Segmentation of Images Used in Unmanned Aerial Vehicles Navigation Systems

Yeromina N.[1], Udovenko S.[2], Tiurina V. [3] Boychenko O.[4], Breus P.[5], Onishchenko Yu.[6], Gnusov Yu. [6], Svitlychnyi V.[6]

[1] Kharkiv National University of Radio Electronics, Kharkiv, Ukraine
[2] Simon Kuznets Kharkiv National University of Economics, Kharkiv, Ukraine
[3] Kharkiv National Air Force University named after Ivan Kozhedub, Kharkiv, Ukraine
[4] State Scientific Research Institute of Armament and Military Equipment Testing and Certification, Cherkasy, Ukraine
[5] Flight Academy of the National Aviation University, Kropyvnytskyi, Ukraine
[6] Kharkiv National University of Internal Affairs, Kharkiv, Ukraine

Abstract. The paper presents the results of the study of a two-stage procedure for selecting a reference object in the current image formed by a correlation-extreme system used for autonomous navigation of unmanned aerial vehicles. The aim of this paper is to theoretically evaluate the probability of selecting low-dimensional low-contrast objects in the segmented current image according to the proposed two-stage procedure. To achieve this goal, the problem of segmentation of images of the sighting surface and subsequent selection of the reference object in the presence of heterogeneous objects differing in brightness and area characteristics is solved. The most significant result is the justification of application of two-stage procedure of selection of the reference object in the current image by brightness and area parameters using the set thresholds. The significance of the obtained results consists in establishing the dependence of the probability of correct selection of the reference object on the noise level of the current images. It is shown that the probability of correct selection of the object in the image is a function of the threshold value and can be maximised by choosing its value. This approach allows to consider the influence of various factors leading to image noise on the quality of images formed by the navigation system. It is shown that when noise distorts more than 31% of the image pixels, the proposed two-stage procedure allows to ensure the selection of the reference object in the image with a probability not lower than 0.9.
Keywords*:* correlation-extremal navigation system, unmanned aerial vehicles, information features, image segmentation method, decision function.

DOI: https://doi.org/10.52254/1857-0070.2023.4-60.03
UDC: 62-758.381

Segmentarea imaginilor utilizate în sistemele de navigație de vehicule aeriene fără pilot

Eromina N.S.[1], Udovenko S.G.[2], Tiurina V.Yu. [3], Boycenko O.I.[4], Breus P.P.[5], Oniscenko Yu.N.[6], Gnusov Yu.V.[6], Svetlicinâi V.A.[6]

[1] Universitatea Națională de Radio Electronică din Harkiv, Harkiv, Ucraina
[2] Universitatea Economică Națională Semyon Kuznets Harkov, Harkiv, Ucraina
[3] Universitatea Națională a Forțelor Aeriene din Kharkiv, numită după Ivan Kozhedub, Harkiv, Ucraina
[4] Institutul de Cercetare de Stat pentru Testarea și Certificarea Armelor și Echipamentelor Militare, Cherkasy, Ucraina
[5]Academia de Zbor a Universității Naționale de Aviație, Kropyvnytskyi, Ucraina
[6] Universitatea Națională de Afaceri Interne din Harkiv, Harkiv, Ucraina
Rezumat. Articolul prezintă rezultatele unui studiu al unei proceduri în două etape de identificare a unui obiect de referință într-o imagine curentă generată de un sistem de corelație-extremă utilizat pentru navigarea autonomă a vehiculelor aeriene fără pilot. Scopul acestei lucrări este de a estima teoretic probabilitatea de selecție a obiectelor de dimensiuni mici, cu contrast scăzut într-o imagine curentă segmentată, în conformitate cu procedura propusă în două etape. Pentru a atinge acest obiectiv, a fost rezolvată problema segmentării imaginilor suprafeței de vizualizare și a selectării unui obiect de referință care diferă ca luminozitate și caracteristicile zonei. Cel mai important rezultat este motivarea utilizării unei proceduri în două etape pentru selectarea unui obiect de referință din imaginea curentă pe baza parametrilor de luminozitate și a dimensiunilor zonei folosind praguri stabilite. Semnificația rezultatelor obținute constă în stabilirea dependenței probabilității de selecție corectă a obiectului ancoră de gradul de zgomot din imaginile curente. Se arată că probabilitatea de selecție corectă a unui

obiect dintr-o imagine este o funcție a valorii de prag și poate fi maximizată prin alegerea valorii acestuia. Această abordare ne permite să luăm în considerare influența diverșilor factori care duc la zgomotul imaginii asupra calității imaginilor generate de sistemul de navigație. Se arată că atunci când mai mult de 31% dintre pixelii imaginii sunt distorsionați de zgomot, utilizarea procedurii propuse în două etape face posibilă selectarea obiectului ancora în imagine cu o probabilitate de cel puțin 0.9.
Cuvinte-cheie: sistem de navigație de tip corelație-extrem, vehicule aeriene fără pilot, caracteristici informaționale, metoda de segmentare a imaginii, funcție de decizie.

Сегментация изображений, используемых в системах навигации беспилотных летательных аппаратов

Еремина Н.С.[1], Удовенко С.Г.[2], Тюрина В.Ю. [3], Бойченко О.И.[4], Бреус П.П.[5], Онищенко Ю.Н.[6], Гнусов Ю.В.[6], Светличный В.А.[6]

[1] Харьковский национальный университет радиоэлектроники, Харьков, Украина
[2] Харьковский национальный экономический университет имени Семена Кузнеца, Харьков, Украина
[3] Харьковский национальный университет Воздушных Сил имени Ивана Кожедуба, Харьков, Украина
[4] Государственный научно-исследовательский институт испытаний и сертификации вооружения и военной техники, Черкассы, Украина
[5] Летная академия Национального авиационного университета, Кропивницкий, Украина
[6] Харьковский национальный университет внутренних дел, Харьков, Украина

Аннотация. В статье представлены результаты исследований двухэтапной процедуры выделения объекта привязки на текущем изображении, формируемом корреляционно-экстремальной системой, применяемой для автономной навигации беспилотных летательных аппаратов. Целью данной работы является теоретическая оценка вероятности селекции малоразмерных слабоконтрастных объектов на сегментированном с помощью информационных признаков текущем изображении по параметрам яркости и размерам площади в соответствии с предложенной двухэтапной процедурой. Для достижения поставленной цели решена задача сегментации формируемых системой навигации изображений поверхности визирования и последующей селекции объекта привязки при наличии разнородных объектов, отличающихся яркостными и площадными характеристиками. Наиболее существенным результатом является обоснование применения двухэтапной процедуры селекции объекта привязки на текущем изображении по параметрам яркости и размерам площади с использованием установленных порогов. Значимость полученных результатов состоит в установлении зависимости вероятности селекции объекта привязки от степени зашумленности текущих изображений. Особенность полученных результатов заключается в определении значений порогов квантования изображений по информативным признакам с учетом возможности возникновения ошибок первого и второго рода, при которых обеспечиваются требуемая вероятность селекции объекта привязки. Показано, что вероятность селекции объекта на изображении является функцией величины порога и может быть максимизирована выбором его значения. Такой подход позволяет учитывать влияние различных факторов, приводящих к зашумлению изображений, на качество формируемых системой навигации изображений за исключением геометрических, что позволяет упростить этап первичной обработки и повысить быстродействие системы. Показано, что при искажении более 31% пикселей изображения применение предлагаемой двухэтапной процедуры позволяет обеспечить селекцию объекта привязки на изображении с вероятностью не ниже 0,9. Отличие от известных работ заключается в осуществлении селекции объекта привязки на текущем изображении с использованием двухэтапной процедуры по значениям яркости и площади объектов в условиях, приводящих к формированию зашумленных изображений.
Keywords: корреляционно-экстремальная система навигация, беспилотные летательные аппараты, информационные признаки, сегментация изображений, селекция объекта.

INTRODUCTION

Unmanned aerial vehicles (UAVs) are used for monitoring hard-to-reach surface areas at a considerable distance. They are extensively used in the military search and rescue operations, in assessing the degree of destruction of various objects on land and water. Therefore, it is necessary to further improve navigation systems, the functioning of which is based on the extraction of information about the objects of sighting in various conditions. These tasks are most effectively solved by UAVs equipped with correlation-extreme navigation systems (CENS). The functioning of these systems is based on the comparison of two-dimensional images formed by different sensors depending on the physical nature of the signals with the reference images (RI) prepared in advance and stored in the memory of the onboard computer [1]. In these systems, the review-comparative method of forming the solving function is implemented. It characterizes the degree of deviation of the true location of the navigation object from the specified one [1, 2]. CENS functioning is mainly determined not by the type of signals used, but by the quality of information support based on the processing of informative features of sighting objects [1, 3, 4]. Low quality of information support is the reason of discrepancy between the current images (CI) formed during monitoring and preformed reference images [1, 2]. The information support depends on the conditions of image acquisition, especially identical conditions of obtaining the initial information during the formation of reference and current images, the presence in some cases of many heterogeneous and similar objects [2, 4]. The consequence of the mismatch of the compared images is a decrease in the accuracy characteristics of the navigation system, which necessitates the elimination of possible mismatch. A possible direction of eliminating such inconsistency is to reduce the influence factors both at the stage of CI formation and development of the algorithms of primary and secondary processing of CENS [1, 5]. In addition, the principles of CI formation onboard the UAV should be like the principles of RI formation. Considering the time constraints caused by the UAV flight speed and geometrical conditions of sighting (low altitude), the process of CI formation and its comparison with RI should be operative. This circumstance requires consideration of computational and time costs and imposes restrictions on the use of appropriate stable information features (invariants) about the objects of the sighting surface (SS) [1, 2]. Considering these factors necessitate further development of image segmentation methods for selection of navigation landmarks on CI as applied to CENS. A considerable number of publications are devoted to the development of methods and algorithms of image formation and processing based on various segmentation methods and algorithms. However, these publications do not consider the mentioned peculiarities of the construction and functioning of CENS used on UAVs, as well as the characteristics and peculiarities of the description of SS objects depending on the type of the geophysical field used to obtain the initial information about the objects [1].

Therefore, the task of sighting surface image segmentation and selection of the reference object in the images formed and used in CENS in the presence of many heterogeneous objects that differ in brightness and area characteristics is important and requires the search for new solutions.

I. PUBLISHED LITERATURE ANALYSIS

Abdollahi A. & Pradhan B. (2021) proposed an integrated method for road extraction in images, characterised by the ability to extract roads even in the presence of obstacles with the same colour and spectrum values as the road class. The disadvantage of the proposed method is that it is multi-stage and selects a single class of objects of interest.

Bakhtiari H. R. R., Abdollahi A., Rezaeian H. (2017) improved a method for road extraction in images using Canny method for boundary extraction, followed by merging adjacent segments, classification using support vector method and mathematical morphology techniques. The method is characterised by high accuracy but is effective for a single class of objects.

Senthilnath J., Rajeshwari M., Omkar S. N. (2009) developed a normalised cut method for automatic road detection. In the first stage, unwanted objects are removed and in the second stage, road segments are extracted using progressive image texture analysis and graph-based method.

Singh P. P. & Gard R. D. (2013) They demonstrated an image segmentation method for extracting extended objects. Its essence consists in applying adaptive thresholding and further using morphological operators. However, the method does not consider noise and texture component of the image.

Grinias I., Panagiotakis C., Tziritas G. (2016) have developed a method of automatically selection buildings and roads in images. The method has a high speed of object classification. But it allows to select objects of interest only in Red-Green-Blue (RGB) images.

Li X., Li T., Chen Z. et al. (2022) applied attention modules that collect contextual information while processing all pixels of an image for semantic image segmentation. The proposed approach has high boundary extraction accuracy but is characterised by high computational and time costs.

Kit O., Lüdeke M., Reckien D. (2012) proposed to use a line detection algorithm on satellite images to generate a binary dataset for further lacunarity analysis. The disadvantage of the method is processing not the whole image at once, but sequentially by a grid of a certain size.

Zhao S., Wu H., Tu L., Huang B. (2014) showed the use of vector model of geometric primitives to mark spatial objects in the image. The advantage of the development is thematic segmentation of images of urban areas, and the disadvantage is the transition from raster format of data storage to vector format and subsequent storage of vector data in graphics.

Pan Z., Xu J., Guo Y., Hu Y., Wang G. (2020) proposed a method based on U-net deep learning architecture. The method is characterised by good building extraction in high population density images. The disadvantage of the method is training and testing on urban village plots and availability of vector file of building boundaries.

Mhangara P., Odindi J. (2013) proposed to use texture information to identify objects of interest. The essence of the method is to apply spectral features and object-oriented texture features of Haralick for thematic segmentation and classification of urban land use. The disadvantage of the method is certain difficulties in recognising spectra between several types of objects.

Körting T. S., Fonseca L. M. G., Dutra L. V., Silva F. C. (2010) proposed a re-segmentation method. Its essence is to use a preliminary already over-segmented image as a source image to obtain a new set of objects of interest. The disadvantage of the method is the possible variant of non-fused objects for further analysis.

Dikmen M., Halici U. (2014) developed a two-stage re-segmentation method. The advantage of the method is the post-processing of the image to eliminate some false object segments, and the disadvantage is the presence of some error in assigning shadow segments to the object.

Pandey S. & Khanna P. (2014) They proposed a hierarchical approach to semantic clustering of images. The disadvantage of the approach is the loss of information that a representative image denotes any other image belonging to a cluster. To automatically obtain the total number of clusters, this loss of information is tracked, which is an advantage.

Dhanachandra N., Manglem K., Chanu Y.J. (2015) proposed the image segmentation using subtractive clustering. The advantage of the method is to apply a median filter after k-means algorithm to the resulting image to remove the "unwanted" region in the given image. The disadvantage of the approach is the presence of many "unwanted" regions after subtractive clustering.

To eliminate the drawback regarding the dependence of clustering results on the initial selection of cluster centres, Dao N., Anh D. N. (2015) developed unsupervised segmentation method by incremental clustering. The computational complexity of the approach is compensated by the unnecessary determination of the initial number of clusters and the avoidance of re-clustering the whole image when the number of clusters increases.

Niharika K., Adeeba H., Krishna A. S. R., Yugander P. (2017) proposed an image segmentation method based on k-means and Otsu thresholding clustering methods. The use of the median filter allowed obtain good results of image segmentation with available speckle noise, but only for radar images of the radar.

For segmenting colour images, Zheng X., Lei Q., Yao R., et. al. (2018) developed an adaptive k-means clustering method without prior introduction of the number of clusters. This method features reduced light influence on segmentation results, segmentation of colour images of different colour representation models and adaptive selection of the number of clusters. The disadvantages are the impossibility of universal clustering of tone and colour images, as well as the need to represent colour images in the LAB colour model.

Shah N., Patel D., Fränti P. (2021) performed image segmentation by k-means algorithm using Mumford-Shah model. When using k-means algorithm for colour quantization in colour models of image representation, pixels are grouped into clusters only in colour space. The method allows optimising both the shape of segments and their content.

Abeysinghe W., Wong M., Hung C.-C., Bechikh S. (2019) proposed a multi-objective evolutionary clustering algorithm to find optimal cluster centres. The efficiency of the algorithm depends on the choice of the target function, i.e., maximising the inter-cluster distance or minimising the intra-class compactness. The advantage is the generation of a set of "non-dominated" solutions no longer under consideration during the algorithm. The disadvantage of the algorithm is the dependence of its efficiency on the choice of the target function.

The results of analysing the segmentation methods of the most closely represented images in CENS in compressed form are shown in Table 1.

Table 1.

Analysis of segmentation methods.

Name	Advantages	Disadvantages
The k-means method	The segmentation process takes place without prior training. Easy to implement.	Additional processing of the obtained homogeneous areas is required.
Method of emphasising boundaries	The result of segmentation is similar to the results of segmentation by an expert. Easy to implement. High speed performance.	Sensitivity to noise. Difficulty in working with low-contrast images. Additional processing of the results is required.
Break and merge method	Utilises information about the spatial characteristics of points in the image. Excellent results on images with few homogeneous areas.	Sensitivity to the effects of noise. Difficulty in determining unambiguous signs of homogeneous areas.
Segmentation method based on physical properties of objects	Excellent results when the correct object model is selected. Resistant to noise and image defects.	Complexity of segmentation algorithms. Requires initial information about the shape of objects.
Graph theory method	Fast segmentation algorithms are used.	Local point features are more important than global area features. Difficulty in determining weights of graph nodes and branches.

Thus, the analysis has shown that although there are a significant number of image segmentation techniques, they have limited application depending on the specific task and cannot be directly applied in CENS.

METHODS, RESULTS AND DISCUSSION

In accordance with the approaches adopted in [1 – 5], the decision function formed by CENS at a point in time t by comparing the current and reference images is of the form:

$$\mathbf{R}(\mathbf{r},t,\theta,\theta_i)=\mathbf{F}_{SP}\left(\mathbf{S}_{CI}(\mathbf{r},t,\theta),\ \mathbf{S}_{RI}(\mathbf{r},\theta_i)\right),\quad (1)$$

where $\mathbf{F}_{SP}$ is an image comparison operator;

$\mathbf{S}_{CI}(\mathbf{r},t,\theta)$ is a current image obtained for the sighting angle of view θ at the moment of time t;

$\mathbf{r}=\|r_i\|=\|x \quad y\|^{\mathrm{T}}$ are coordinates of the georeferencing area;

$\mathbf{S}_{RI}(\mathbf{r},\theta_i)$ is reference image formed in advance for one of the sighting angles θ_i.

The current image is represented by brightness values of objects and backgrounds of the viewed surface in resolution elements:

$$\mathbf{S}_{CI}=\|S(i,j)\|,\quad (2)$$

where,

$$S(i,j)=\begin{cases}S_v(i,j), & \text{when } S(i,j)\in\mathbf{S}_v\\ S_w(i,j), & \text{when } S(i,j)\in\mathbf{S}_w\end{cases};\quad (3)$$

$S_v(i,j)$ is the brightness of the image element v-th of the object $\mathbf{S}_v$;

$S_w(i,j)$ is brightness of the image element w-th of background $\mathbf{S}_w$;

V and W are the numbers of objects and backgrounds of different brightness and shape in the original image.

The RI is also described by a matrix of brightness values of corresponding pixels:

$$\mathbf{S}_{RI}=\|S_{RI}(m,l)\|,\ m=\overline{1,M},\ l=\overline{1,L},$$

where M, L are dimensions of RI.

Model (1) does not explicitly consider the influence of various factors on the formation and processing of CI. Such factors as daily, seasonal, and meteorological conditions, the use of masking materials on objects, object saturation, attenuation of signals on the propagation path from the object to the receiving device (for passive systems), additive noise of the sensor of received signals, interpixel, perspective and scale distortions [4]. Depending on the type of sensor, its operating frequency, the influence of several factors may have different significance. To a lesser extent it concerns radar, relief and radiometric sensors, as they operate in the long-wave part of the millimeter and short-wave part of the centimeter range. But on sensors operating in the visible range, the influence of factors is much higher. At the same time on the formed image irrespective of sensor type object saturation, electrophysical and area characteristics of objects and backgrounds, and interpixel and geometrical distortions essentially influence. These factors can lead to a reduction and blurring of the contrasts of the object-background pair, and, consequently, to a decrease in the signal-to-noise ratio in the image. As a result, it will lead to erroneous selection of the object of reference in the image.

Problem Statement. The UAV equipped with CENS is supposed to be used in the conditions of developed infrastructure, where there are objects with insignificant differences in brightness and geometric characteristics. Erroneous determination of the object of reference on the CI will inevitably lead to a decrease in the accuracy and probability of UAV location, and when controlling the state of objects, for example, in their destruction – to an erroneous assessment of the degree of destruction.

CI model. Let us use the CI model "object on background" [1, 2], considering that the object is in the viewing area and has a stable contrast with respect to the surrounding background [1, 2], assuming that the object is in the viewing area and has a stable contrast with respect to the surrounding background.

Due to the instability of the brightness of individual elements of the underlying surface and the contrast between the object and the background, we will assume that the CI is defined by the contrast sign of the object and its geometric shape, i.e., as a binary image. The elements of the object correspond to the values 1, and the elements of the background correspond to the values 0. We will solve the problem under the following assumptions and constraints:

1) the background is formed by signals of the surface area, and the object has a negative contrast with respect to the background;

2) the object is homogeneous in brightness;

3) the background around the object has the same property;

4) each ij-th CI element is a normally distributed value with dispersion σ_{ij}^2 and average brightness value $S(i,j)$, which in the absence of interference can take two values: $S_v(i,j)$ and $S_w(i,j)$;

5) the noise dispersion in the receiving channels of CENS is the same, i.e. $\sigma_{ij}^2=\sigma^2$.

Let us denote the contrast of the sought object with respect to the surrounding background by $\Delta S=S_v(i,j)-S_w(i,j)$. Then the brightness distribution densities of the background and the object are defined by the expressions [4]:

$$w_w(S)=\frac{1}{\sqrt{2\pi}\sigma}exp\left[-\left(S-S_w\right)^2/2\sigma^2\right], \quad (4)$$

$$w_v(S)=\frac{1}{\sqrt{2\pi}\sigma}exp\left[-\ S+S_v\ ^2/2\sigma^2\right]. \quad (5)$$

For the considered CI models and object and background brightness distributions, it is required to solve the problem of CI segmentation. Its use will provide a high probability of selecting the object of reference. In its turn, it will allow to obtain the minimum error of CENS binding $\Delta\mathbf{R}(\mathbf{r},t,\theta,\theta_i)\rightarrow\min$, and in the case of estimation of the object destruction degree - its high accuracy.

Problem solution. The use of brightness and geometric features for segmentation of CI SS with the presence of poorly distinguishable small-sized and low-contrast objects leads to the necessity of combining two stages of object selection: by geometric dimensions and by brightness. Suppose that there are no variations of brightness values within a pixel of homogeneous zones [1]. The brightness values of neighboring objects differ insignificantly, but the sensitivity of sighting sensors allows to distinguish them.

According to these conditions, it is necessary to develop an algorithm for image segmentation using brightness and geometric features, which will provide a high probability of selecting the desired object. Let's consider that as geometric features of objects their area is used. The step-by-step process of selection of objects by the selected feature will be carried out in accordance with the selected value of quantization threshold. The threshold values will be chosen in such a way as to select the object in the background considering the presence of similar objects.

At the first stage of object selection by brightness indicator, let's represent CI in the form of image matrix sweep by rows, resulting in a sample of volume J_0. Let J_ρ is the number of cells in the frame with signals from a similar object. Then

$$J_\rho + J_\nu + J_w = J_0 , \qquad (6)$$

where J_0 is the total number of frame elements that have fallen into the field of view;

J_ν, J_w is the number of frame elements occupied by the anchor object and the background. Mutually incompatible events, consisting in belonging of the sample element to the signal of the background, anchor object and similar object, form a complete group. Consequently, the obtained sample is divided into three non-intersecting classes ω_i corresponding to signals from the background (ω_w), similar object (ω_ρ) and anchoring object (ω_ν). Taking this into account, the sampling distribution density J_0 is defined by the expression [7]:

$$w(S) = \sum_{i=1}^{3} p_i w_i(S) , \qquad (7)$$

where $p_i = J_i / J_0 , (i = 1,2,3)$ are apriority class probabilities;

$w_i(S) = w(S \mid \omega_i))$ are conditional probability densities of the random variable S, if it belongs to the class ω_i, which are defined by expressions (4), (5).

Thus, the sample consisting of elements of three classes should be divided into two classes to optimally separate the signals of the object from the background signals with respect to the quality indicator to be further specified.

We consider the threshold l of quantization of the sample into two classes to be known. To one of them belong the signals of the object, to the other – the background. Then considering expressions (4), (5) probabilities of errors of the first (second) kind (when the signal belonging to the first (second) class refers to the second (first) class are defined by expressions [5]:

$$\alpha = \int_{S_w - l}^{\infty} w_\nu(S) dS , \qquad (8)$$

$$\beta = \frac{1}{1+V} \int_{-\infty}^{S_w - l} \left[w_\rho(S) + S w_w(S) \right] dS , \qquad (9)$$

where $V = p_\rho / p_w$.

For a given threshold l, we convert the original $\mathbf{S}_{CI}$ image into a binary image $\mathbf{H}$ by the rule:

$$\mathbf{H}_i = \begin{cases} 1, & S_i \le S_\rho - l;\ S_i > S_{\max}; \\ 0, & S_{\max} > S_i > S_\rho - l; \end{cases} \quad i \in \overline{1, F_0}$$

Let us estimate the probability of selecting an object in the image as follows. Let the size of the object be $T_1 \times T_2$ cells. Let us partition the CI matrix into rectangular submatrices $T_1 \times T_2$. If at such a partitioning of the CI it does not contain an integer number of cells with the object, then increase the frame size to contain an integer number of submatrices $T_1 \times T_2$, which we denote by $K+1$. In this case, the estimates of the probability of selection of the object on the CI are underestimated due to the frame enlargement. Let us assume that the true position of the object falls into one of the submatrices and denote by $\mathbf{H}^0 \subset \mathbf{H}$ the fragment of the CI corresponding to the RI, and by $\mathbf{H}^i , i \in \overline{1,K}$ the fragments located in the other submatrices.

Let the probability of occurrence 1 in $\mathbf{H}^i$ is equal to r_i. For comparison of fragments $\mathbf{H}^i$ with RI consisting of 1, it is more convenient to operate with numbers:

$$z_i = J_\nu - s_i , i \in \overline{0,K} , \qquad (10)$$

each of which represents the number of units in the fragment $\mathbf{H}^i$. In (10), J_ν is the number of elements of the object.

With this in mind, the decisive rule will be that the fragment $\mathbf{H}^j \subset \mathbf{H}$, for which:

$$z_j = \sup_{i \in \overline{0,K}} z_i , \qquad (11)$$

is declared to coincide with RI according to this information feature.

Then the numbers z_i are distributed according to the binomial law:

$$P(z_i) = C_{J_\nu}^{z_i} r_i^{z_i} \left(1 - r_i\right)^{J_\nu - z_i} , z_i \in \overline{0, J_\nu} . \qquad (12)$$

The probability of object selection when using the solving rule (11) is equal to the probability that the number of ones z_0, corresponding to a match between the RI and the object, exceeds all other numbers $z_i, i \in \overline{1,K}$. Let us denote by A_0^j the event consisting in the appearance of $z_0 = j \in \overline{1,J_\nu}$ ones in $\mathbf{H}^0$, and by $A_i^j, i \in \overline{1,K}$ - the event consisting in the fact that the number of ones z_i will not exceed $j-1$. The events $A_i^j, i \in \overline{1,K}$ are independent in aggregate, since $H^i \bigcap H^k = \varnothing \forall i,k \in \overline{0,K}$. According to formula (11), the probabilities of events A_i^j are defined by the expressions:

$$P(A_i^j) = \begin{cases} C_{J_\nu}^j r_0^j \left(1 - r_0\right)^{J_\nu - j}, & i = 0; \\ \sum_{k=1}^{j-1} C_{J_\nu}^k r_i^k \left(1 - r_i\right)^{J_\nu - k}, & i \in \overline{1,K}. \end{cases} \quad (13)$$

where $C_{J_\nu}^k$ are binomial coefficients.

Then by the probability multiplication theorem the probability of the event $L_j = \bigcap_{i=0}^{K} A_i^j$ is equal to:

$$P(L_j) = \prod_{i=0}^{K} P(A_i^j), j \in \overline{1,J_3}.$$

Since the events $L_j, j \in \overline{1,J_\nu}$ in the aggregate are inconsistent, the probability that the number of ones $\mathbf{H}^0$ in exceeds the number of ones in all other fragments $\mathbf{H}^i$, will be determined as follows:

$$P_S = \sum_{j=1}^{J_\nu} P\left(L_j\right) = \sum_{j=1}^{J_\nu} \prod_{i=0}^{K} P\left(A_i^j\right), \quad (14)$$

where the probabilities $P(A_i^j)$ are defined by formulae (12). Given that:

$$r_i = \begin{cases} 1 - \alpha, & i = 0; \\ \beta, & i \in \overline{1,K}, \end{cases}$$

(probabilities α, β are given by relations (8), (9)), for the probability of object selection by brightness we obtain the final expression:

$$P_S = \sum_{j=1}^{J_3} C_{J_\theta}^j \left(1 - \alpha\right)^j \alpha^{J_\nu - j} \left[\sum_{k=0}^{j-1} C_{J_\nu}^k \beta^k \left(1 - \beta\right)^{J_\nu - k} \right]^K. \quad (15)$$

According to expressions (4 - 8), we write down:

$$\alpha = \alpha(l') = \int_{S_\omega - l}^{\infty} w_\nu(S) dT = 1 - \Phi\left(q - l'\right); \quad (16)$$

$$\beta = \beta(l') = \frac{1}{1+S}\left[\Phi(-l') + Se^{-\lambda' l'}\right], \quad (17)$$

where $l' = l/\sigma$ is relative threshold;

$\lambda' = \lambda\sigma$.

At the first stage of object selection on CI, the influence of perspective distortions caused by sighting geometry is not considered. Therefore, at the second stage of object selection by area it is necessary to consider the possibility of occurrence of errors of the first and second kind caused by distortion of geometrical shape of objects depending on the sighting angles [3].

The use of the object area as an information feature is convenient, because when changing the geometry of sighting, it is not the area that changes, but only the shape of the object. Consequently, it is possible to simplify the process of CI formation because there is no need to perform affine transformations.

By analogy with the first stage, at the second stage the errors of the first and second kind will be determined in accordance with analytical expressions:

$$\alpha_1 = S_1\left(G_S\left(x\right)\right) / S_2\left(G\left(x\right)\right), \quad (18)$$

$$\beta_1 = 1 - S_3\left(G_S\left(x\right)\right) / S_4\left(G\left(x\right)\right), \quad (19)$$

where $S_1\left(G_S\left(x\right)\right)$ is background area erroneously attributed to the object in the segmented image $G_S\left(x\right)$;

$S_2\left(G\left(x\right)\right)$ is background area of the segmented image $G\left(x\right)$;

$S_3\left(G_S\left(x\right)\right)$ is area of correctly selected objects in segmented image $G_S\left(x\right)$;

$S_4(G(x))$ is area of the object in the segmented image $G(x)$.

In this approach to the implementation of object selection in the background, the connectivity of adjacent pixels in the image $G(x)$ is taken into account [6].

Let us consider the principles of threshold processing in this case. At the first stage quantisation is performed using thresholds $L_m, m=\overline{1,M}$. Each quantisation threshold has a corresponding size of objects $S_k, k=\overline{1,K}$. As a result, a certain set of slices is formed according to the selected threshold L_{m_i}. On them, the objects having the corresponding area will be segmented and the better objects will be selected. In fact, each individual slice is a matrix with the corresponding pixel value. The area that has the larger number of pixels is the object being searched for on the CI. As a criterion for selecting an object on the CI, we choose the total relative area index. The matrices S_i are element by element combined with each other. As a result, the final matrix S_Σ will be a set of independent samples in the form of integral area indices. The element $S_{ij\Sigma}$ with the largest number of pixels is considered to be the result of the presence of the selection object in the matrix S_Σ.

The probability of object selection on the image P_c does not depend on the results of correlation-extreme processing for other segmentation thresholds. Consequently, the resulting probability of selection of the sought object on CI will be determined according to the expression:

$$P_{c\Sigma} = 1-(1-P_c)^K = \\ = 1-\left[(1-P_{c_1})(1-P_{c_2})...(1-P_{c_K})\right], \quad (20)$$

where P_{c_i} is probability of object selection at the *i*-th step.

Using formula (15) we can calculate the probability of object selection in the image, which increases with each step. This is explained by the increase in the signal-to-noise ratio of the image.

It can be shown that the value of the signal-to-noise ratio of the image q, taking into account errors of the first and second kind, when the required value of the probability of selection of the object in the image takes place, on the basis of the maximum likelihood method using expressions (16 – 17) will be determined by the formula [7]:

$$q = \Phi^{-1}(1-\alpha)+\Phi^{-1}(1-\beta), \quad (21)$$

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

The probability of exceeding the threshold for each step is defined as:

$$P(k \geq K_L) = \sum_{k=m}^{n} C_{J_\nu\,n}^{j\;k} \beta^k (1-\beta)^{n-k}. \quad (22)$$

At large values k, the binomial distribution is approximated by a Gaussian distribution.

Thus, based on the above, image segmentation has been proposed to carry out in two stages. The latter include a sequence of the following operations:

1. Estimation of the characteristics of the original image by segmentation features.
2. Selection of the feature type.
3. Selection of objects according to the selected features.
4. Formation of a set of segmented images.

As an indicator of the segmentation method efficiency, we will use the probability of correct image segmentation and selection of the binding object. Therefore, it is sufficient to use relations (15) and (20) to estimate the efficiency of segmentation. This approach allows us to consider the influence of various factors that lead to image noise on the quality of image formation and the evaluation of the effectiveness of CENS functioning.

According to the above approach to image segmentation used in UAV CENS, the structure of the image segmentation algorithm using luminance and geometry will have the form shown in Fig. 1.

<u>Modelling results.</u>

Let us choose a radio-metric receiver as the CENS sensor. Using the zone model of the image, by processing the aerial image of the reference area, a matrix of numbers is constructed, the elements of which characterise the distribution of radio brightness temperatures of the given area.

In this matrix, a rectangular $M_1 \times M_2$-submatrix of RI is selected, including the object and some area around it. The matrix should not contain $M_1 \times M_2$-submatrices "similar" to the RI.

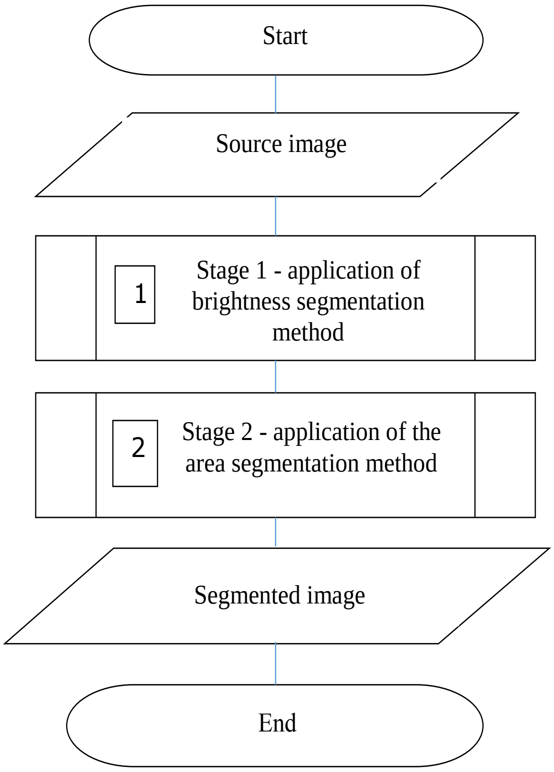

Fig. 1. Structure of the algorithm for image segmentation using bright and geometric features.

This means that the coefficient of mutual correlation of these submatrices with RI exceeds a certain threshold, so that a priori not to reduce the probability of correct selection of the object. In the initial matrix, the $N_1 \times N_2$-submatrix of the unnoised CI containing RI is selected. The coordinates of the upper left corner of the RI matrix in the CI matrix i_{op}, j_{op} represent the estimated parameter. The principle of CI and RI modelling implicitly assumes that:

1) the grids of RI and CI coincide, i.e. there is no need to shift RI within half-width of the resolution element;

2) there is no rotation of RI relative to CI.

To simulate the noise component in the image caused by the noise of the radiometric channels, a normally distributed value with zero mean and variance σ^2 is added to each element of the modelled image (for simplicity, the noise variance of all channels is chosen to be the same). This completes the modelling part of the algorithm.

Modelling conditions:

- RI matrix: 15×15 elements;
- information content: binary image, object is formed by "1", background is "0";
- object size: 5×5 elements;
- shape of the object is a square of dimension 3×3;
- CI matrix: 8×8 elements;
- information content: binary image, object is formed by "1", background is "0";
- object matrix: 3×3 elements;
- object shape: the object is inscribed in a square matrix.

The total number of realisations processed in the series of realisations used to calculate one value of the probability of correct selection of an object in a segmented image P_c was N_z = 400.

Figures 2 – 7 show the results of the estimation of the object selection performance on the segmented image for two values of the signal-to-noise ratio $q = 0$ and $q = 4$.

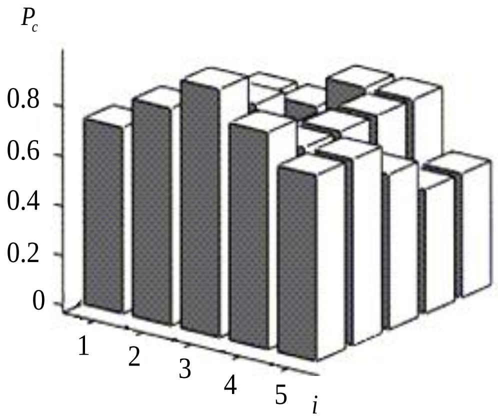

Fig. 2. The results of estimating the probability of object segmentation at: S = 50%, q ≈ 4.

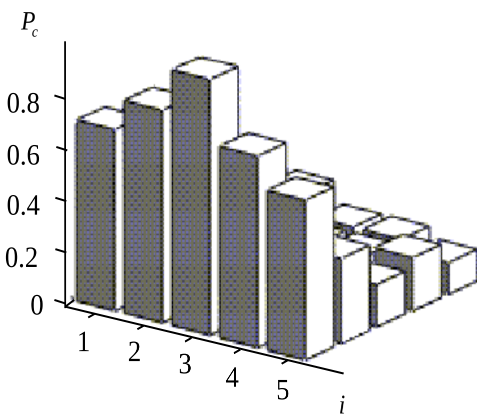

Fig.3. The results of estimating the probability. of object segmentation at: S = 50%, q ≈ 0.

The results of estimation of the probability of correct selection of an object in the segmented image are invariant with respect to the size and nature of the initial data, because P_c in accordance with (15 – 19) is determined by the values of the signal-to-noise ratio.

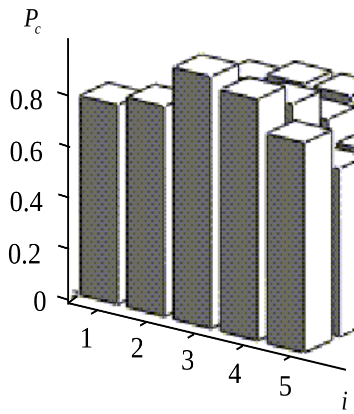

Fig. 4. The results of estimating the probability of object segmentation at: S = 70%, q ≈ 4.

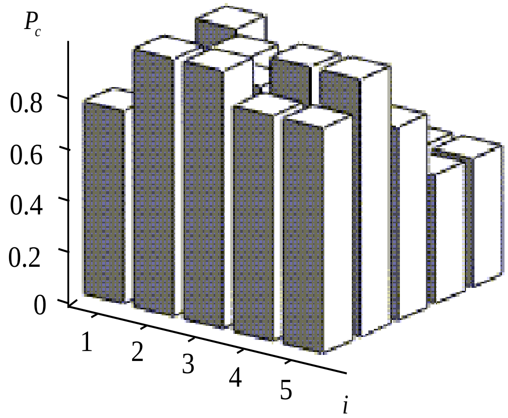

Fig. 5. The results of estimating the probability of object segmentation at: S = 70%, q ≈ 0.

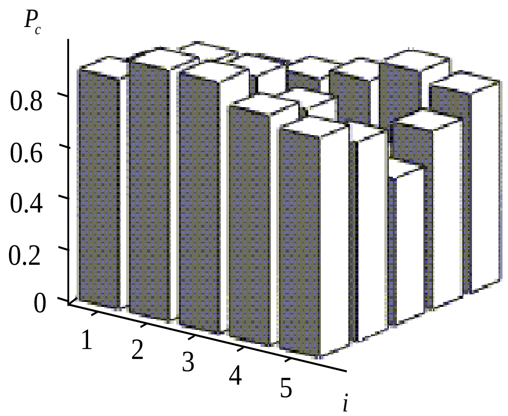

Fig. 6. The results of estimating the probability of object segmentation at: S = 90%, q ≈ 4.

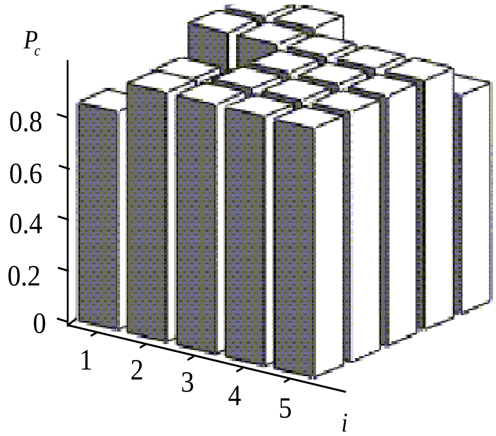

Fig. 7. The results of estimating the probability of object segmentation at: S = 90%, q ≈ 0.

The results of dependence $P_c = f(q)$ analysis showed that the influence of noise for CI of 8×8 size at distorted pixel area S from 0 to 0.31 provides P_c =0.9998...0.9172 for values β = 0.0161...0.1216, respectively. Distortion of more than 31% (S=0.31) of the image- pixels results in a reduction P_c to 0.9.

CONCLUSIONS

Thus, as a result of this research, a two-stage image segmentation procedure has been developed. It allows selecting the object of reference on the CI formed by the UAV's CENS. It is considered that the brightness of objects and backgrounds is measured by CENS sensors and processed information characteristic of SS. It allows to use the zone representation of the formed images due to the contrast between them.

It is shown that it is necessary to additionally use area characteristics of objects for selection of the object of reference on CI of sighting surfaces with heterogeneous and similar objects. As a result, the influence of perspective distortions of CI on the selection of the object of reference will decrease. Analytical relations for estimation of probability of correct selection of objects are obtained. These relations are a function of the selected quantisation threshold at each step of object selection considering errors of the first and second kind.

By means of modelling the efficiency of object selection on segmented CI depending on the quality of initial images is estimated. It is shown that application of the proposed approach to image segmentation allows to carry out object selection with probability not lower than 0.9 for typical values of signal-to-noise ratios of images formed by CENS in real conditions.

References

[1] Antyufeev V. Matrix radiometric correlation-extreme navigation systems for aircraft: monograph Ukraine, Kharkov: KhNU V.N. Karazin, 372 p.

[2] Sotnikov O., Kartashov V., Tymochko O., Sergiyenko O., Tyrsa V., Mercorelli P., Flores-Fuentes W. Methods for ensuring the accuracy of radiometric and optoelectronic navigation systems of flying robots in a developed infrastructure (eds) Machine Vision and Navigation. Springer, Cham, https://doi.org/10.1007/978-3-030-22587-2_16.

[3] Sotnikov A., Tarshyn V., Yeromina N., Petrov S., Antonenko N. A method for localizing a reference object in a current image with several bright objects, Eastern-European Journal of Enterprise Technologies. 2017. Vol. № 9 (87). pp. 68–74. DOI: 10.15587/1729-4061.2017.101920.

[4] Sterzhanov, M. V. Isolation of connected components in line binary images / M. V. Sterzhanov // Bulletin of TSU. – 2010. – T. 15, issue. 6. – S. 1934–1938.

[5] Kulikov E. I., Trifonov A. P. Estimation of signal parameters against a background of interference.— M.: Sov. radio, 1978. - 296 p.

[6] Abdollahi, A., Pradhan, B. (2021). Integrated technique of segmentation and classification methods with connected components analysis for road extraction from orthophoto images. Expert Systems with Applications, 12, 114908. https://doi.org/10.1016/j.eswa.2021.114908.

[7] Abdollahi, A., Pradhan, B. (2021). Integrated technique of segmentation and classification methods with connected components analysis for road extraction from orthophoto images. Expert Systems with Applications, 12, 114908. https://doi.org/10.1016/j.eswa.2021.114908.

[8] Bakhtiari, H. R. R., Abdollahi, A., Rezaeian, H. (2017). Semi automatic road extraction from digital images. The Egyptian Journal of Remote Sensing Space Science, 20 (1), 117-123. https://doi.org/10.1016/j.ejrs.2017.03.001.

[9] Senthilnath, J., Rajeshwari, M., Omkar, S. N. (2009). Automatic road extraction using high resolution satellite image based on texture progressive analysis and normalized cut method. Journal of the Indian Society of Remote Sensing, 37, 351361.

[10] Singh, P. P., Gard, R. D. (2013). Automatic road extraction from high resolution satellite image using adaptive global thresholding and morphological operations. Journal of the Indian Society of Remote Sensing, 41, 631-640.

[11] Grinias, I., Panagiotakis, C., Tziritas, G. (2016). MRF-based segmentation and unsupervised classification for building and road detection in peri-urban areas of high-resolution satellite images. ISPRS Journal of Photogrammetry and Remote Sensing, 122, 145-166. DOI: https://doi.org/10.1016/j.isprsjprs.2016.10.010.

[12] Li, X., Li, T., Chen, Z, et al. (2022). Attentively Learning Edge Distributions for Semantic Segmentation of Remote Sensing Imagery. Remote Sensing, 14 (1), 102. DOI: https://doi.org/10.3390/rs14010102.

[13] Kit, O., Lüdeke, M., Reckien, D. (2012). Texture-based identification of urban slums in Hyderabad, India using remote sensing data. Applied Geography, 32 (2), 660-667. DOI: https://doi.org/10.1016/j.apgeog.2011.07.016.

[14] Zhao, S., Wu, H., Tu, L., Huang, B. (2014). Segmentation of Urban Areas Using Vector-Based Model. 2014 IEEE 14th International Conference on Scalable Computing and Communications and Its Associated Workshops, 15557408. DOI: 10.1109/UIC-ATC-ScalCom.2014.89.

[15] Pan, Z., Xu, J., Guo, Y., Hu, Y., Wang, G. (2020). Deep Learning Segmentation and Classification for Urban Village Using a Worldview Satellite Image Based on U-Net. Remote Sensing, 12 (10), 1574. DOI: https://doi.org/10.3390/rs12101574.

[16] Mhangara, P., Odindi, J. (2013). Potential of texture-based classification in urban landscapes using multispectral aerial photos. South African Journal of Science, 100, 3-4. ISSN 1996-7489.

[17] Körting, T. S., Fonseca, L. M. G., Dutra, L. V., Silva, F. C. (2010). Image resegmentation applied to urban imagery. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXVII, B3b, 393-398. DOI: https://doi.org/10.13140/2.1.5133.9529.

[18] Dikmen, M., Halici, U. (2014). A Learning-Based Resegmentation Method for Extraction of Buildings in Satellite Images. IEEE Geoscience and Remote Sensing Letters, 11 (12), 2150-2153. DOI: https://doi.org/10.1109/LGRS.2014.2321658.

[19] Pandey, S., Khanna, P. (2014). A hierarchical clustering approach for image datasets. 9th International Conference on Industrial and Information Systems (ICIIS). DOI: 10.1109/ICIINFS.2014.7036504.

[20] Dhanachandra, N., Manglem, K., Chanu, Y. J. (2015). Image Segmentation using K-means Clustering Algorithm and Subtractive Clustering Algorithm. Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015), 764-771. DOI: 10.1016/j.procs.2015.06.090.

[21] Dao, N., Anh, D. N. (2015). Segmentation by Incremental Clustering. International Journal of Computer Applications, 111, 12, 24-30. DOI: 10.5120/19591-1360.

[22] Niharika, K., Adeeba, H., Krishna, A. S. R., Yugander, P. (2017). K-means based noisy SAR image segmentation using median filtering and Otsu method. 2017 International Conference on IoT and Application (ICIOT). DOI: 10.1109/ICIOTA.2017.8073630.

[23] Zheng, X., Lei, Q., Yao, R., Gong, Y., Yin, Q. (2018). Image segmentation based on adaptive K-means algorithm. EURASIP Journal on Image and Video Processing, 68 DOI: 10.1186/s13640-018-0309-3.

[24] Shah, N., Patel, D., Fränti, P. (2021). k-Means image segmentation using Mumford–Shah model.ränti // Journal of Electronic Imaging. – 2021. – Vol. 30. – Is. 6. DOI: 10.1117/1.JEI.30.6.063029.

[25] Abeysinghe, W., Wong, M., Hung, C.-C., Bechikh, S. (2019). Multi-Objective Evolutionary Algorithm for Image Segmentation. IEEE Southeast Con. DOI: 10.1109/SoutheastCon42311.2019.9020457.

Сведения об авторах / Information about authors.

Yeromina Nataliia Sergeevna
PhD, Senior Lecturer of the Department, Kharkiv National University of Radio Electronics. Area of interest: aircraft navigation, computer systems and technologies, EMR protection methods.
E-mail:ereminaport@gmail.com
ORCID: https://orcid.org/0000-0002-0463-2342

Tiurina Valeriia Yuryivna
PhD student (full-time) of the scientific and organizational department, Kharkiv National Air Force University named after Ivan Kozhedub, area of scientific interests: navigation.
E-mail:
valery.kharkiv@gmail.com

Breus Pavlo Petrovich,
PhD student, Deputy General Director of "URGA" Airlines, ATPL TRI Airbus A-320.
Area of interest: cybersecurity.
E-mail: ua-aircraft@ukr.net

Gnusov Yurii Valeryevich
PhD, Kharkiv National University of Internal Affairs.
Area of interest: cybersecurity.
E-mail: gyvduke@gmail.com
http://orcid.org/0000-0002-9017-9635

Udovenko Sergey Grigorievich
Doctor of Technical Science, Professor, Head of Department Simon Kuznets Kharkiv National University of Economics. Area of interest: intelligent systems digital data processing.
E-mail:
serhiy.udovenko@hneu.net ,
ORCID: https://orcid.org/0000-0001-5945-8647

Boichenko Oleksii Igorevich,
leading researcher – senior tester – parachutist of State Scientific Research Institute of Armament and Military Equipment Testing and Certification; area of scientific interests: search and rescue with the help of aviation on a water surface.E-mail:
aleksej_boichenko@ukr.net
ORCID: https://orcid.org/0000-0003-4664-4023

Onishchenko Yurii Nikolaevich
PhD, Kharkiv National University of Internal Affairs Area of interest: cybersecurity, artificial intelligence, management of cybersecuurity of critical infrastructure objects.
E-mail:
onischenko1980@gmail.com
ORCID: http://orcid.org/0000-0002-7755-3071

Svitlychnyi Vitalii Anatolievich,
PhD, Kharkiv National University of Internal Affairs
Area of interests: cybersecurity, artificial intelligence, E-mail:
vit.svet@ukr.net
ORCID: http://orcid.org/0000-0003-3381-3350