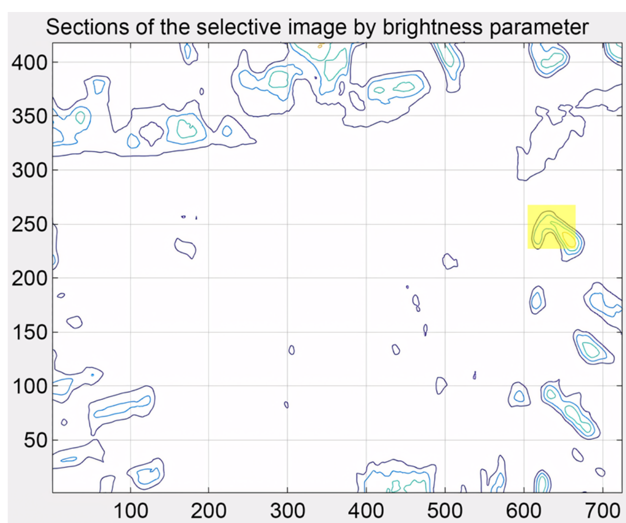

Fig. 4. Segmented image based on object area indicator (CMC=0.7)

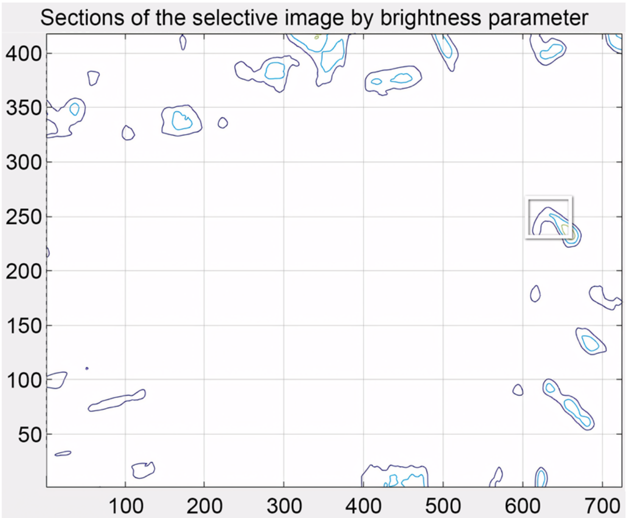

Fig. 5. Segmented image by brightness indicator (CMC=0.8)

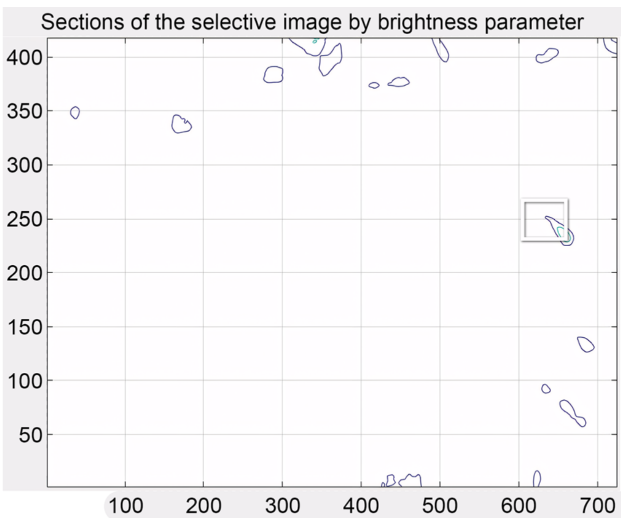

Fig. 6. Segmented image by brightness indicator (CMC=0.9)

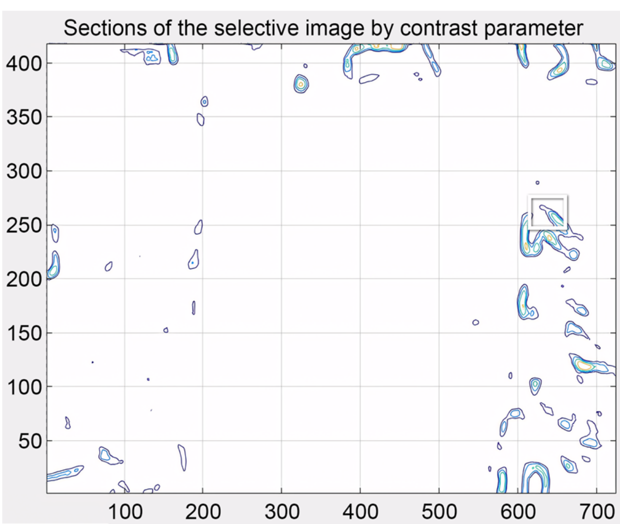

Fig. 7. Segmented image by contrast parameter (CMC=0.7)

The selection of the object on the selected image leads to the construction of TVS DF, which is shown in Fig. 10.

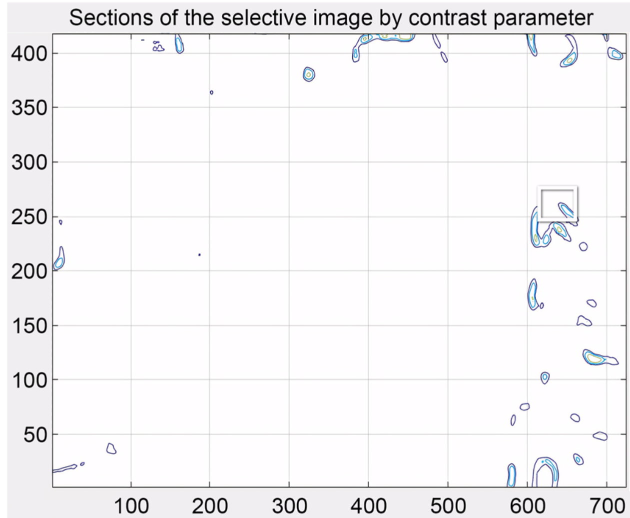

Fig. 8. Segmented image by contrast parameter (CMC=0.8)

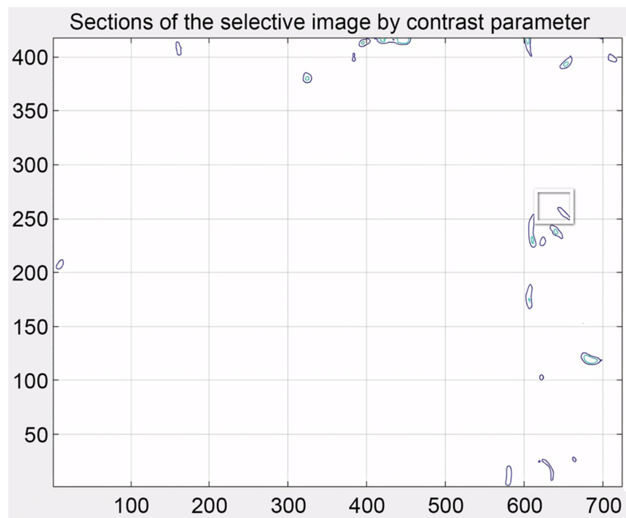

Fig. 9. Segmented image by contrast parameter (CMC=0.9)

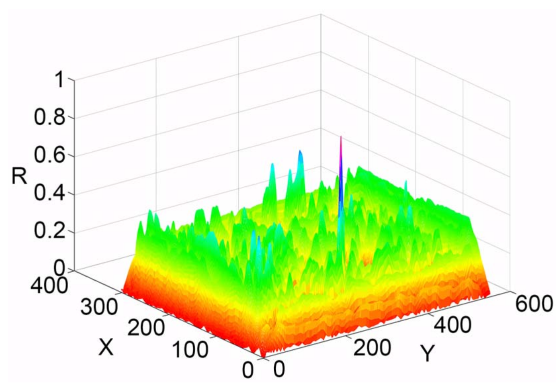

Fig. 10. Decision function corresponding to object selection at CMC 0.9

An assessment of the probability of selection of the object on CI was performed. The zone model of CI was used in the simulation. The CI is represented in the form of a matrix of numbers, the elements of which characterize the distribution of brightness and contrast of a given area. In this matrix, a rectangular submatrix M_1*M_2 RI is selected, which includes the object and some area around it. The matrix should contain M_1*M_2 submatrices similar to RI, i. e., the CMC of which exceeds a certain threshold, so that a priori it does not reduce the probability of the correct selection of the object. In the original matrix, a submatrix of noise-free CI containing RI is selected. The coordinates of the upper left corner of the RI matrix in the CI matrix (i_0, j_0) represent the parameter being evaluated.

The principle of modeling CI and RI implicitly assumes that:

1) the RI and CI grids coincide, that is, there is no need to shift the RI within the half-width of the discrimination element;

2) there is no turning of the RI in relation to the CI.

To simulate the noise component in the image, a normally distributed value with zero mean and variance σ^2 is added to each element of the simulated image. This completes the modeling part of the algorithm.

3) there is no rotation of the RI in relation to the CI.

Simulation conditions:

– RI matrix: 9*9 elements;

– informational content: the image is binary;

– the size of the object on CI is 3*4 elements;

– CI matrix – 16*16 elements;

– shape of the object: rectangular matrix.

The results of numerical modeling are shown in Fig. 10 in the form of dependences P_c on the value of the relative threshold and the signal-to-noise ratio at different values of the interference environment parameter. Calculations were performed for typical values of the signal-to-noise ratio, taking into account possible CI noise. The impact of noise on CI was taken into account through different values of the interference parameter *V*.

The parameter *V* is defined as the ratio $V=J_W/J_\rho$.

To determine *V*, J_0 denotes the total number of frame elements that have reached the inspection area of TVS, J_ρ – the number of cells in the frame with signals from a similar object, J_W – the number of frame elements occupied by OP, J_V – the number of frame elements that occupy in the background.

Based on this:

$$J_0 = J_\rho + J_v + J_w. \quad (15)$$

The signal-to-noise ratio will be chosen in the range from 1 to 5. The total number of processed realizations in the series, used to calculate one value of the probability of object selection P_c in the image, is N=500.

For the selected conditions, the results of the numerical simulation of the probability of selection of the object on CI are shown in Fig. 11.

The total number of processed in a series of implementations used to calculate one value of the probability of object selection P_c in the image is N=500.

It can be seen from the simulation results that each curve of the family has a maximum, the position of which shifts as the relative threshold increases from $l'_{opt}=1.3$ at V=0 to $l'_{opt}=1.6$ at V=0.32, which corresponds to the number of image elements distorted by interference signals, J_ρ=78. At the same time, the probability of object selection depending on the number of distorted elements of the frame changes from 0.79 to almost 1 for the conditions of the absence of distortions.

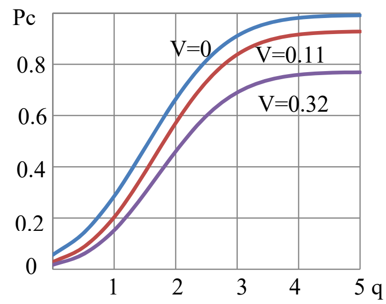

Fig. 11. Dependence of the probability of object selection on the current image for different values of the signal-to-noise ratio at different values of the interference parameter

6. Discussion of results of investigating the construction of a decision function under the influence of interference

We report the results of the development of a method for the construction of a unimodal DF in the case of CI noise based on the use of a set of IFs of VS objects with weakly pronounced brightness and contrast characteristics, as well as their small geometric dimensions. A new statement of the problem to devise a method for constructing DF under the conditions of CI noise of a developed infrastructure in the presence of small-sized, low-contrast, and similar objects with brighter characteristics is proposed. Solving the problem in the proposed statement allows for the assessment of the state of CIO when they are destroyed, which is especially important under the conditions of a natural disaster or war. The method devised, in contrast to [8], in which object selection is carried out on the image only by radio brightness temperature, makes it possible to ensure the required value of the probability of object selection with a significantly lower signal-to-noise ratio of CI. Thus, in [8], the probability of object selection, which is close to one, and the construction of a unimodal DF occur at values of the signal-to-noise ratio of about 20. In this case, the size of the object is not determined, but only compared with the size of false objects, which may appear due to a change in the geometric conditions of visualization. In this study, according to the results of numerical modeling (Fig. 11), the object occupies an area of 4.68 % of the image area, that is, it is small. At the same time, the probability of object selection, which is close to one, is achieved at values of the signal/noise ratio of about 4. In [9], a set of geometrically related objects with an averaged value of the radio brightness temperature was chosen as an invariant of the object of selection. And the probability of object selection, close to one, is achieved at values of the signal/noise ratio greater than 6, provided that its area is no more than 30 % of the area of CI. The peculiarity of our method is the implementation of a four-stage object selection procedure on CI using a set of informational features of imaging objects measured by the TVS sensor. Each stage of object selection in CI involves the following sequence of operations:

1. Selection of the type of feature.
2. Evaluation of the characteristics of the original image according to the characteristics of selection.
3. Selection of the object according to the selected feature.
4. DF construction.

At the first stage of the selection of the object, the use of the area as the IF significantly simplifies the process of preparing the CI for comparison with the RI. The simplification is due to the fact that there is no need to convert the CI in order to eliminate prospective distortions caused by a change in the imaging geometry of TVS sensors. In addition, there is no need to use a set of RI for different imaging conditions, which also reduces the number of operations that must be performed when selecting a fragment of RI for further comparison with the CI. The selection of appropriate values of the quantization threshold by area ensures a reduction of errors of the first and second kind (6), (7), which will ensure an increase in the probability of object selection at the first stage (8). By choosing quantization thresholds based on other features in the third and fourth stages, the necessary probability of object selection (13) is provided, which is determined taking into account the signal-to-noise ratio (12), quantization thresholds, and errors of the first and second kind. It is due to such a decision that the problematic part of DF construction under the conditions of the noise of CI of the developed infrastructure in the presence of small-sized, low-contrast, and similar objects with brighter characteristics is closed.

The disadvantage of the method is the dependence of the number of operations, as well as the speed of DF construction process, on the selection procedure based on the number of selected quantization thresholds at each stage based on various characteristics. This limits the use of the method for high-speed MR imaging. At the same time, the proposed method makes it possible to form a unimodal DF under certain conditions.

An experimental study of object selection in the image was conducted. The first stage of object selection by area is shown in Fig. 4. To demonstrate the method, the area quantization threshold (CMC=0.7) was deliberately chosen. This is done so that after the selection, a part of the VS objects, which slightly exceed and are smaller than the area of the selection object, will remain. It is clear that objects with a size smaller than the selection object, by choosing the appropriate threshold, will also be removed in the selected image. That is, objects with an area close to the area of the object will remain on the image. Next, the selection of the object was carried out according to brightness and contrast. The results of object selection on CI using two values of quantization thresholds for brightness and contrast are shown in Fig. 5–9. From the analysis of the simulation results, it can be seen that the application of the proposed approach makes it possible to select the necessary object and ensure the construction of unimodal DF (Fig. 10). This became possible thanks to the application of the CI's step-by-step quantization procedure based on area, brightness, and contrast indicators.

The use of relation (14) by applying the Monte Carlo method made it possible to evaluate the effectiveness of the four-stage object selection procedure on CI, taking into account the degree of image noise for different values of the relative threshold and the signal-to-noise ratio. The calculation diagram is shown in Fig. 11. The analysis of the calculation results showed that the application of a four-stage procedure allows for the probability of selection of a small-sized object in the range from 0.78 to 0.99, depending on the disturbing situation that leads to the noise of CI.

The results of our research can be implemented in the informational processing algorithms used in optical-electronic TVS for the navigation of unmanned aerial vehicles.

It is advisable to focus further research on the improvement of the method from the point of view of reducing the number of operations during the DF construction for its application on high-speed aircraft. In addition, it is necessary to pay attention to the development of algorithms for DF construction using a four-stage procedure for the selection of an object in CI.

7. Conclusions

1. The problem has been stated and the method to construct TVS DF was developed, which, unlike the known ones, is based on the use of a set of informative features of the object, namely, its brightness, contrast, and area. This enables the selection of the object on CI and the localization of MR under the conditions of reducing the signal-to-noise ratio of CI when using VS with available small-sized, low-contrast, and similar objects with brighter characteristics. The selection of the object on CI under the specified conditions is proposed to be carried out sequentially in the form of a four-stage procedure by quantization according to the selected thresholds in accordance with IFs. At the same time, errors of the first and second kind are taken into account for each type of IF. An analytical expression was obtained for the probability of object selection on CI, taking into account the features of object selection at each of the stages.

2. Simulation of the object selection process was carried out on CI, a fragment of which was randomly selected from Google Earth Pro. It is shown that the application of a four-stage object selection procedure on CI enables the construction of unimodal DF. Numerical modeling has been used to estimate the probability of construction of a unimodal DF under conditions of noise in CI of VS with weakly pronounced brightness and contrast characteristics of objects, as well as in the case of their small geometric dimensions. It was established that the four-stage object selection procedure makes it possible, depending on the value of the selected threshold values, to ensure the probability of the construction of DF in the range from 0.78 with a distortion of 32 % of CI to 0.99 for an undistorted image.

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

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.

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