Study of the Impact of Changes in Image Informative Features in Navigation Control Systems on the Operation of Unmanned Aerial Vehicles

[1]Sotnikov A.M., [1]Tiurina V.Yu., [2]Petrov K.E., [2]Lukyanova V.A., [3]Dmitriiev O.N., [4]Udovenko S.G. and [4]Kobzev I.V.

[1]Kharkiv National Air Force University(KNAFU), Kharkiv, Ukraine
[2]Kharkiv National University of Radio Electronics, Kharkiv, Ukraine
[3]Institute of Armament and Military Equipment Testing and Certification, Cherkasy, Ukraine
[4]Simon Kuznets Kharkiv National University of Economic, Kharkiv, Ukraine

Abstract. The objective of this article is to determine the permissible changes in the informative characteristics of navigation control systems under the influence of destructive effects used to describe objects on the observation surface (OS), while maintaining a given level of unmanned aerial vehicles (UAV) efficiency. This objective is achieved by establishing an analytical relationship between the UAV efficiency indicator and the probability of localizing a reference object in the image; by studying the dependence of this probability on the characteristics of the decision-making function (DMF) it generates, with subsequent determination of its relationship with the permissible changes in the informative characteristics (IC). The solution to the first problem is based on a probabilistic approach to assessing the effectiveness of UAVs under destructive effects on objects on the observation surface (OS). The solution to the second problem is based on establishing a mathematical relationship between the probability of localizing a reference object and the characteristics of the decision-making function (DMF) it generates. The solution to the third problem consists in assessing the permissible changes in stable informative features of an image (IF), at which the computer vision system (CVS) remains operational. The study was conducted in the MATLAB software environment using images obtained from Google Earth. It has been shown that the permissible changes caused by destructive impacts, in terms of the change in the area of the reference object, are within the range of (10–15)% of their total area, regardless of the type of observation surface (OS).
Keywords: unmanned aerial vehicle, computer vision system, reference object, informative features, destructive impact.

DOI: https://doi.org/10.52254/1857-0070.2026.1-69.06
UDC: 629.7.05-52:004.932

Studiu al impactului modificărilor caracteristicilor informațiilor de imagine asupra funcționării vehiculelor aeriene fără pilot în sistemele de control al navigației

[1]Sotnikov A.M, [1]Tiurina V.Yu., [2]Petrov K..E., [2]Lukyanova V.A.,[3]Dmitriiev O.N., [4]Udovenko S.G., [4]Kobzev I.V.
[1]Universitatea Națională a Forțelor Aeriene din Harkov (KNAFU), Harkov, Ucraina
[2]Universitatea Națională de Radioelectronică din Harkov, Harkov, Ucraina
[3]Institutul de Testare și Certificare a Armamentului și Echipamentului Militar, Cerkasî, Ucraina
[4]Universitatea Națională de Economie Simon Kuznets din Harkov, Harkov, Ucraina
Rezumat. Scopul lucrării este de a determina modificările permise în sistemele de control al navigației ale caracteristicilor informative sub influența efectelor distructive utilizate pentru a descrie obiectele suprafeței de ochire (SS), la care se menține un anumit nivel de eficiență a vehiculelor aeriene fără pilot (UAV). Acest obiectiv este atins prin stabilirea unei relații analitice între indicatorul de eficiență al UAV și modificările permise ale caracteristicilor informative sub influența factorilor distructivi. Soluția la prima problemă se bazează pe o abordare probabilistică a evaluării eficienței UAV. Soluția la a doua problemă se bazează pe stabilirea unei relații matematice între probabilitatea localizării unui obiect de referință și caracteristicile funcției de decizie. Se obțin relații analitice pentru o estimare asimptotică a probabilității localizării obiectelor de referință. Soluția la a treia problemă implică evaluarea modificărilor permise ale caracteristicilor informative ale imaginilor. Studiul a fost efectuat în mediul software MATLAB utilizând imagini preluate de pe Google Earth. Se demonstrează că modificările permise cauzate de impacturi distructive în ceea ce privește modificarea ariei unui obiect de referință se încadrează în (10...15)% din aria lor totală, indiferent de tipul suprafeței de ochire. Cel mai semnificativ rezultat este determinarea modificărilor permise ale caracteristicilor informative care mențin un anumit nivel de eficiență a UAV-ului. Semnificația rezultatelor obținute constă în determinarea

erorii permise în localizarea unui obiect, care leagă valorile funcției de decizie cu varianța și intervalul de corelație al acesteia.
Cuvinte-cheie: vehicul aerian fără pilot, sistem de vedere artificială, obiect de referință, caracteristici informative, impact distructiv.

Исследование влияния в системах управления навигацией изменений информативных признаков изображений на функционирование беспилотных летательных аппаратов

[1]Сотников А.М., [1]Тюрина В.Ю., [2]Петров К.Э., [2]Лукьянова В.А.,[3]Дмитриев О.Н., [4]Удовенко С.Г., [4]Кобзев И.В.
[1]Харьковский национальный университет Воздушных Сил имени Ивана Кожедуба, Харьков, Украина
[2]Харьковский национальный университет радиоэлектроники, Харьков, Украина
[3]Институт испытаний и сертификации вооружения и военной техники, Черкассы, Украина
[4]Харьковский национальный экономический университет имени Семена Кузнеца, Харьков,
Аннотация. Целью статьи определение допустимых изменений в системах управления навигацией информативных признаков под влиянием деструктивных воздействий, используемых для описания объектов поверхности визирования (ПВ), при которых сохраняется заданный уровень эффективности беспилотных летательных аппаратов (БПЛА). Поставленная цель достигается путем установления аналитической связи показателя эффективности БПЛА с вероятностью локализации объекта привязки на изображении; исследования зависимости этой вероятности от характеристик формируемой ею решающей функции (РФ) с последующим определением ее связи с допустимыми изменениями информативных признаков (ИП) под воздействием деструктивных факторов. Решение первой задачи основано на вероятностном подходе к оценке эффективности БПЛА в условиях деструктивных воздействий на объекты поверхности визирования (ПВ). Получено аналитическое соотношение для оценки вероятности местоопределения БПЛА, показана ее взаимосвязь с РФ. Решение второй задачи базируется на установлении математической зависимости между вероятностью локализации объекта привязки и характеристиками формируемой ею РФ. Получены аналитические соотношения для асимптотической оценки вероятности локализации объектов, численно связанные с параметрами РФ. Решение третьей задачи заключается в оценке допустимых изменений робастных ИП изображений, при которых система технического зрения (СТЗ) сохраняет работоспособность. Исследование выполнено в программной среде MATLAB с использованием изображений, взятых из Google Earth. Показано, что допустимые изменения, обусловленные деструктивным воздействием по показателю изменения площади объекта привязки, находятся в пределах (10…15)% от их общей площади, независимо от типа ПВ. Наиболее существенным результатом является определение допустимых изменений ИП, при которых сохраняется заданный уровень эффективности БПЛА. Значимость полученных результатов состоит в определении допустимой ошибки локализации объекта, связывающей значения РФ с ее дисперсией и интервалом корреляции, а также в возможности прогнозирования эффективности применения БПЛА на этапе формирования РФ.
Ключевые слова: беспилотный летательный аппарат, система технического зрения, объект привязки, информативные признаки, деструктивное воздействие.

INTRODUCTION

The intensive development of unmanned aerial vehicles (UAVs), continuously accompanied by rapid modernization, has led to a significant expansion of their application domains [1]. This has been made possible by improvements in sensing and data acquisition technologies, the adoption of new methods for real-time data processing, the emergence of lightweight and high-strength materials, and the capability for autonomous operation without operator involvement.

Owing to their ability to ensure high efficiency and accuracy of monitoring, UAVs have become an integral component in the inspection of critical infrastructure facilities, such as energy and transportation infrastructure, industrial sites, agricultural crops, forests, and many other objects requiring survey and assessment. In addition, UAVs have been widely adopted in search and rescue operations, in the monitoring of natural disasters, and for the prompt assessment of evolving situations.

A key role in the autonomous navigation of UAVs is played by strapdown inertial systems, which are complemented by computer vision systems. These systems, along with refining the UAV position, simultaneously perform monitoring and visual inspection of the surveyed objects [2–3].

The composition of a computer vision system may vary significantly depending on the intended purpose of the UAV, which determines the possibility of using such information acquisition sensors as radar, radiometric, and optoelectronic sensors.

The quality of system operation and, consequently, the quality of the extracted information depend on many factors, the influence of which inevitably leads to variations in the informative features characterizing the observed objects.

These factors can be divided into three groups. The first group of factors is associated with the state of the propagation medium of the computer vision system operating signals. The second group is related to the information acquisition sensors themselves and to the system of primary and secondary data processing. Finally, the third group is associated with the information source, which is the viewing surface (VS) and the objects located on it.

Factors determining the state of the signal propagation medium include any physical obstacles that may, for example, cause signal blockage or reflection, as well as signal shielding. They also include weather conditions associated with precipitation, fog, and cloud cover, which lead to signal absorption or scattering.

The second group of factors includes UAV vibration and instability, which affect the formation and processing of the acquired information. Finally, the third group of factors comprises the source of the original information itself, namely the viewing surface and the monitoring objects located on it.

A considerable number of studies [2–9] are devoted to the influence of these factors on the efficiency of computer vision systems, proposing various approaches to mitigating their effects. The influence of the first two groups of factors has been studied in the greatest detail. The third group has also been addressed from the standpoint of the source of the original information. In this case, it is commonly assumed that the information source is stable in its characteristics and invariant over time, possesses certain geometric and structural features, and provides sufficient discriminability by the corresponding sensors to ensure reliable operation of the UAV computer vision system. However, changes in the original information caused, for example, by destruction, deformations, or changes in the positions of objects, the appearance of new objects leading to alterations in the overall image structure, or the rapid intentional modification of geometric dimensions through the use of masking materials and films, will inevitably result in changes in the informative features used by the computer vision system sensors and, consequently, in a reduction in UAV operational effectiveness. Based on this, there arises a need to investigate the permissible robust changes in informative features under which the system remains operational with the required level of effectiveness.

Literature Review.

In computer vision systems, the determination of the position of autonomous UAVs is based on the comparison of reference and current images generated during the UAV flight. Discrepancies between these images critically affect UAV operational effectiveness and may even result in failure to accomplish the intended mission. The problem of UAV position determination using computer vision systems under conditions that cause image mismatches has been addressed in numerous studies, particularly in [1–5].

Methods for improving the efficiency of computer vision systems, based on the use of additional informative features for image description, are discussed in [10–21].

In [10], an approach to object image recognition in unmanned systems based on the image signatures of their contours was investigated. In [11], to address mismatches between visual features of a reference map fragment and images captured from the UAV, it is proposed to use correspondences of deep features extracted through unsupervised learning using a triplet-loss framework. Additionally, the study suggests the supplementary use of visual odometry with a procedure for anchoring to the reference map after obtaining a sufficient number of features, accompanied by the generation of hypotheses regarding the UAV's position. This approach enables the planning of flight paths over terrain with sufficient feature diversity required for navigation.

In [13], the results of modeling the influence of meteorological conditions on UAV automatic landing performance are presented. Methods for simulating meteorological conditions were developed, and UAV landing tests on a platform were conducted under conditions simulating wind, changes in illumination, fog, precipitation, as well as their combinations. Analysis of the results demonstrated the impact of meteorological conditions on the UAV landing time, with consideration of wind leading to a significant increase in landing duration.

In [14], to reduce the impact of scale and viewpoint changes on image matching accuracy, a localization method using semantic segmentation and topological features was proposed. This method reduces the effect of scale and orientation variations on image matching accuracy, improves the precision and reliability of matching, and significantly lowers computational requirements for the reference map database.

In [15], a hybrid CNN–Transformer network model is proposed for the detection and matching of image features. ResNet50 is used as the backbone network for feature extraction. An enhanced feature fusion module is employed to combine feature maps from different levels, followed by a Transformer encoder–decoder structure for feature matching to obtain preliminary correspondences. To eliminate mismatched points based on the geometric similarity of internal points, a geometric outlier removal method is applied, resulting in more reliable correspondences.

In [16], to improve learning efficiency, an enhanced deep reinforcement learning approach is proposed, comprising two distinct training stages: reinforcement learning and self-supervised learning. During the reinforcement learning stage, a deep Q-network (DQN) was implemented and trained using the Bellman equation loss function. The self-supervised learning stage, on the other hand, is responsible for fine-tuning the DQN’s base layers and is guided by a contrast loss function. The main advantage of incorporating the self-supervised stage is the accelerated encoding of the input scene captured by the UAV camera. To further enhance navigation efficiency, an obstacle detection model was implemented, reducing the number of UAV collisions.

In [17], a method for detecting ground landmarks during autonomous mobile robot navigation is proposed, based on the distribution features of average color intensity across the columns of the robot’s camera matrix. It is shown that exceeding the threshold value of the determinant product indicates the detection of a ground landmark.

In [18], the use of autonomous navigation for mobile robots in indoor environments with vision sensors is examined. It is shown that computer vision systems can be used for object recognition in robot control applications. The results demonstrate that a mobile robot can be successfully controlled using a webcam that detects objects and distinguishes a tennis ball based on its color and shape.

In [19], a navigation algorithm is proposed that simultaneously determines the positions of robots and updates landmarks within an industrial environment. The study investigates the improvement of localization accuracy for mobile robots in continuous operation, where a Kalman filter is applied to integrate odometry data with scanner data to achieve the required reliability and precision.

In [20], a system for object detection by an autonomous mobile robot using an artificial neural network is presented. It is noted that autonomous robotic systems with obstacle detection capabilities are relatively complex, as extracting information from an image stream of the environment, consisting of the robot and obstacles, can be a very challenging task to achieve real-time performance with minimal computational cost. It is demonstrated that the use of computer vision enables the development of systems capable of navigating the surrounding environment.

In [21], the behavior of stereo vision based on correlation is analyzed with the aim of identifying ways to improve its quality while maintaining real-time applicability. Three methods are proposed: two are aimed at enhancing disparity images, and one is designed to detect potential errors overall.

Results are presented for real stereo images with ground-truth data. Comparison with five standard correlation methods shows that improvements to basic stereo correlation are achievable in real time on modern computer hardware.

In [22], a method for calculating the reliability of computer vision systems is presented. A probabilistic approach using a neural network demonstrated that the probability of errors in information processing and the probability of code combination transformation are negligibly small compared to the probability of incorrect image classification.

Thus, despite a wide range of studies, to date, issues related to the impact of changes in informative features extracted by computer vision systems under the influence of destructive effects and infrastructure alterations—while ensuring the required level of UAV operational effectiveness—have not been adequately addressed.

The aim of the study is to determine the permissible changes in informative features within navigation control systems, under the influence of destructive effects used to describe viewing surface objects, at which a specified level of UAV effectiveness is maintained.

This will make it possible to avoid incorrect localization of the reference point (RP) or the inspected control object depending on the degree of destructive effects on VS objects, and, consequently, to ensure the required operational effectiveness of UAVs.

To achieve the stated goal, it is first necessary to address the following tasks:

1. Formulate the problem of assessing the effectiveness of UAVs equipped with computer vision systems under conditions of destructive effects on viewing surface (VS) objects.
2. Justify a criterion for determining the permissible localization error of the reference object.
3. Determine the limits of permissible changes in the informative features of observed objects, under which the computer vision system remains operational.

METHODS, RESULTS AND DISCUSSION

According to the findings of [2, 4, 22], the probability of accomplishing the mission is used as the indicator of effectiveness for UAVs equipped with computer vision systems (CVS). This probability serves as an integral measure, taking into account both the reliability of the UAV itself and the efficiency of its navigation system. Let us consider that the hardware of an autonomous UAV navigation system includes a strapdown inertial navigation system (SINS) and an auxiliary computer vision system that corrects the UAV's coordinates. Based on this, the probability of accomplishing the mission by autonomous UAVs—represented as the probability of UAV position determination P_M — can be expressed as:

$$P_M = P_к \left(1 - e^{-(R_{кс}/\sigma_и)^2}\right)\left(1 - e^{-(R_{оп}/\sigma_{кс})^2}\right) + \left(1 - P_к\right)\left(1 - e^{-(R_{оп}/\sigma_и)^2}\right), \tag{1}$$

where:

$P_к$ – probability of successful position correction by the CVS;

$R_{кс}$ – effective radius of the CVS;

$\sigma_и$ – root mean square error (RMSE) of the strapdown INS;

$R_{оп}$ – dimensions of the reference object;

$\sigma_{кс}$ – RMSE of the corrective CVS.

Formulation of the Problem of assessing UAV effectiveness equipped with computer vision systems under destructive effects on viewing surface objects.

In (1), the probability of successful CVS correction $P_к$, generally depends on a multitude of random factors, grouped above into three categories. Since the UAV navigation problem is solved taking into account only the impact of destructive factors on viewing surface (VS) objects $P_к$ is effectively determined by the probability of localizing the reference object in the image $P_л$. This probability, in turn, is determined by the decision function (DF) generated by the CVS, which at time t can be represented as:

$$\mathbf{R}(\mathbf{r},t) = \mathbf{F}_{SP}\begin{pmatrix} \mathbf{S}_{CI}(\mathbf{r},t), \\ \mathbf{S}_{RI} = \left\| S_{RI}(i,j) \right\|_{\substack{i=\overline{1...M} \\ j=\overline{1...N}}} \end{pmatrix}, \tag{2}$$

where:

$\mathbf{F}_{SP}$ – image comparison operator;

$\mathbf{S}_{CI}(\mathbf{r},t)$ – current image (CI) of $\mathrm{M} \times \mathrm{N}$;

$\mathbf{r}$ – UAV spatial position vector;

$\mathbf{S}_{RI}$ – reference image (RI);

i, j – coordinates of the viewing surface image element.

Based on the above reasoning, the effectiveness of UAVs equipped with computer vision systems under destructive effects on viewing surface (VS) objects will be determined by the correspondence of the current image (CI) to the reference image (RI) stored in the onboard computer memory.

Thus, to ensure the required effectiveness of UAVs equipped with computer vision systems under destructive effects on VS objects, it is necessary to maintain an appropriate probability of localizing the reference point (RP) in the image $P_л$ in accordance with the selected global threshold of the decision function.

Since the CI and RI, after the segmentation procedure, represent a set of informative features describing VS objects, there arises a need to investigate the boundary changes of these informative features under the influence of destructive factors, at which the required probabilities $P_л$ and, consequently, P_M are maintained.

2. Justification of the Criterion for Determining the Permissible Localization Error of the Reference Object.

The choice of a criterion for determining the permissible localization error of the reference object is made based on the task solved by the navigation system and the principles of its design.

Since the determination of the UAV's deviation from the specified trajectory is performed by comparing images, the normalized cross-correlation coefficient (NCC) is used as a measure of similarity, allowing the establishment of a strict threshold for the decision function.

The position of the NCC maximum provides an estimate of the object coordinates, while the resulting correlation analysis field enables localization of the reference point with subpixel accuracy. In other words, using the NCC as the criterion for determining the permissible localization error of the reference object allows highly accurate UAV position determination.

In the case of a high degree of similarity between the compared images, the correlation function will be unimodal, with minor side outliers. However, under destructive effects on viewing surface (VS) objects, the correlation analysis field, instead of a single sharp maximum, will exhibit multiple small outliers, and several local maxima of comparable amplitude may appear. In such cases, localization errors of the reference point—referred to as anomalous errors—can occur. When such errors arise, the computer vision system may select a peak that does not correspond to the true position of the reference point in the image, which inevitably leads to a significant reduction in the probability of reference point localization, serious UAV position determination errors, collisions with obstacles, or loss of orientation.

Based on the above reasoning, let us consider the case when, as a result of image comparison, the generated decision function contains, along with the main peak, several additional peaks.

For simplicity of reasoning, let us represent the decision function (DF) in a one-dimensional form.

We then move to a discrete representation in the form of its values $R\ l_i$ at n points $l_i = i\tau_k$.

τ_k – the interval between DF values at points where they become statistically independent (correlation interval).

Thus, the values $R\ l_i = R(i\tau_k)$ will be statistically independent, and one of the n points will coincide with the true value of the parameter l_0. With this representation, the probability of correct localization of the reference point by the computer vision system, according to [23], can be expressed as:

$$P_л = P\left[R(k) > R(i), i = 1,2,\ldots,n,\ i \neq k\right], \qquad (3)$$

where:

$n = \dfrac{L}{\Delta_L} + 1$ – number of DF outliers;

L – a priori interval of possible DF values.

Accordingly, the probability of anomalous localization of the reference point can be expressed as:

$$P_a = 1 - P_л = P[R(i) > R(k), i \neq k]. \qquad (4)$$

Let us denote by $f_{R(k)}(\acute{r})$ the distribution function of DF values at the points corresponding to the true UAV position, and by $f_{R(i)}(\acute{r})$ the distribution function of DF values in the region of side branches. Then expression (3) can be written as:

$$P_л = \int_{-\infty}^{\infty} \prod_{\substack{i=1 \\ i \neq k}}^{N} \left[\int_{-\infty}^{R} f_{R(i)}(y)\,dy\right] f_{R(k)}(R)\,dR, \qquad (5)$$

The multiplier $\prod_{\substack{i=1 \\ i \neq k}}^{N} \int_{-\infty}^{R} f_{R(i)}(y)\,dy$ in expression (5) will be denoted as $P_n(R)$.

Then, assuming that the variables $R(i)$ and $R(k)$ are independent normally distributed random variables and omitting intermediate transformations, expression (5) can be written in its final form:

$$P_Л = \frac{1}{\sqrt{2\pi\sigma_c^2}} \int_{-\infty}^{\infty} exp\left\{-\frac{[y - \langle R(k)\rangle]^2}{2\sigma_c^2}\right\} \times$$
$$\times \prod_{\substack{i \neq k \\ i=1}}^{N} \Phi\left[\frac{y - \langle R(i)\rangle}{\sigma_n}\right] dy, \qquad (7)$$

where:

σ_c^2 – variance of $R(k)$;

$\langle \cdot \rangle$ – expected value;

$\Phi(x)$ – probability integral;

σ_n – root mean square deviation of $R(i)$.

The assumption of normally distributed noise and signals for short accumulation times, which is typical for systems of this class, is a classical and mathematically justified approach.

Taking into account the random nature of the variables in (7) and using the Laplace method to estimate the asymptotics of certain integrals [24], the range of variation of $P_л$ was determined. For this purpose, based on the three-sigma method, which allows determining the boundaries of reliable system operation and identifying anomalous errors, expression (5) is represented as:

$$P_л \approx \frac{1}{\sqrt{2\pi}\sigma_c} \int\limits_{R(k)-S\sqrt{2}\sigma_c}^{R(k)+S\sqrt{2}\sigma_c} e^{-\frac{\left(y-<R(k)>\right)^2}{2\sigma_c^2}} \times \tag{8}$$

$$\times \prod_{\substack{i \neq k \\ i=1}}^{N} \Phi\left(\frac{y-<R(i)>}{\sigma_n}\right) dy,$$

where $S \approx 3...4$.

Taking into account (8), the minimum and maximum values of $P_л$ were determined for $\sigma_c \to 0$ and $\sigma_n \to \infty$, fixing the corresponding expected values and root mean square deviations of the decision function (DF) in the regions of the main peak and side outliers.

For $\sigma_c \to 0$, the asymptotic estimate of $P_л$ is obtained as:

$$P_л \approx \sqrt{\frac{\pi}{2}} \sigma_c F(R(k)) + 0(\sigma_c) \approx \tag{9}$$

$$\approx \sqrt{\frac{\pi}{2}} \sigma_c \prod_{\substack{i=1 \\ i \neq k}}^{n} \Phi\left(\frac{<R(k)> - <R(i)>}{\sigma_n}\right) + 0(\sigma_c).$$

For $\sigma_n \to \infty$, the asymptotic estimate of $P_л$ is obtained as:

$$P_л \approx \frac{1}{\sqrt{2\pi}\sigma_c} \int\limits_{R(k)-A\sqrt{2}\sigma_c}^{R(k)+A\sqrt{2}\sigma_c} e^{-\frac{\left(y-<R(k)>\right)^2}{2\sigma_c^2}} \times \tag{10}$$

$$\times \prod_{\substack{i=1 \\ i \neq k}}^{n} \left[\frac{1}{2} + \frac{1}{\sqrt{2\pi}} \frac{y-<R(i)>}{\sigma_n}\right] dy.$$

Expressions (9) and (10) establish a fundamental mathematical relationship between the probability of reference point localization by the computer vision system and the characteristics of the decision function (DF) it generates. These analytical relationships numerically link the DF parameters (its maximum variance) with the probability of localizing the reference object.

Thus, the proposed approach for selecting the criterion of permissible localization error of the reference object, within the framework of expressions (9) and (10), connects the DF value, above which the system decides that the object is present, with its variance and correlation interval.

The results of the numerical evaluation of $P_л$ under destructive effects on the viewing surface, depending on the number of DF side outliers and the ratio of the root mean square deviations of the DF in the main peak region and in the side outliers, are shown in Fig. 1.

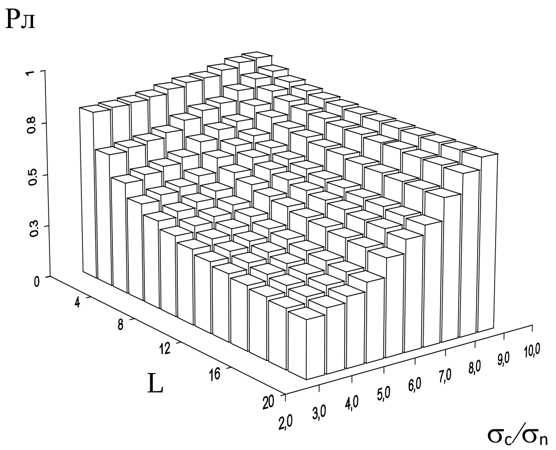

Fig. 1. Graph of the dependence of the probability of localization of an object on the number of side emissions of the decision function and the ratio of the standard deviations of the decision function in the region of the main lobe and side emissions.

From the dependence shown in Fig. 1, it is evident that reducing the correlation interval and the variance of the decision function (DF) decreases the localization error of the reference point.

The proposed approach also allows forecasting $P_{л}$ at the stage of DF formation, based on the physical properties of the reference image (RI) through the correlation interval and the DF formation conditions through the variance.

Moreover, expressions (9) and (10) make it possible to assess how detailed the RI must be or what the minimum size of the reference object should be to ensure the required probability of computer vision system operation, based on the statistical properties of the DF.

At the same time, the direct application of the proposed approach necessitates further research to determine the relationship between the DF and permissible changes in the informative parameters of the reference object under the influence of destructive factors or anthropogenic modifications.

3. Determination of Permissible Changes in Robust Image Informative Features Ensuring Computer Vision System Operability

This task was addressed through modeling in the MATLAB software environment. Cases with varying degrees of changes in viewing surface (VS) images, caused by destruction or anthropogenic alterations, were considered.

<u>Input Data for Modeling:</u>

1. Terrain area images were randomly selected from Google Earth.
2. The images were converted to binary form: black (0) corresponds to the background, and white (1) corresponds to significant objects.
3. The influence of external random factors, other than destructive effects causing image noise, was not considered.
4. The impact of scale and perspective distortions on the images was not considered.
5. Destructive effects on the reference object resulted in changes in its area by 5%, 10%, and 15%.
6. Image comparison was performed using an algorithm based on detection and multi-threshold selection of the reference object in the current image, containing multiple bright objects.

Changes in the area of the reference regions were studied, with the original images shown in Fig. 2 and Fig. 7. The sections highlighted with rectangles were selected as the reference regions, with their corresponding reference images presented in Fig. 3 and Fig. 8.

Images of the reference regions with a 5% change in area are shown in Fig. 4 and Fig. 9, respectively.

Images of the reference regions with a 10% change in area are shown in Fig. 5 and Fig. 10, respectively.

Images of the reference regions with a 15% change in area are shown in Fig. 6 and Fig. 11, respectively.

Fig. 2. The original image of the sighting surface with the reference area highlighted.

Fig. 3. Reference image.

Fig. 4. Current image with the anchor area area changed by 5%.

Fig. 5. Current image with the anchor area area changed by10%.

Fig. 6. Current image with the anchor area area changed by15%.

Fig. 7. The original image of the sighting surface with the reference area highlighted.

Fig. 8. Reference image.

Fig. 9. Current image with the anchor area area changed by 5%.

Fig. 10. Current image with the anchor area area changed by 10%.

Fig. 11. Current image with the anchor area area changed by 15%.

As a result of comparing the reference image (RI) shown in Fig. 2 with the current images (CIs) having modified areas of the reference regions, corresponding decision functions (DFs) were constructed for the images shown in Fig. 4,

Fig. 5, and Fig. 6, presented in Fig. 12, Fig. 13, and Fig. 14.

The DFs obtained from the comparison of the RI shown in Fig. 8 with the CIs shown in Fig. 9, Fig. 10, and Fig. 11 are presented in Fig. 15, Fig. 16, and Fig. 17, respectively.

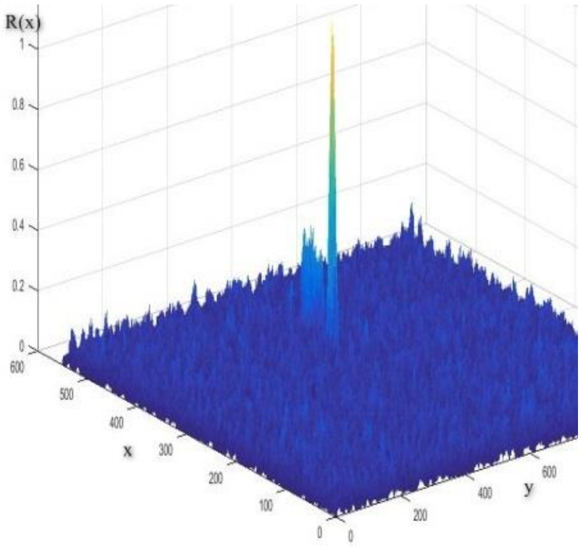

Fig. 12. The decision function for the case of a 5% change in the area of the reference object in the current image.

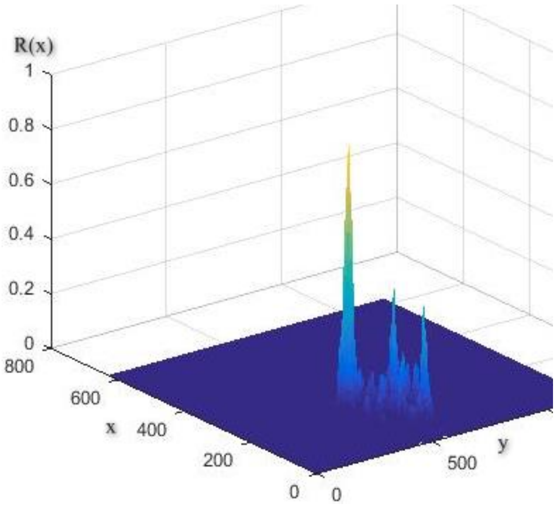

Fig. 13. The decision function for the case of a 10% change in the area of the reference object in the current image.

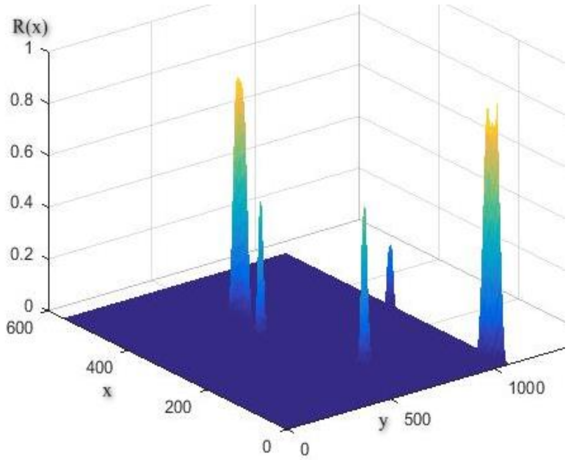

Fig. 14. The decision function for the case of a 15% change in the area of the reference object in the current image.

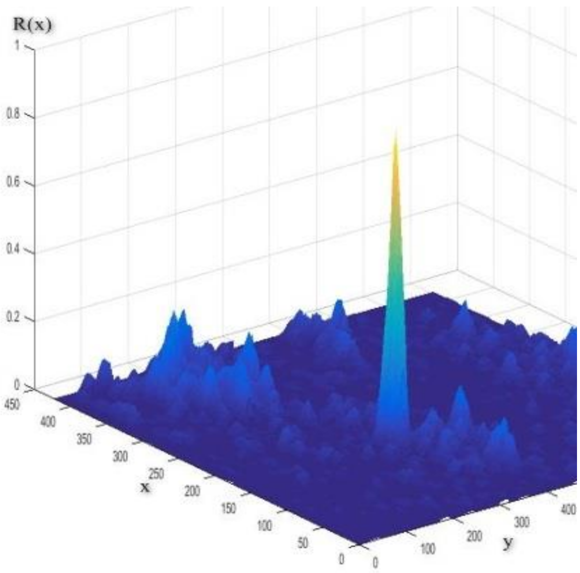

Fig. 15. The decision function for the case of a 5% change in the area of the reference object in the current image.

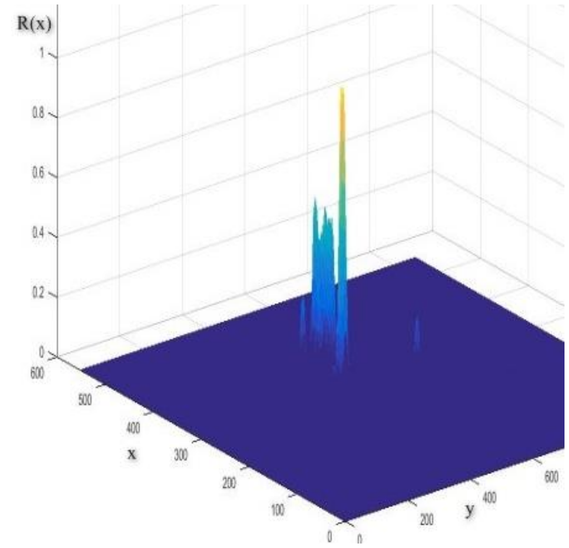

Fig. 16. The decision function for the case of a 10% change in the area of the reference object in the current image.

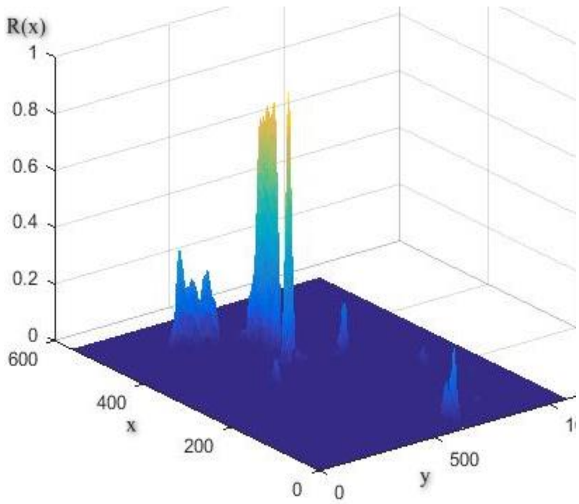

Fig. 17. The decision function for the case of a 15% change in the area of the reference object in the current image.

Analysis of the DF modeling results shown in Figures 12–17 indicates that permissible changes caused by destructive effects on the reference object, measured by changes in its area, lie within the range of 10–15% of its total area, regardless of the type of viewing surface (VS). Under such changes, side outliers appear in the DF that are comparable in magnitude to the main peak. These outliers are sufficiently critical for the effective operation of UAVs under robust changes in informative features, becoming particularly critical when localizing small-sized objects.

To ensure the effective operation of UAVs equipped with computer vision systems under significant changes in informative features, it becomes evident that a shift is needed from classical approaches—which require precise prior knowledge of the statistical characteristics of signals and noise—toward adaptive processing. This adaptive approach allows the system to adjust its parameters to the changing characteristics of input data (images) and the external environment.

In other words, it is necessary to move from a rigid mathematical model to a flexible approach that compensates for emerging uncertainties, thereby reducing anomalous errors under the complex operating conditions of UAVs.

CONCLUSIONS

As a result of the conducted studies, the feasibility of applying a probabilistic approach to assessing UAV effectiveness under destructive effects on viewing surface (VS) objects has been substantiated. An analytical expression was obtained for the numerical evaluation of the probability of UAV position determination under conditions of infrastructural changes and destructive effects on VS objects. The relationship between the probability of UAV position determination and the characteristics of the reference and current images, and consequently the characteristics of the generated decision function (DF), was demonstrated.

A criterion for determining the permissible localization error of the reference object was justified. Within the probabilistic framework, it is proposed to use a statistical probability threshold, whereby an error is considered permissible if the probability that the DF value for the true UAV position exceeds the values for objects outside the region of interest is above the minimally required level.

A mathematical relationship between the probability of reference object localization and the characteristics of the generated DF was established. Analytical relationships were derived for the asymptotic evaluation of object localization probability, numerically linked to DF parameters.

Through modeling in the MATLAB environment, it was shown that permissible changes in the informative features of the reference object, caused by destructive effects and measured by changes in area, lie within 10–15% of the total area, regardless of the type of VS. Under these changes, side outliers appear in the DF, comparable in magnitude to the main peak.

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Information about authors.

Sotnikov Alexander Mykhailovych, Doctor of Technical Sciences, Professor, leading researcher, Kharkiv National Air Force University, Kharkiv, Ukraine; area of scientific interests: Navigation systems for mobile robots.
E-mail: alexsot@ukr.net.
ORCID: https://orcid.org/0000-0003-2985-3704

Tiurina Valeriia Yuryivna
Doctor of Philosophy, Senior Researcher of Scientific and Methodical Department of Kharkiv National Air Force University, Kharkiv,Ukraine, area of scientific interests: Navigation systems .
E-mail: valery.kharkiv@gmail.com
ORCID: https://orcid.org/0000-0003-3444-143X

Petrov Konstantin Eduardovich
Doctor of Technical Sciences, Professor, Department of Information Control Systems Kharkiv National University of Radio Electronics
E-mail: kostiantyn.petrov@nure.ua
ORCID: https://orcid.org/0000-0003-1973-711X

Lukianova Viktoriia Anatolyevna
Doctor of Philosophy, Department of higher mathematics, Faculty of Physics V. N. Karazin Kharkiv National University
E-mail: vlukyanova@karazin.ua
ORCID: https://orcid.org/0000-0001-7476-3746

Dmitriiev Oleh Nikolaevich
Doctor of Engineering Science Professor Leading Researcher of Scientific Research Institute of Armament and Military Equipment Testing and Certification, Cherkasy, Ukraine
E-mail: dmitriievoleh@gmail.com
ORCID: https://orcid.org/0000-0003-1079-9744

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

Kobzev Igor Volodymyrovych
Candidate of Technical Sciences. Associated professor Department of informatics and computer technique Simon Kuznets Kharkiv National University of Economic; area of interest: systems digital data processing.
E-mail: ikobzev12@gmail.com,
ORCID: http://orcid.org/0000-0002-7182-5814