Basics of building a system for detection, accounting and visualization of explosive objects

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Abstract

The aim of the study was to develop a structural and functional model of an automated system for detecting, recording and spatial visualization of explosive objects in the field. The work proposes stages of organizing a system for detecting, recording and visualizing explosive objects using UAVs equipped with infrared sensors. The article describes in detail the fundamental principles of mission organization, including flight log generation and flight controller software. The methodology for creating a survey map of an agricultural area with explosive remnants of war is outlined, justifying its use as the only safe method for conducting stabilization activities in newly liberated areas. A significant part of the work focused on the classification of UAV survey areas and the modelling of the camera focal length. The task of determining the location of objects (remains, explosive devices, debris) in the experimental field was considered and solved. The work performed camera calibration, implemented the projection of spatial points into the image plane using OpenCV, analyzed the increase in errors when deviating from the optical axis and the effect of automatic exposure on contrast, which ensured the correctness of the subsequent determination of object coordinates. The stages of the organization included a comprehensive plan for the implementation of UAVs in high-risk environments. Flight log generation and firmware creation were crucial to ensuring accurate data collection and UAV performance. The creation of survey maps not only helped identify hazardous areas, but also played a crucial role in planning demining operations and ensuring personnel safety. Using infrared sensors, the system was able to detect explosive objects that were invisible to the naked eye, providing a higher level of accuracy and safety. In addition, the classification of the study areas was important for the efficient allocation of resources during mission planning. Modelling the camera's focal length helped optimize the UAV's ability to capture clear and detailed images of the terrain, ensuring accurate documentation of every aspect of the area under investigation, which is vital for the next steps in the demining process.

Keywords

registration and visualization system, flight organization principles, overview map, infrared sensors, classification of objects in the viewing area

1. Introduction

The large-scale military operations on the territory of Ukraine have led to extensive contamination of land with explosive remnants and other hazardous elements. The return of civilians to de-occupied areas and the subsequent restoration of infrastructure, including agricultural and industrial facilities, critically depends on effective and timely demining. In this context, the challenge of ensuring safe land use becomes a strategic priority for decades to come. Traditional demining methods, while indispensable, are characterised by high risk, limited speed, and low efficiency under conditions of complex terrain and irregular contamination patterns. Therefore, there is a growing need for advanced technological solutions capable of increasing the safety, accuracy, and efficiency of mine detection and clearance. The use of automated systems based on unmanned aerial vehicles (UAVs), intelligent mission planning, and spatial visualisation tools offers a promising pathway for achieving these objectives in the context of modern post-conflict recovery operations [1, 2].

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In the work by Smolij et al. [3] the issue of building a minimum working version of a computer vision subsystem for detecting specific objects has been resolved. The use of the specified subsystem on research unmanned aerial vehicle has been proposed. The effectiveness of this subsystem has been assessed by comparing the YOLOv5 and YOLOv8 models. The proposed system can be used as a detector of objects of a larger area. Work by Smolij et al. [4] was devoted to ensuring effective UAV control and real-time video transmission. The results obtained increase the accuracy and efficiency of observations. The proposed scheme helps to improve existing technologies and develop new approaches to UAV control. In this article, a PPM-to-PWM system is developed. The conversion of PWM signals for multiple devices, the so-called scheme scaling, is investigated.

According to Tang et al. [5], a method for controlling the trajectory tracking of an unmanned aerial vehicle based on deep deterministic policy gradient (DDPG) is used. The problem of controlling the trajectory of a fixed-wing UAV is combined with a reinforcement learning infrastructure and transformed into a Markov decision process. The DDPG agent is created within the TensorFlow framework. Simulation, model optimization in a 3D environment, and trajectory tracking control resulted in an integrated trajectory tracking controller based on DDPG. A digital simulation system is proposed to verify the proposed method, which takes into account the effects of parametric uncertainties, measurement-induced noise, and control system response delay.

Mosov and Neroba [6] have developed a heavy-duty drone that can be used in marine environments and withstand coastal winds of up to 40 km/h. It can lift and carry a payload of instruments weighing 10 kg, collect ocean data, and even take seawater samples.The 10 kg UAV payload can contain a conductivity temperature depth (CTD) sensor, a programmable seawater sampler, and a multi-parameter sensor (MPS) for ocean data collection, as well as a light detection and ranging (LiDAR) device integrated with a high-frame rate camera system for coastal mapping and digital elevation model (DEM) applications.The UAV system is connected to a global positioning system (GPS), barometric pressure sensor, compass, high-precision gyroscope, 15-megapixel surveillance camera, and accelerometer sensor, connected to a robust orange flight module with a redundant 32-bit controller via a serial peripheral interface (SPI).

In [7] an image-based crack detection system is proposed. Frequent inspection is important for maintenance, and automatic crack inspection is a significant advantage considering its efficiency and accuracy. An image-based crack detection system using a deep convolutional neural network (DCNN) is developed. The UAV images are converted into three-dimensional models of the supports, from which composite images are created. The proposed method is applied to localize cracks in composite images using the sliding window technique. Putkiranta et al. [8] examined the capacity of UAV-based hyperspectral imaging to model vegetation communities in lowland oroarctic tundra landscapes in Saariselkä, Finland. Given the fine-scale spatial heterogeneity of these ecosystems, the study compared UAV hyperspectral imagery (112 narrowband channels) with 4- and 5-channel broadband multispectral UAV imagery. Using field plot data, the authors estimated key vegetation parameters including aboveground biomass, leaf area index, species richness, Shannon diversity index, and community composition. The analysis demonstrated the added value of hyperspectral data when combined with topographic information for high-precision vegetation modelling.

Bakirci [9] addressed the challenge of air pollution mapping by proposing a UAV-based solution capable of identifying pollutant distribution and sources with high spatial precision. While sensors and UAVs are increasingly applied in environmental monitoring, the potential of multi-UAV systems remains underutilised. The study demonstrates an approach involving multiple autonomous UAVs, enabling the creation of horizontal pollution maps at various atmospheric layers and vertical profiles across the entire study area. This is achieved through coordinated mission planning: subdividing the territory, matching UAV capacities to tasks, and executing decentralised mapping operations. Engineering analysis revealed that the coverage area of individual UAVs could be expanded by over 30%, reducing the required fleet size by up to 25% for large-scale surveys, thus enhancing mapping efficiency and consistency.

Bounding box regression (BBR) is one such problem addressed by Liu et al. [10], who considered it as a fundamental task for object detection. They observed that existing IoU-based loss functions imposed inappropriate penalty factors, causing anchor boxes to expand during regression and significantly hindering convergence. To overcome this, the authors introduced a novel Powerful-IoU (PIoU) loss function, which combines a target size-adaptive penalty factor with a gradient-adjusting function based on anchor box quality. This guided anchor boxes along more efficient regression paths, resulting in faster convergence. They further enhanced the model by adding a non-monotonic attention layer, creating the PIoU v2 loss function that improves focus on medium-quality anchor boxes. Integration of PIoU v2 into detectors such as YOLOv8 and DINO improved average precision on benchmark datasets (MS COCO, PASCAL VOC), demonstrating the effectiveness of the proposed improvements.

Talaat and ZainEldin [11] proposed a smart fire detection system (SFDS) for urban environments, based on the YOLOv8 deep learning algorithm. Their system integrates IoT components with fog and cloud computing to enable real-time detection and data processing. SFDS demonstrated a high detection accuracy of 97.1% while reducing false alarms. The approach is suitable for applications in fire safety management, forest fire surveillance, and intelligent security systems.

The goal of the work was to create fundamental principles for organizing and building a system for detecting, recording, and visualizing explosive objects in the form of an overview map of an agricultural area with explosive remnants of war for planning demining operations. It is necessary to develop a mathematical basis for classifying UAV surveillance zones and modelling the camera focal length, which in turn will allow generating flight logs and creating control microprograms to ensure accurate data collection and efficient organization of UAV missions.

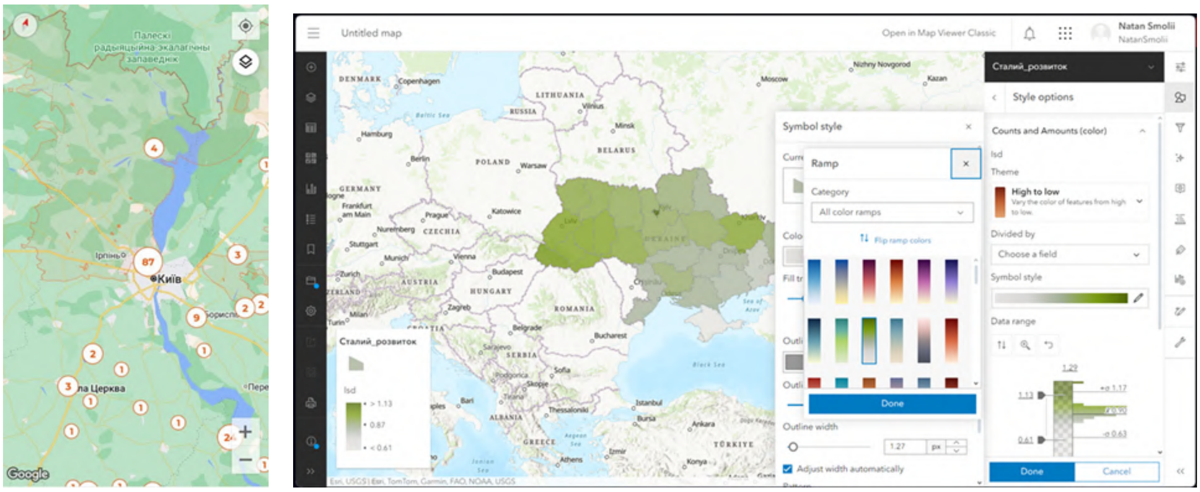
2. Materials and methods

The research involved the structural and functional modelling of an automated system for detecting, recording, and spatially visualising explosive objects in open-field conditions. The system architecture was implemented using UAVs equipped with infrared radiation sensors, which provided the capability to scan and register thermal anomalies on the terrain surface. The methodological framework included a series of sequential stages for mission planning, which incorporated flight path configuration, flight log generation, and the programming of the UAV's onboard flight controller using ArduPilot-based open-source firmware. Particular attention was paid to establishing the software parameters that governed autonomous navigation and sensor synchronisation. The study analytically addressed the problem of optimising aerial inspection parameters for effective object detection. Specifically, the model determined the optimal flight altitude, camera focal length, and inspection grid size required to reliably detect objects of predefined dimensions with the necessary spatial resolution. This optimisation was conducted using geometric modelling methods and applied analytical geometry principles.

The research method was geometric modelling using elementary optics and analytical geometry. In the work, ArcGIS Online [12] was used to build visualization maps of the studied areas, Desmos and DrawIO were used as modelling tools, calculations were performed in the MathCAD environment, and flight controllers were programmed using open software from the ArduPilot developers. The study analysed how the efficiency of object detection depended on the camera's focal length, the parameters of the observation zones, and the characteristics of the terrain relief. Particular attention was given to the spatial resolution constraints, where the minimum detectable object size and the number of pixels required for reliable recognition were identified as limiting factors. These dependencies were assessed using geometric modelling, allowing the determination of threshold conditions under which object classification remained accurate.

Mission planning was conducted by UAV operators using autonomous and centralised task scheduling, with coordination modes adapted to synchronous or asynchronous field operations. For each UAV, a detailed on-board log was created and uploaded prior to deployment. After mission execution, collected data were analysed by a central processing unit, incorporating artificial intelligence tools to improve the detection and recognition of explosive objects. Crew deployment was managed with the goal of maximising the surveyed agricultural area while minimising operational costs, including fuel consumption, labour, and consumables, through an optimised allocation algorithm. The mobile application was used to visualise the results obtained by each demining team and to monitor the condition of agricultural land in real time. This functionality was essential for enhancing coordination between multiple field expeditions and for accelerating the operational workflow. The system was designed to predict not only the borders of hazardous areas but also to georeference detected objects against a cartographic background.

A key methodological step involved overlaying the mission data onto existing geographic maps using the tools of the Esri [12]. All information collected during the UAV missions was systematically processed and integrated into an exchange database intended for use by pyrotechnic and emergency response services. This database enabled the classification, updating, and spatial referencing of identified explosive objects. The MineFree hazardous object map was initially generated (figure 1, a) and subsequently updated with mission-specific detections using ArcGIS Online tools (figure 1, b). The process of creating a map of hazardous objects detected during the mission using online tools in the ArcGIS Online.



(a) (b)

Figure 1: CSIMQ main research areas.

Explosive objects, in particular metal parts, elements (these can be not only mines, but also shells, fragments of missiles, weapons, etc.) accumulate heat in different ways, unlike the ground, grass and trees, and stand out well among the surrounding landscape in infrared radiation. To identify explosive objects, a method based on the detection of infrared (IR) radiation was applied, relying on the differential thermal properties of materials.

The IR radiation detected by the UAV sensors covered the wavelength range from 0.74 to 100 micrometres. For the purposes of modelling and classification, the radiation was divided into short-wave $(0.74 < \lambda \leq 2.5\,\mu\mathrm{m})$, medium-wave $(2.5 < \lambda \leq 50\,\mu\mathrm{m})$, and long-wave $(50 < \lambda \leq 100\,\mu\mathrm{m})$ bands, based on the sensor specifications. The sensors recorded the emitted radiation intensity, which was then converted into thermal signatures within digital images for further analysis.

The collected thermal data were automatically processed to classify and localize objects in the shared exchange database, where each object was assigned specific parameters (size, intensity, coordinates, and shape). The detection efficiency was influenced by several disturbance factors, including terrain relief, vegetation density, and weather conditions. These factors were considered during the computation of coverage accuracy and while modelling the UAV's observation zones. Two examination areas, designated as A and B, were defined and analysed to evaluate the efficiency of UAV-based inspection. In area A, a survey cell was outlined in the form of an inscribed square, within which multiple subzones were classified based on visibility and coverage geometry. The classification model is illustrated in figure 2.

Each cell was subdivided using a colour-coded classification scheme to represent detection reliability. Green zones denoted areas of guaranteed effective survey, where the target objects could not be obscured by minor relief variations or surface obstacles. Yellow zones indicated regions suitable for cross-validation using overlapping data from adjacent cells. Blue areas represented zones with limited

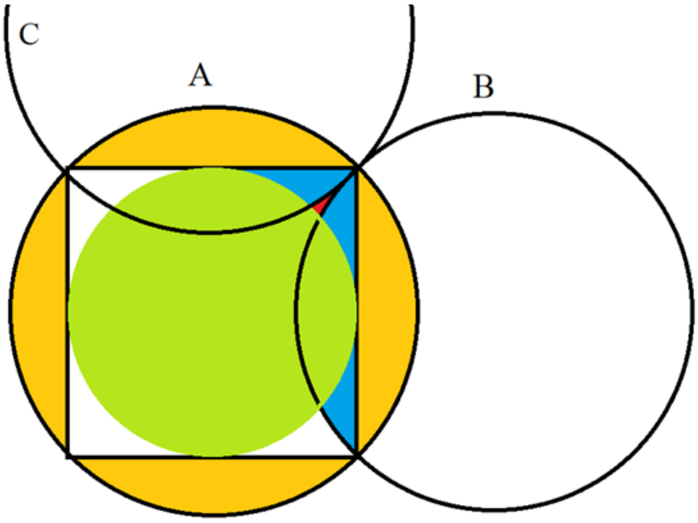


Figure 2: Classification of territory survey zones using UAVs: green – guaranteed good review zone, yellow – cross-examination from two points, blue – will not fall into the guaranteed good review zone, red – does not fall into the normal review zone and the cross-examination zone.

or partial visibility, falling outside the optimal observation geometry. Red areas fell completely beyond both guaranteed and cross-examination zones, and thus required adjustment of flight altitude or field cell configuration. This classification enabled the refinement of field grid parameters to improve overall coverage and minimise undetected sectors. The geometric model took into account UAV altitude and surface microrelief to define the extent of each classified zone.

3. Data processing methodology

The presence of metal in agricultural lands causes a certain temperature gradient, a change in the colour of the soil and plants, etc. that can be serve as indicators of the presence of explosive objects. It is expedient and rational to use both individual and a combination of different types of sensors to detect and analyse existing polluting factors. Relatively safe non-contact (remote) work with explosive objects using UAV attachment equipment has a significant impact on the components, interactions and the structure of the detection, accounting and visualization systems.

In order to fulfil the requirements of safe work of identification of the remnants of war it is required to adjust approach to the synthesis of the system. In particular, it is necessary to specialize the filling of subsystems, the functional completeness of each module, the minimization of connections and the amount of transmitted information, the speed of the analysis processes implementation, the thoroughness of the made decisions, the efficiency of process management analysis of certain areas, etc. In particular, a software application for mission planning, a system for processing results, a subsystem for object detection with the help of AI and a subsystem for exchanging data with relevant services, including emergency situations and demining, etc., should be provided. The evaluation parameters and target functions presented in the work, integrated into the general universal system of detection, detection, accounting and visualization of explosive objects, should be considered separately, relying on the work of each of the proposed subsystems (figure 3), as much as possibility to achieve greater flexibility, to adapt to a specific area and type of pollution, to achieve efficiency in the context of the maximum speed of returning demined de-occupied territories to the bosom of land for growing agricultural products.

The organization and components of the system for detecting, recording and visualizing explosive objects were systematically analysed.

The specified decentralization is expedient and effective for freed and deoccupied territorial commu-

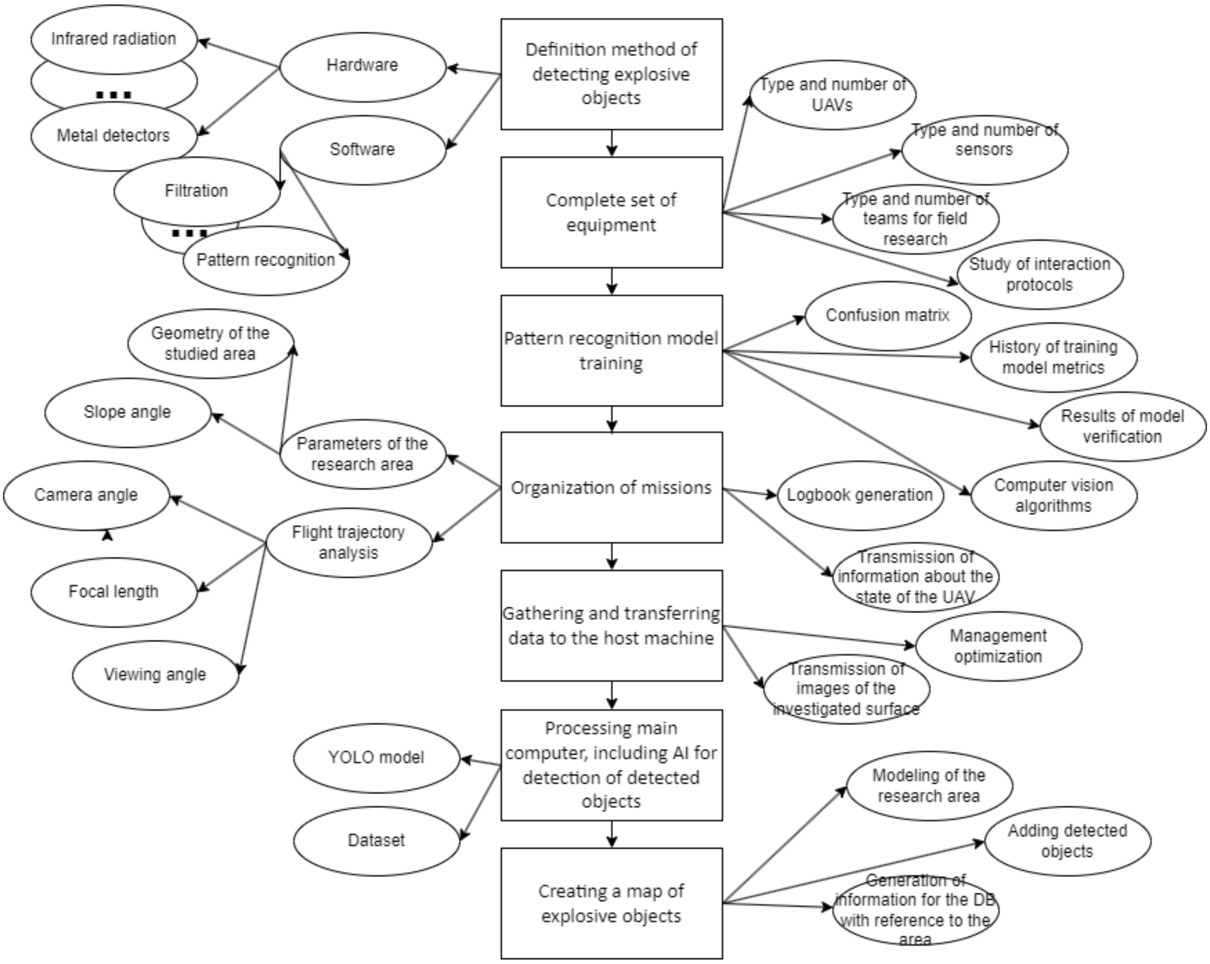


Figure 3: Stages of organization of the system of detection, detection, accounting and visualization of explosive objects.

nities and owners of agricultural, water and forest lands, who seek to resume specialized activities in the shortest possible time without large losses of time and economic resources in conditions of shortage of qualified specialists and equipment, since a very large volume demining is needed throughout the country. As mentioned above, the approach of detecting mines with the help of UAVs, creating a map of the location of explosive objects based on this data, followed by clarification of their types and features is required.

Mines that are in the soil for a long time and at fairly large distances from the surface should be determined using a complex of spectral sensors by detecting certain chemicals washed into the soil (they get into the grass and leaves, which changes their colour). It is also advisable to use infrared cameras that are installed on inexpensive UAVs in order to detect, by analysing temperature anomalies, a certain range of explosive devices (debris, objects, remains, etc.) that remained unexploded. Explosive objects heat up and cool down is significantly more intense than the surrounding soil and therefore infrared cameras can detect their location with high accuracy. It is also possible to use small detonators for detonation, which allows you to achieve the required result of decontamination of the object almost 20 times faster [13] than using other demining technologies.

It should be noted that the specific configuration of each subsystem and the minimization of the cost of both the equipment and the demining process will allow in the future to create a "turnkey demining" service in the conditions of a sustained recession of the country's economy, a frantic demand for the specified service in the de-occupied territories and a significant limitation in personnel and material resources. Consider a mine buried on the earth's surface as having the shape of a circle with radius r. The field (land area) should be surveyed for small objects, taking into account the intensity of infrared radiation, the resolution of the camera, and the possible margin of time for the mission, since the size of the searched objects affects the size of the surveyed cell (inverse proportionality), which affects the duration missions. The camera parameters are: field of vision in horizontal and vertical planes a_h and a_ω, resolution of the camera in pixels r_h and r_ω, width and height of the image w_p and h_p, effective range of vision of the thermal imager t_d. The parameters of the Earth's surface are: the maximum height of the examined area h, the maximum angle of the trench recorded on the examined surface t_a.

These parameters are determined through preliminary studies of topological maps of the area of interest, since it is dangerous to physically be in the de-occupied territories during stabilization measures without prior demining. The specified system of intellectual analysis of soil contamination (de-occupied territories) with explosive residues is a safe and effective tool for analysing the possibility of human entry into the specified territories. Consequently, the task of surveying the territory is reduced to the task of flying over the centers of cells for research at a height that satisfies the condition of determining an object of size $2r_l$ located at the zero height of the field at an angle t_a in the form of a group with a minimum cross section of n pixels.

The task of detecting an object of a certain size at a certain distance in the form of an object of n pixels is possible only with a preliminary calibration of the camera. For this, an object of size d should be set at a distance a from the camera and its size in pixels p should be measured. This procedure ensures the determination of the focal length of the camera f:

$$f = \frac{p * a}{d} \tag{1}$$

From where the distance from the UAV camera to the detected object of size d in the form of a region of pixels with a diameter of p will be equal to:

$$a = \frac{d \cdot f}{p} \tag{2}$$

Knowing the method for determining the focal length of the camera (f), or assuming that it can be adjusted in hardware to determine the flight height, one needs to determine the size of the object (d), since the parameter p depends on the requirements of the object classification algorithms and is assumed to be known.

An illustration of the solution to the specified problem is shown in figure 4. The size of the object d can be found based on the segment AB. Red – effective detection object area

The task of finding an object of length AB ($AB = d$) as a set of pixels of length p is equivalent to finding an object of length $A'B$ as a corresponding number of pixels. It can be noted that the condition of the object can be fixed.

$$ABP' < PBP' < 90\,. \tag{3}$$

Since calculations in pixels do not fit well with geometric tasks, it is necessary to move from pixels to angular values. This transition takes place according to the following formula:

$$APB = \frac{p}{\min(\omega, h)\, p} \cdot a_{\min(\omega,h)}\,. \tag{4}$$

The following notations were introduced: the angle APB is denoted as ε, the angle $P'PA$ is denoted as β, and the angle $P'PB$ is half of the smallest viewing angle (horizontally or vertically) of the camera.

The following relations were obtained:

$$A'B = APB - APA'\,, \tag{5}$$

$$APB = d \cdot \left|\cos(180^\circ - t_a)\right|\,, \tag{6}$$

$$APA' = APA \cdot \tan(APAA') = AB \cdot \sin(180^\circ - t_a) \cdot \tan(APAA')\,. \tag{7}$$

The angle $APAA'$ is equivalent to the angle $P'PA$ and is equal to $\beta - \varepsilon$. Accordingly:

$$A'B = d \cdot \cos(180^\circ - t_a) - d \cdot \sin(180^\circ - t_a) \cdot \tan(\beta - \varepsilon)\,. \tag{8}$$

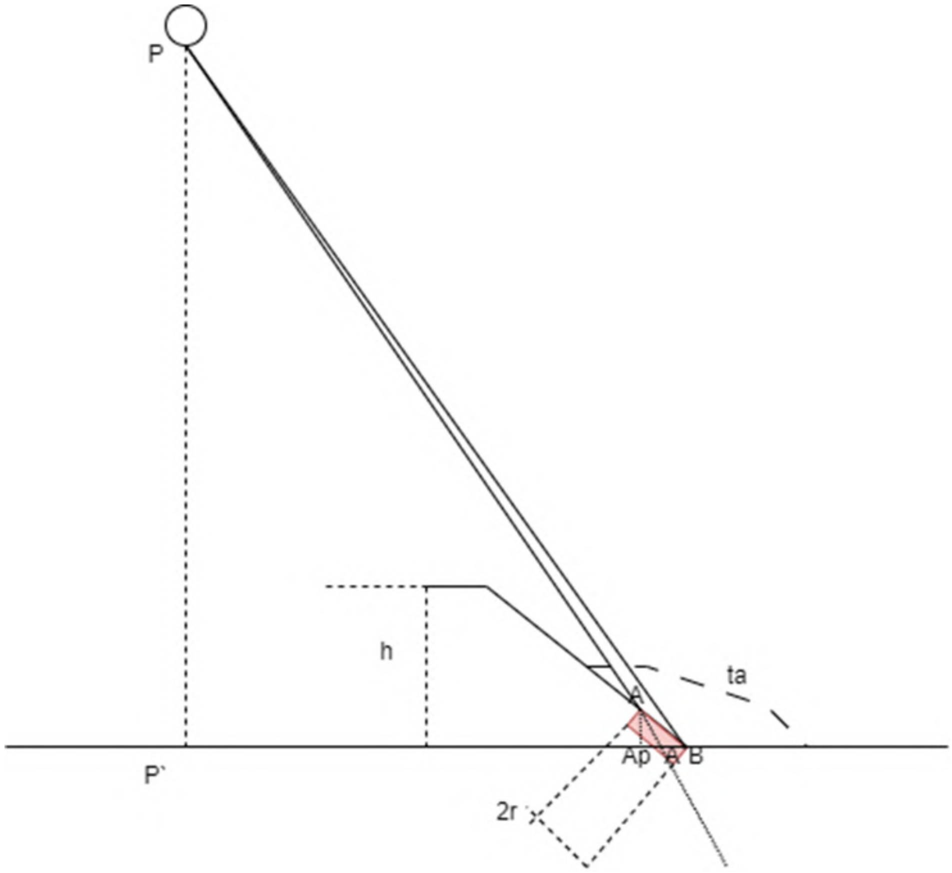


Figure 4: Location of the object in the area.

Substituting this value following formula was obtained:

$$a = \frac{(d \cdot \cos(180^\circ - t_a) - d \cdot \sin(180^\circ - t_a) \cdot \tan(\beta - \varepsilon)) \cdot f}{p} \,. \tag{9}$$

Knowing the viewing height, from the last equation, the calculation of the maximum possible side length of the examination cell can be performed, based on the minimum viewing angle of the camera. It is worth noting that, for greater detection reliability, this value d should be less than the real size of the detected objects:

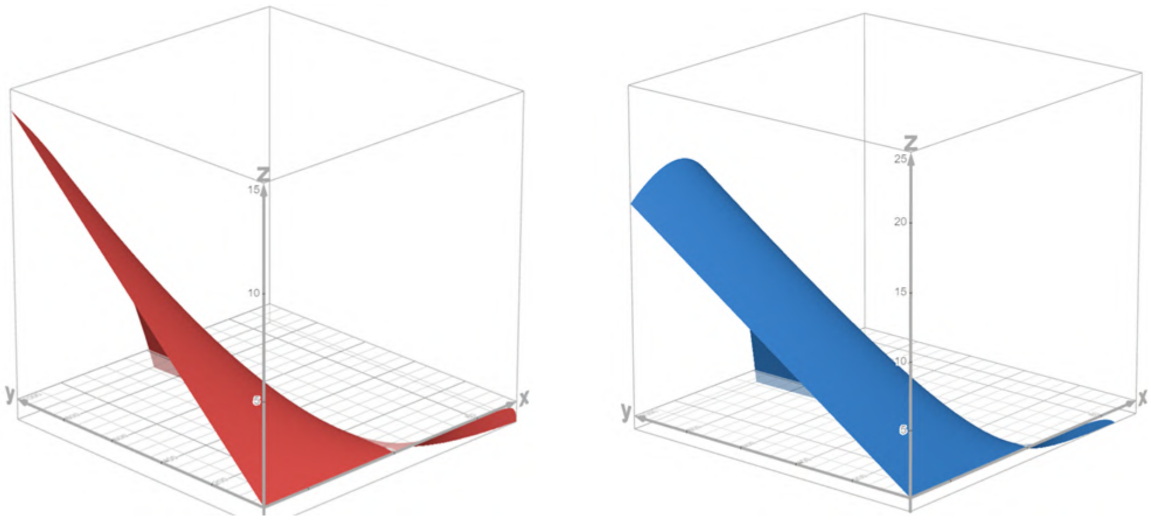
$$c = 2 \cdot a \cdot \tan(\beta) \,. \tag{10}$$

Because in the most of portable cameras, the focal length and the angle of view are not constant and can be changed ad infinitum. Figure 5 shows graphs of the dependence of the values a and c as functions of the focal length and the angle of view.

The dependence of the focal length on various parameters was investigated, a – demonstrates the dependence of the flight height on the focal length and viewing angle of the camera, b – demonstrates the dependence of the side of the viewing area cell on the focal length and viewing angle of the camera.

Figure 5 shows graphs of the dependence of the value of this function on the focal length for typical values of the other parameters: object diameter $d = 12$ cm $= 0.12$ m; fixed minimum slope angle $t_a = 150°$; number of pixels in the direction of the smallest viewing angle $h_p = 720$; required number of pixels to detect an object $p = 5$. The camera angle of view is $[30, 90]°$ on the x-axis, along the y axis is the focal length $[0.6, 1000]$ mm.

Calculations were performed for the following parameters: object diameter $d = 0.12$ m; fixed minimum slope angle $t_a = 150°$; smallest viewing angles are $a - h = 80°$ and $\beta = 40°$; number of pixels in the direction of the smallest viewing angle $h_p = 720$; required number of pixels to detect an object $p = 5$; focal length of the camera lens $f = 150$ mm.



(a) (b)

Figure 5: Tools for displaying detected explosive objects.

As a result, the angle ε is equal

$$\varepsilon = \frac{p}{h_p} \cdot a_h = \frac{5}{720} \cdot 80 = 0.56\,, \tag{11}$$

$$a = \frac{(0.12 \cdot \cos(30°) - d \cdot \sin(30°) \cdot \tan(39.4°)) \cdot 1500}{5} = 1.6368\,. \tag{12}$$

The results obtained demonstrate the dependence of the required UAV flight altitude on the camera's angle of view and focal length, which allows adjusting the UAV flight altitude depending on the installed video camera, its field of view, and resolution. It also allows you to plan trajectories and mission durations when conducting research and directly plan missions based on the maximum possible coverage (observation, research) of the territory.

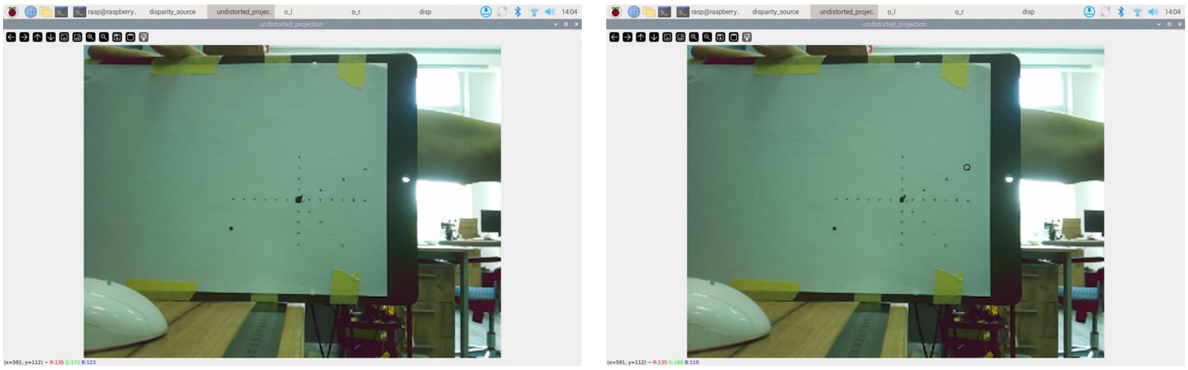
4. Calibration and assessment of the working environment

The calibration procedure is required to perform transformations from image space to the space of the coordinate system associated with the camera.

To build a system, it is necessary to have mathematical tools for projecting a point in space into image space. Programming this is possible using the OpenCV library, which has functionality for performing this kind of transformation, however, it is necessary to represent the desired point as a vector related to the camera coordinate system (figure 6).

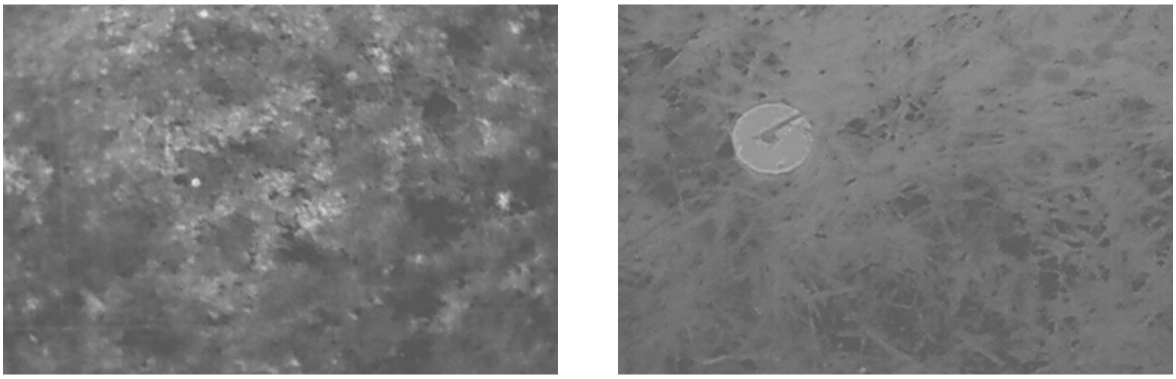
For this purpose, the OpenCV library provides functionality in the form of the projectPoints function, which implements the following steps: Conversion to the camera coordinate system, Perspective projection, Correction for lens distortion, Conversion to pixel coordinates.

The accuracy of the transformations was assessed by building a test layout in which the camera lens and the breadboard with a hole pitch of 2.54 mm were located at a distance of 137 mm. The expected result of the tests was the translation of a point with coordinates corresponding to the centre between the 4 camera holes into the image space. This allows you to build a value image for orientation to the waypoint and horizon. The alignment of the centre of the reticule along the calibrated optical axis of the lens is shown in the figure 7, a. Checking the retention of a point in a circle when the lens is far from the optical axis is shown in the figure 7, b.



(a) (b)

Figure 6: Examples of projecting a point in space onto an image on an example test with a 10mm grid at a distance of 370 mm.



(a) (b)

Figure 7: Large and small distances of the camera lens to the ground surface.

The main goal of these studies is to correctly (accurately, reliably, adequately) convert the pixels of the image into spatial coordinates. A plane is set at a certain distance from the lens and a coordinate grid is depicted on the plane. If the camera is correctly calibrated, the circle moves along the points of the coordinate grid, ignoring lens distortions.

Using the above calibration method, we determine the coordinates of the most "interesting" objects and phenomena. We demonstrate the accumulation of error when shifting from the optical axis of the camera. The further from the centre, the greater the error. The coordinates of the object that will fall into the specified zone will have the smallest "distortions". Their further analysis will be required.

Changing the contrast of the image when the camera lens approaches the surface of the earth leads to a decrease in contrast due to the automatic adjustment of the camera.

5. Discussion

The results obtained shows a clear mathematical relationship between UAV flight altitude and camera focal length combined with angle of view. These dependencies allow the prediction and adjustment of flight parameters based on the technical specifications of onboard imaging systems, enabling more efficient mission planning, minimisation of observation gaps, and maximisation of terrain coverage. Such modelling results not only validate the analytical approach but also serve as a conceptual basis for further development of decision-support systems in UAV-assisted demining operations. A similar methodological trajectory can be observed in precision agriculture, where remote analysis informs ground-level actions, as shown in herbicide impact studies by [14]. The ability to pre-calculate optimal viewing configurations contributes to the accuracy of detection and the safety of operations. To place these findings in a broader research context, it is relevant to compare them with other studies exploring the application of UAVs, imaging systems, and algorithms in related fields, including ecological monitoring, geological mapping, infrastructure inspection, and agricultural surveillance. These comparisons allow for the assessment of the universality, limitations, and practical transferability of the proposed approach.

The work by Liu et al. [15] was devoted to automated multi-animal feature detection for animal research, conservation, and ecosystem monitoring. A model was developed that mitigates the problems associated with the large number of parameters and calculations in existing animal feature detection methods. A backbone network with enhanced representational capabilities was created. This network combines the basic structure of the Transformer model with a large-selection kernel (LSK) module, known for its wide perceptual field. The model was evaluated using the publicly available AP-10K animal dataset, which included 50 annotated categories.

Fanti et al. [16] reported the use of UAVs to create a high-resolution topographic map of the Guriliin Tsav fossil site in the Gobi Desert, southern Mongolia. This project aimed to address the lack of accurate maps by plotting the geographic and stratigraphic distribution of palaeontological resources. UAV-based mapping enabled the first detailed palaeoecological interpretation of the site and facilitated comparisons with other fossil localities. According to Buatik et al. [7], UAV imagery combined with a deep convolutional neural network (VGG16) was used to detect cracks in concrete structures with 95% accuracy. The proposed system processes mosaic images of 3D footing models using a sliding window technique, enabling efficient inspection of large areas.

Rangan et al. [17] presented a heavy-lift UAV developed for maritime applications, capable of carrying up to 10 kg of instrumentation and withstanding strong coastal winds. The drone integrates LiDAR and high-resolution imaging systems for coastal mapping and digital elevation model (DEM) generation. Field tests confirmed its suitability for ocean data collection and coastal monitoring. [18] developed a U-Net-based semantic segmentation model for mapping peach orchards using UAV, Google Earth, and Sentinel-2 images. The model incorporates ResNet50 as a backbone and uses CycleGAN for style alignment across datasets. Results show high segmentation accuracy (MIoU up to 97.39%) and superior performance compared to other deep learning models, demonstrating the effectiveness of UAV imagery combined with deep neural networks for agricultural monitoring.

Path following is a critical challenge for small fixed-wing UAVs, as described by Byun et al. [19]. This study introduces a Lyapunov-stable path guidance law designed to follow specific planar curved paths. To ensure smoothness, a modified saturation function was developed for the guidance law. An analysis was conducted to explore the relationship between control parameters and input constraints, identifying the appropriate parameter ranges. To optimize the guidance law parameters, the NMPC technique was applied, resulting in the PFC_NMPC method. This method enhances the UAV's performance in following both straight-line and circular paths. Using Lyapunov stability arguments for switched systems, the stability of the nonlinear switched system was ensured.

Koval and Saryboha [20] investigated unmanned vehicles (smart cars, drones, robots) in the environment to enable them to react while performing their tasks. Therefore, they must have vision capabilities to identify objects and their coordinates. Kinect, an alternative to conventional computer vision, was used to detect objects and measure their distance. The results showed that the Kinect sensor, together with machine learning algorithms, can detect the presence of objects in its field of view and measure the distance to them.

Thus, it is reasonable to install Kinect on unmanned vehicles as a vision sensor, instead of a conventional video camera, and also in piloted vehicles to notify drivers; however, computer vision plays a crucial role in vehicles without human intervention.

The article presents a vision system for a drone using Kinect, instead of a conventional camera for processing streaming video. The system allows the drone to perform various tasks such as detecting and tracking objects, building a map of the environment, planning a trajectory, and avoiding obstacles.

The system consists of three main modules: an image processing module, a localization module, and a control module. The image processing module is responsible for acquiring and analyzing Kinect data, the localization module is responsible for determining the position and orientation of the drone in space, and the control module is responsible for generating commands for the drone's engines.

As a result of the analytical review by Kushnir and Paramud [21], it was found that smart sensor units are one of the main components of a cyber-physical system. One of the tasks assigned to such units is targeting and tracking moving objects.

The algorithm for targeting such objects using surveillance equipment is considered. This algorithm is able to continuously track the results of observation, predict the direction of movement with the highest probability, and generate a set of commands to bring the moving object as close as possible to the center of the information frame. The algorithm is based on the DDPG reinforcement learning algorithm.

The algorithm has been tested on an experimental physical model using a drone. The object recognition module is developed using the YOLOv3 architecture. An iOS application is designed to communicate with the drone via a WiFi access point using UDP commands. Advanced filters have been added to improve the quality of recognition results.

The results of experimental studies on the mobile platform have confirmed the operation of the targeting algorithm in real time.

Popov et al. [22] propose a general approach to landmine detection using drones equipped with multiple optical imaging sensors is described. The height of the drone's aerial survey is chosen so that enough pixels are captured within the site of landmine installation. This circumstance ensures the statistical representativeness of detection by each separate sensor. Next, the decision-level data fusion for different sensors is performed. Preliminary estimates of landmine detection probability by different statistical methods in multispectral and infrared imagery are presented.

In the article by Cherednychenko et al. [23] an analysis of explosive objects of various types was conducted and their characteristics were provided. Their unmasking feature is the material of the main part (body), it was noted that high-explosive mines are characterized by the use of a plastic body, for fragmentation mines – a metal one, and the most difficult to detect are mines with a plastic body. Methods of detecting explosive objects are considered in comparison with those currently used in Ukraine. Unfortunately, given the scale of mined territories, they are ineffective, so it is clearly necessary to develop more effective solutions for their detection and neutralization based on modern technological advances. Foreign countries have developed and use modern mobile robotic complexes for demining based on unmanned aerial vehicles with various types of sensors installed on them.

The work by Mosov and Neroba [6] is devoted to the analysis of the modern experience of foreign countries in solving the issues of using unmanned aircraft to accomplish tasks of mine reconnaissance, detection, and remote destruction of mines both during combat operations and in the frontline zone and on the state border.

The emphasis is on the complex state of the issue related to the mine situation in the world in connection with the use of anti-personnel explosive devices by the parties to armed and border conflicts. Statistics are provided on the facts of detonation of anti-personnel mines remaining after armed conflicts (border confrontations) by law-abiding civilians, among which a significant number are detonated by children.

The situation regarding the development of the direction related to the creation of mobile robotic complexes for demining the terrain is analyzed. The latest approaches to the use of unmanned aircraft to solve demining tasks are considered. One of the directions is indicated as an approach based on the use of mine detectors, which are installed as a payload on a drone. Another approach is based on the use of multispectral equipment mounted on a drone for mine reconnaissance and mine detection. Yet another approach is the use of infrared equipment mounted on a drone that responds to the temperature difference between the mine and the terrain surface. The possibility of remote mine clearance using an unmanned aerial vehicle is also considered.

Conclusions were drawn about the existence of a global problem of demining territories that fall into an armed conflict zone; the presence of a large number of mined territories around the world; the need for operational demining using the latest achievements of scientific and technological progress; and the promising application of unmanned aircraft to solve mine clearance issues.

The following areas of further research are indicated: development of mine signatures; development of methods for decomposition of the mine situation; development of technical requirements for the creation of mobile robotic complexes based on UAVs for conducting mine reconnaissance, detecting mines, and remotely destroying them.

In current research, the use of infrared sensors to detect explosive objects that are invisible to the naked eye was substantiated, providing a higher level of accuracy and safety. Classification of research areas is important for the effective allocation of resources during mission planning. Modelling the camera focal length helps optimize the UAV's ability to capture clear and detailed images of the terrain. This ensures accurate documentation of every aspect of the surveyed area, which is vital for the subsequent steps of the demining process.

6. Conclusions

Detection system organization stages, accounting and visualization of explosive objects on the basis of UAVs with the help of attached sensors of infrared radiation are proposed in the work. The basic principles of mission organization with the generation of the flight log and the firmware of the flight controller are presented. The principles and features of creating a survey map of an agricultural area littered with explosive objects are proposed and its use as the only safe means of carrying out stabilization measures in de-occupied territories is justified.

For the demining brigade configuration, the type and equipment of the UAV were investigated with the following values: object diameter $d = 0.12$ m; fixed minimum slope angle $t_a = 150°$; smallest viewing angles are $a - h = 80°$ and $\beta = 40°$; number of pixels in the direction of the smallest viewing angle $h_p = 720$; required number of pixels to detect an object $p = 5$; focal length of the camera lens $f = 150$ mm.

It was obtained that the angle ε is equal 0.56. The distance from the UAV to the ground in order for the camera to detect an object of size d in the form of a region of pixels with a diameter of p is equal to 1.6368 m.

The camera calibration required for correct coordinate conversion between image space and the coordinate system associated with the camera has been performed. Mathematical means of projecting spatial points into the image plane were implemented using the OpenCV library, which required representing the points as vectors in camera coordinates and allowed determining the positions of the most significant objects. An analysis of errors was conducted, which confirmed their growth with displacement from the optical axis of the camera, which necessitates further refinement of the coordinates of objects located in peripheral zones. Additionally, the influence of automatic exposure adjustment was investigated, and a decrease in image contrast was found when the camera approaches the surface, which was taken into account during further data processing.

The results obtained demonstrate a clear mathematical relationship between UAV flight altitude, camera focal length, and angle of view. These dependencies allow for the prediction and adjustment of flight parameters based on the technical specifications of onboard imaging systems, enabling more efficient mission planning, minimization of observation gaps, and maximization of terrain coverage.

The effectiveness of the process of detecting, recording, and spatially visualizing explosive remnants in agricultural and other areas of frontline and deoccupied territories using non-contact technology with a specific UAV configuration was confirmed. Detailed attention is paid to the classification of territory survey zones with the help of UAVs and to the modelling of the focal length of the camera.

The problem of finding the object on the experimental site has been solved. Prospects for further exploration include the generation of autopilot programs for controlling multiple UAVs (in order to accelerate the research and demining process) taking into account the determined dependencies of the total viewing area (viewing zone, effective research zone) on focal length and viewing cone.

Author contributions

Conceptualization, Oleksandr I. Rolik and Viktorija M. Smolij; methodology, Viktorija M. Smolij; software, Natan V. Smolij; writing – original draft, Viktorija M. Smolij; writing – review and editing, Oleksandr I. Rolik. All authors have read and agreed to the published version of the manuscript.

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Conflicts of interest

The authors declare no conflict of interest.

Declaration on Generative AI

The authors have employed a generative AI tools – ChatGPT and Grok – to refine the paper text. After using these tools, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

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