KAPITEL 4 / CHAPTER 4 [4]
OBJECT RECOGNITION SYSTEMS USING INTELLIGENT TECHNOLOGIES IN UAV

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Introduction

The modern development of technologies, in particular unmanned aerial vehicles (UAVs), opens up new perspectives for the use of intelligent technologies in the field of object recognition. The relevance of the study of object recognition systems in UAVs lies in the need to improve their functionality and efficiency in various fields, from military applications to civilian surveillance and research.

The purpose of this work is the systematization and research of intelligent technologies used in object recognition systems in unmanned aerial vehicles. The work is aimed at analyzing and improving existing methods and algorithms to ensure the accuracy and speed of the process of object recognition in real time. The subject of research is specific methods and technologies used in object recognition systems in UAVs. Various research methods are used in the process of studying the topic, including analysis of literary sources, comparative analysis of existing systems, mathematical modeling of algorithms, and experimental research using real and simulated data. This makes it possible to implement a comprehensive approach to the consideration of the problem and obtain objective results that will contribute to the further improvement of object recognition systems in unmanned aerial vehicles.

One of the key components of this work is a contribution to the development of a scientific approach to object recognition systems in unmanned aerial vehicles. Scientific novelty consists in the development and improvement of algorithms that use intelligent technologies for effective and accurate recognition of objects in real time. The obtained results have a significant contribution to improving the autonomy and reliability of UAV operation.

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One of the main tasks of the work is to ensure the practical significance of the obtained results for solving specific tasks and challenges facing modern UAV systems. The developed and improved object recognition systems have the potential to be used in a wide range of areas, including military, civilian and research segments. This opens up new perspectives for the use of UAVs in real conditions and assigns the developed technologies to a wide range of applications.

4.1. Theoretical aspects of the use of uavs in modern technologies

4.1.1. Classification by purpose of UAVs

Unmanned aerial vehicle (UBLA English name: Unmanned aerial vehicle - UAV) - an unmanned aerial vehicle. Unmanned aerial vehicles repeatedly fulfill their functional purpose, repeatedly implement them again and again. This commonly used term has a rather broad meaning and does not always fully reflect the characteristics of the aircraft. Therefore, this class does not include unmanned modifications of production aircraft used as aerial targets, as well as ballistic and cruise missiles of any type. Remotely piloted aircraft (RPA) is an unmanned aerial vehicle capable of continuous maneuvering.

An unmanned aerial vehicle that is continuously controlled in any way from a stationary or mobile control point, and that implements its functional tasks according to algorithms and automated modes. (for example, cruise missiles, reconnaissance aircraft). In recent years, the aerospace forces have been intensively developing UAVs to replace manned combat aircraft. In other countries, they are called unmanned combat aircraft (UAV). However, given the way the aircraft interacts with the pilot-operator, it is more appropriate to call them remotely piloted aircraft (RPA). RPAs are unmanned aerial vehicles.

It is an unmanned aerial vehicle that performs its functional tasks mainly autonomously with periodic intervention of the pilot-operator for the following purposes of redirection and reprogramming of the airframe control system; The RPA

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is equipped with advanced artificial intelligence, which ensures the process of independent determination of not only the flight, but also the use of on-board weapons, which makes the RPA a separate group of remotely piloted aircraft systems, and not a new generation BpAK Remotely controlled aircraft systems (RPAs) are promising for remotely piloted aircraft ,

Their characteristics and capabilities are very similar to the characteristics and capabilities of manned aircraft with similar purposes. Such aircraft are controlled from a control point (ground or air, stationary or mobile) in a separate pulse mode and perform assigned combat tasks in accordance with their own functional algorithms, information about the situation and movement of troops, as well as external control commands (from the control point). The current functional taxonomy used by foreign military analysts is based on such basic distinctions as unmanned combat aircraft and unmanned support aircraft.

Combat UAVs include specialized multi-use attack UAVs and single-use attack devices. The greatest attention in the development of combat attack UAVs is paid to specialized multi-use attack devices, which in terms of their tactical and technical characteristics are close to modern tactical fighters. In the initial period of any regional conflict, when the enemy's air defense system is still combat-ready, an effective role in its suppression (especially in the destruction of radar stations and control points) can be played by UCAV (Unmanned Combat Vehicle) attack UAVs. Such devices will be part of the first echelon of an air strike and will be used against cruise missiles (CR) and combat aircraft.

Characteristic representatives of specialized multi-use UAV strike systems include: RQ-1A "Predator" and "Predator-B" (General Atomic Aeronautical Systems Inc, USA), RQ-3 Dark Star (Boeing, Lockheed Martin, USA), UCAV-N ("Northrop-Grumman", USA), UCAR and "Black UCAV" ("Lockheed-Martin", USA), UCAV (European corporation "EADS"), ASN-206 (Xian ASN Technology Group Company, China), "Grand Duck" ("Dasso", France) and some others. Most of the existing combat UAVs, despite their rather high cost, are designed for multiple use, that is, the mandatory return of the UAV after completing the task is required. According to calculations, specialized strike UAVs will satisfy the "cost-effectiveness" criterion if they can perform at least 5-9 sorties.

However, there is a growing number of UAV types that do not pose a problem with return. Single-engine attack UAVs designed to attack not only enemy radio-emitting targets, but also other small ground targets, including mobile ones.

Such UAVs attack targets using the kamikaze method - pointing the aircraft at the target and detonating the warheads it carries. Typical single strike UAVs are: "Harpy" (Israel Aircraft Industries - IAI, Israel), "Cutlass" (IAI, Israel, Raytheon, 'Ferret' (Northrop Grumman Corporation, USA), LEWK (Advanced Technologies, USA) and Typhoon UAV .Typhoon (STN-Atlas, Germany).

Support UAVs are differentiated as reconnaissance, target and transport platforms. Target and transport platforms are essentially successors to the development of reconnaissance UAVs. Specialists highlight the main existing and prospective tasks for UAVs. Modern high-altitude and medium-altitude strategic reconnaissance UAVs differ in many ways from the first generation UAVs, first of all, by a much smaller take-off mass (by 3-10 times) with a much longer flight duration, measured not in hours, but around the clock. Such characteristics became possible thanks to the use of the latest achievements in subsonic aerodynamics, the technology of manufacturing light structures from composite materials, as well as highly economical engines.

Sensors located on board unmanned aerial vehicles (UAVs) are critical components that ensure the collection and transmission of important information for the effective functioning of the device in various conditions. These sensors can include different types of sensors for measuring different parameters. Global positioning systems (GPS) are one of the key types of sensors on board UAVs. HSPs allow you to determine the exact geographic position of the device in real time using satellite signals. This is critical for navigation, route planning and precision tasks in large spaces.

Unmanned aerial vehicles, including drones, UAVs (unmanned aerial vehicles), UUVs (unmanned underwater vehicles) and UGVs (unmanned ground vehicles), use a wide range of instruments and sensors to enhance vehicle performance or collect data.

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Unmanned vehicles are ideal remote sensing platforms for many applications, including military, industrial, geodetic, and environmental monitoring, due to their lower cost of operation compared to manned vehicles. and their ability to operate in hostile or inaccessible environments.

UAV Sensors: Fuel Level and Fuel Level Fuel Flow. Unmanned vehicles with large fuel tanks, especially larger UAVs, may need sensors to monitor the level and rate of fuel flow. Current UAV sensor technologies include ultrasonic fuel flow sensors and capacitive fuel level sensors, both of which use no moving parts and are ideal for the harsh, high-vibration conditions typical of UAV applications.

UAV sensors also include inertial measurement units (IMUs), which combine information from various sensors, such as gyroscopes, accelerometers, and magnetometers, to provide measurements that can be used to calculate the drone's orientation and speed. This data can be combined with another source of information, such as GPS, to further improve the accuracy of the calculations.

LiDAR sensors for drones and drones Autonomous vehicles. LiDAR (Light Detection and Ranging) sensors, which measure the reflection time of a pulsed laser beam, have various applications in drones and unmanned systems. They can be used for navigation and collision avoidance with UAVs and autonomous driving systems, as well as for mapping and other imaging applications such as agricultural and forestry imaging. LiDAR is an alternative to traditional photogrammetry methods when the mapped area contains many obstacles.

Other imaging sensors that can be installed on unmanned vehicles and drones include thermal imagers for building inspection, search and rescue and security, and other electro-optical (EO) sensors that operate in the visible spectrum. Agricultural drones' hyperspectral precision sensors measure reflected light to provide data on crop health, allowing farmers to optimize pesticide and fertilizer applications and maximize yields.

Inertial sensors (accelerometers and gyroscopes) are used to determine the movement and orientation of the device in space. They allow the UAV to adjust its position and direction, even if signals from the GPS are temporarily unavailable (for example, when flying in a tunnel or in a deep forest).

Cameras and video systems are used for visual observation and recording of events. This can include conventional optical cameras, infrared cameras for nighttime or low-visibility applications, and specialized cameras for specific tasks, such as capturing highly enlarged images or creating 3D maps.

Radar systems are used to detect objects on the ground and surrounding aircraft. These systems determine the distances and directions of objects, which allows you to avoid collisions and interact with other objects in the air.

Pressure sensors and altimeters are used to determine flight altitude and analyze atmospheric conditions. This is useful for accurate route planning, as well as for adapting to changes in weather conditions.

Thermal cameras and sensors provide the ability to detect and track heat trails, allowing UAVs to be used to locate people, animals, or even detect fires.

In addition, modern drones often use surround vision sensors, spectral sensors (to analyze different parts of the spectrum, such as infrared or ultraviolet), magnetometers and other sensors that expand the functionality of UAVs in various conditions and tasks. The overall efficiency and accuracy of UAV operation depends on the optimal integration and pairing of measurement sensors, which makes them extremely versatile and effective in a variety of usage scenarios.

Unmanned aerial vehicles (UAVs) can also be equipped with audio sensors or microphones that allow for acoustic monitoring. This can be useful in the field of security to detect abnormal sounds or events, as well as in various additional applications, such as environmental monitoring or working with acoustic signals.

Gas sensors can also be used on board UAVs to detect concentrations of various gases in the air. This can be useful for detecting air pollution or detecting harmful substances in environmentally sensitive areas. In the field of scientific and research applications, UAVs can be used to collect soil or water samples using special sensors. This is important for studying soil properties, analyzing water quality and monitoring the ecological state of the environment.

Object Detection Systems use computer vision technologies to automatically detect and identify various objects, such as cars, buildings, people, etc. This is important for tasks in a variety of scenarios, including autonomous driving, security, and area monitoring.

Height and vibration sensors allow you to determine the height of the UAV flight and detect vibrations that may indicate problems or malfunctions in the device.

With advances in artificial intelligence and machine learning technologies, UAVs can also use sensors to collect environmental data that is used to train machine learning algorithms that make the drone more autonomous and adaptive.

For example, in agriculture, light level sensors can be used to determine optimal watering times or moisture sensors can be used to analyze soil conditions and irrigation needs. Medical missions can use pulse and temperature sensors to monitor the condition of patients while transporting medical supplies. Increasing the number and variety of sensors on board UAVs allows expanding the areas of application of these devices and increasing their effectiveness in various conditions and tasks.

4.1.2. Methods of data processing in UAVs. Modern applications of UAVs in various fields

Data collection and processing is an integral part of the functionality of unmanned aerial vehicles (UAVs). The use of various sensors and information collection systems requires appropriate methods of processing, analysis and interpretation of the received data. In this section, we will consider the main methods of data processing in unmanned aerial vehicles.

Collection and accumulation of data. The first stage of data processing is their collection and accumulation. UAVs are equipped with a variety of sensors, such as cameras, radar systems, thermal cameras, altimeters, and others. The collected information can be of different nature, from visual images to numerical data about altitude, speed, temperature, etc.

Data filtering and cleaning. The data obtained may be subjective or contain errors. Data filtering and cleaning includes the use of algorithms that remove artifacts and other inaccuracies, ensuring reliability of information for further analysis.

Automatic object detection. The task of object recognition is an important part of data processing in UAVs. Using computer vision and artificial intelligence algorithms, you can automatically identify and classify objects in images or videos.

Tracking and navigation. One of the key functions of a UAV is the ability to navigate autonomously in space. Data processing includes determining the exact location of the UAV, correcting its trajectory and ensuring the accuracy of the movement.

Analysis and output of results. Data processing in UAVs also includes analysis of received information for decision-making. It can be identifying potential threats, detecting anomalies, or providing a report on completed tasks.

Protection of information. Taking into account the importance of preserving the confidentiality and integrity of data, cyber security measures are an important stage of processing. Encryption, authentication and other technical means are used to protect information from unauthorized access.

Therefore, UAV data processing is a complex and multifaceted process that combines various scientific and technical directions aimed at ensuring the effective and safe functioning of unmanned systems.

Modern applications of unmanned aerial vehicles (UAVs) cover various fields. In the military field, UAVs are used for reconnaissance and surveillance, providing accurate data on enemy positions and actions in real time. Some of them are armed and used to carry out attacks and shelling.

In civil aviation, UAVs are used to monitor infrastructure such as power plants, gas pipelines and pipelines. They also find applications in the field of fire safety, helping to determine the spread of fire and finding cut-off zones.

In the agricultural sector, farmers use UAVs to monitor the condition of crops, detect diseases or pests, and optimize irrigation and watering systems.

In the medical field, UAVs can be used to deliver medical drugs to hard-to-reach or emergency areas, as well as for telemedical assistance and transportation of sensors to collect medical data.

In the energy and mining sector, UAVs are used to inspect and maintain infrastructure such as power plants and gas facilities, as well as for geological exploration of mineral deposits.

In the field of environmental protection, UAVs are used to monitor air, water and soil pollution, as well as to protect nature and vulnerable ecosystems.

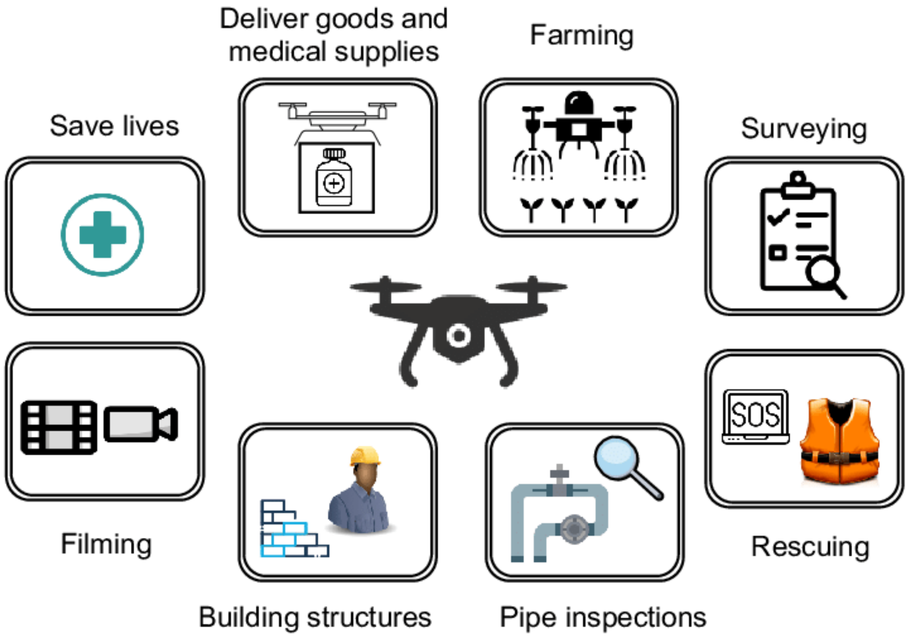

Fig. 1.1 - Application of UAVs in various industries

In the context of energy and resource extraction, UAVs are widely used to monitor and survey solar power plants, wind farms, and power grids. They provide an opportunity to detect the efficiency of solar panels, as well as to respond to possible breakdowns or malfunctions in wind turbines.

In the field of transport and logistics, UAVs can be used to monitor and optimize logistics processes, including warehouse management and cargo transportation. They can also be used for safe transportation of goods or hard-to-reach materials.

In the field of telecommunications, UAVs can serve to create temporary communication networks during natural disasters or accidents, when traditional communication infrastructures may be unavailable.

In the field of scientific research, UAVs are used to collect data and images in various research projects, such as climate change studies, water resources research, archaeological excavations and other research.

Finally, in the field of entertainment and mass media, UAVs are used to create spectacular aerial shots and videos that are used in films, commercials and other creative projects.

4.1.3 Technological aspects of using UAVs for object recognition. Intelligent technologies in the field of image processing

The use of unmanned aerial vehicles (UAVs) for object recognition is a key direction in modern technologies. Technological aspects in this context include various systems and sensors designed to collect and process information that allows high-quality object recognition in real time.

One of the key technologies is optical systems, which include high-resolution cameras and special lenses. These systems provide an opportunity to capture details of objects even at great distances. Also, the use of thermal cameras allows you to recognize objects by their thermal radiation, which is especially useful in conditions of limited visibility or at night.

Lidars (laser radars) are another important technology for object recognition. They use laser beams to measure distances and create accurate three-dimensional models of objects and the environment. This allows obtaining detailed spatial information for further analysis and recognition.

Radar sensors are effective for object recognition, especially in conditions of limited visibility or in densely populated areas. They determine the position of objects based on the reflection of radio signals, which provides an additional opportunity to accurately determine the location of objects.

Technological aspects also include the development of software for processing and analyzing the collected information. The use of artificial intelligence and machine learning algorithms allows you to automate the process of object recognition, increasing the accuracy and speed of data analysis.

Summarizing, the technological aspects of using UAVs for object recognition have taken a huge step forward, ensuring the efficient and accurate use of these systems in various fields, from the military to the civilian sphere.

Additional progress in the technological aspects of the use of unmanned aerial vehicles (UAVs) for object recognition is determined by the development of image analysis systems and the processing of large volumes of data. Modern object mapping and classification algorithms can take into account different contexts, including changing lighting conditions, variations in textures and object shapes.

Geospatial analysis system integration is another key technological feature. This allows the UAV to effectively interact with geodetic data, map information and global positioning systems, ensuring the accuracy of recognition of objects on the ground.

Particularly important is the development of autonomous decision systems that allow UAVs to independently determine priority objects for recognition and choose optimal shooting or intervention strategies. This makes them more effective in situations where speed of decision-making is of great importance, such as military operations or emergency situations.

In addition, the development of data transmission and storage technologies allows UAVs to efficiently process and transmit large amounts of information in real time. This is especially important in areas that require a quick response to events such as fires, natural disasters or military conflicts.

In general, the technological aspects of the use of UAVs for object recognition continue to be actively developed, making a significant contribution to various industries where these devices are used for security, monitoring and control of various processes.

The analysis of intelligent technologies in the field of image processing shows a significant progress and revolution in the use of intelligent systems for the analysis and processing of a large volume of images. These technologies include artificial intelligence (AI), machine learning (ML), computer vision, and other innovative approaches to automate and improve image processing in various industries.

Artificial intelligence in image processing allows systems to "understand" and "learn" images using algorithms that simulate the work of the human brain. Machine learning plays a key role in this context, where algorithms can learn by themselves on large volumes of data and improve their performance over time.

One of the important directions in image analysis is the recognition of objects, faces, text and other elements in photographs or video recordings. Modern systems are able to recognize and classify objects with impressive accuracy, which is important in various industries, from security and medicine to the automotive industry.

Computer vision includes algorithms that allow systems to recognize shapes, colors, textures, and other characteristics of images. This becomes the basis for creating three-dimensional models of objects and cutting out details for further analysis.

Special attention is paid to intelligent technologies in the fields of medicine and diagnostics. Systems can detect pathologies, analyze changes in tissues and provide valuable information for doctors.

In the field of security and military equipment, intelligent technologies are used to detect suspicious objects, monitor traffic, and automate the analysis of large volumes of video data.

In general, the analysis of intelligent technologies in the field of image processing indicates that these technologies not only improve existing processes, but also open new opportunities for automation and improvement of activities in various economic sectors.

The use of intelligent technologies in the field of image processing also includes expanding the possibilities of recognizing emotions and moods on people's faces. Machine learning algorithms can analyze microexpressions and other cues to determine a person's emotional state. This finds its application in advertising, medicine (for example, in psychiatry to determine the mental state of patients) and in other fields where understanding emotions can be of strategic importance.

Another important field is the development of video tracking and analysis systems. Intelligent algorithms can automatically detect and track objects in the video, taking into account their trajectories and interactions. This is useful in the field of video surveillance to ensure security at facilities or in the field of transport to improve traffic management systems.

One of the promising directions is the development of deep learning systems to improve the quality of image processing. Deep neural networks can automatically identify important features and dependencies in complex images, leading to significant improvements in the accuracy and efficiency of analytical systems.

In the field of medicine, much attention is paid to the development of systems for automated analysis of images from medical examinations, such as computer tomography or magnetic resonance imaging. This allows early detection of diseases and increases the efficiency of diagnostics.

An important aspect of the development of intelligent technologies in the field of image processing is ensuring the confidentiality and security of processed data. Consideration of these issues becomes key due to the growing volume of personal and confidential data processed by such systems.

In general, intelligent technologies in the field of image processing continue to evolve, opening up new opportunities for use in various fields of science, industry and everyday life.

4.2. Basic principles of object recognition systems in UAV

4.2.1. Classification of object recognition systems. Algorithms and methods of object recognition

Pattern recognition is a branch of the theory of artificial intelligence that studies object classification methods. By tradition, an object subject to classification is called a pattern. An image can be a digital photograph (image recognition), a letter or number (symbol recognition), a speech recording (speech recognition), etc.

Within the framework of the theory of artificial intelligence, pattern recognition is included in a broader scientific discipline — the theory of machine learning (machine learning), the purpose of which is to develop methods for building algorithms capable of learning. There are two approaches to learning: inductive and deductive. Inductive learning, or learning by precedent, is based on identifying general properties of objects based on incomplete information obtained empirically. Deductive learning involves the formalization of experts' knowledge in the form of knowledge bases (expert systems, etc.). In our course, we will be interested only in inductive learning, so we will consider machine learning and learning by precedents as synonyms. It should be noted that, like

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every mathematical discipline, pattern recognition has its own mathematical apparatus, which includes mathematical statistics, optimization methods, discrete mathematics, algebra and geometry.

Pattern recognition has wide application and is used in the creation of all computer systems that rely on intelligent functions, that is, functions related to decision-making instead of a person: medical diagnostics, forensic examination, information retrieval and intelligent data analysis, etc. A precedent is an object whose membership in a given class is determined in advance. A precedent can be, for example, a set of features of a patient with a known diagnosis, with which a set of features of a person whose diagnosis is not yet known should be compared. Each image is a set of numbers that describe its properties and are called features. An ordered set of features of an object is called a feature vector. A feature vector is a point in feature space. A classifier, or decision rule, is a function that matches a feature vector of an image with the class to which it belongs.

The task of pattern recognition can be divided into a number of subtasks:

1. Feature generation — measurement or calculation of numerical features characterizing an object.

2. Feature selection — determination of the most informative features for classification (this set may include not only primary features, but also functions from them).

3. Construction of a classifier (classifier construction) — construction of a decisive rule on the basis of which classification is carried out.

4. Classification quality assessment (classifier estimation) — calculation of classification correctness indicators (accuracy, sensitivity, specificity, errors of the first and second kind).

Recognition systems can be classified depending on the use of physically homogeneous or physically heterogeneous information to describe recognized objects and the presence of features used to describe the alphabet of classes. Here are two categories of such systems:

1) Simple recognition systems: These systems are recognized by the fact that they

use a limited set of features to recognize objects. For example, automated reading devices, where objects are recognized by their linear dimensions, or machines in the subway for changing coins, where the weight of coins is used as a feature for recognition.

2) Complex recognition systems: These systems use various features to describe recognized objects. For example, medical diagnostic systems that use blood tests and cardiograms as signs to determine the state of the driver or recognize the state of the vehicle's units. These complex systems can be further divided into single-level and multi-level systems depending on whether the posterior information is measured directly or based on indirect measurements.

3) Single-level complex systems: They determine a posteriori information directly based on the results of experiments and measurements.

4) Multi-level complex systems: A posteriori information is determined based on indirect measurements, providing a deeper level of analysis.

Regarding the principle of classification based on the availability of a priori information about recognized objects, recognition systems are divided into untrained, self-learning and self-learning systems.

The text above describes multi-level complex recognition systems, where B1, B2, ..., In represent meters of different physical nature, AO is an a priori description of the classes of recognition objects, AK is a classification algorithm, and SAU is an automatic control system (algorithm) recognition.

One of the main differences between multi-level systems and single-level systems is that not all features from heterogeneous physical meters are directly used to solve the recognition problem. Instead, they combine the signatures of several gauges and use appropriate processing to obtain the side signatures. These secondary features can be used in the classification algorithm, or become the basis for further unification, creating the 2nd, 3rd and further levels of features that determine the multi-level recognition system.

In addition, it is indicated that subsystems carrying out the association of features can also function as recognition devices that can determine local complex recognition

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systems. The scheme of this multi-level system is similar to the scheme of a single-level system, but it is complicated by the relationships between features and classification algorithms.

Therefore, in single-level recognition systems, a posteriori information about the features of the object is formed directly on the basis of the processing of direct measurements. In contrast, in multi-level systems, information about features is formed on the basis of indirect measurements, which are the result of the operation of auxiliary recognition devices, for example, the measurement of the range by the radar according to the delay time of the emitted pulse.

The third classification principle concerns the amount of initial a priori information. Here, the important question is whether a priori information is sufficient to determine an a priori alphabet of classes, build an a priori dictionary of features, and describe each class in the language of these features during direct processing of the source data.

According to this principle, recognition systems are divided into:

- Systems without learning: Where a priori information is sufficient for object recognition.

- Learning systems and self-learning systems: Where training is needed to improve or change a priori information.

It is important to note that multi-level complex recognition systems cannot always be clearly assigned to these classes, since each of the local systems that comprise these systems can be an untrained system, a learning system, or a self-learning system.

The widespread use of small unmanned aerial vehicles (UAVs) has led to a number of problems, among which it is worth noting the inappropriate behavior of some owners, unauthorized monitoring of territories and objects of state importance, as well as the increase in cases of violation of privacy and the possibility of using UAVs for terrorist and intelligence purposes. Regardless of the field of application, the full-scale performance of UAV missions includes the detection, localization and identification of targets, as well as tracking and targeting.

In many cases, the problem of detecting UAVs in the air becomes relevant. The most vulnerable part of UAVs is their electromagnetic radiation. Some electromagnetic unmasking features include on-board responder signals, radar station signals reflected from the UAV body and assemblies, signals from television repeaters and communication base stations, commands and control channels, as well as side-view radar signals and others.

The main methods of detecting UAVs in the electromagnetic spectrum are the use of infrared thermal imagers, optical cameras, radar stations and radio monitoring.

Modern UAV detection methods can be classified as follows:

- Audio detection: detection by sound signals generated by the UAV.
- Visual detection: use of optical cameras to detect visible signs of UAVs.
- Detection by thermal trace: use of thermal imagers to determine the thermal traces of UAVs.
- Radar: detection using radar systems that use reflected signals.
- Radio (RF): detection of electromagnetic radiation such as communication and control signals.
- Wi-Fi: Detection using Wi-Fi of signals that can be generated by a UAV.

These methods can be used alone or combined to achieve greater UAV detection efficiency. Let's consider in more detail each of the specified UAV detection methods:

1. Audio detection:

- Based on the sounds produced by the UAV during operation.
- Research in this area includes tracking sound signatures using a database of known UAV sound signatures.
- May be unreliable in noisy environments or with UAV modifications.

2. Visual detection:

- Uses cameras to detect moving objects in the air.
- Tries to distinguish UAVs from birds by size, flight path and movement style.
- Infrared cameras can detect UAV thermal signatures.

3. Thermal detection:

- Detects the heat signature of UAVs, but the plastic bodies of small UAVs emit a minimal heat signature.

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4. Radio (RF) detection:

- Includes monitoring of 2.4 GHz and 5.8 GHz radio frequencies used for UAV data transmission.

5. Wi-Fi detection:

- Possibly, since many commercial UAVs have SSIDs and MAC addresses that are broadcast over Wi-Fi.

6. Radar (radiolocation):

- Effectively detects the presence of UAVs at a long distance.
- Able to combine with other technologies such as RF or optics.
- The radar system emits radio waves and tracks their reflection or scattering by objects, which allows you to determine the shape, size and density of the object.

These methods can be used separately or combined for more effective detection of UAVs in various conditions. Each method has its advantages and limitations, and their use depends on the specific conditions and detection tasks.

4.2.2. Convolutional neural networks and detection of moving targets

Convolutional Neural Networks (CNN) are often used to recognize objects in unmanned aerial vehicles (UAVs). Convolutional neural networks are among the most powerful tools for image processing due to their ability to automatically extract useful features from input data.

The basic idea of convolutional neural networks is to use specialized spheres (convolutional spheres) to detect different characteristics of an image, such as boundaries, textures, and shapes. Each roll learns different characteristics and passes them on to the next ball for further analysis.

After several convolutional spheres, fully connected spheres are usually used to classify the image into specific categories or recognize objects in the image. During training, a convolutional neural network optimizes its weights in such a way as to recognize and classify objects in images as efficiently as possible.

In the context of UAVs, object recognition using convolutional neural networks can be used for tasks such as target detection and tracking, landscape recognition, obstacle detection, or automatic route determination. These systems help UAVs perform a variety of tasks with high precision and reliability.

In most cases, target detection is aimed at determining the presence of objects that may appear or disappear in the observed scenario. The indicator of moving targets determines the operating mode of the radar, which allows the system to distinguish between moving and stationary objects in the control zone. The principle of the Doppler effect is important for this, since stationary objects do not lead to a Doppler shift of the frequency of the observed signals.

According to the Doppler principle, the frequency shift of the backscattered signal increases as the target moves toward the radar line-of-sight (LOS) direction and decreases as the target moves away. This mode filters high-frequency components, removing low-frequency elements associated with stationary targets. It is important to note that such processing only provides information regarding the presence or absence of dynamic targets, without providing specific information regarding their number or an estimate of their Doppler shifts. Nevertheless, it remains an effective tool due to its simplicity in implementation. Filters are typically simple low-order finite impulse response (FIR) designs, also known as delay lines. An example is a two-pulse digital filter that filters pulses using a sequence of complex baseband (I/Q) data samples from the same range over two consecutive pulses. The discrete time transfer function of this filter is simple $H(z)=1-z^{-1}$. The frequency response as a function of the Doppler frequency fD is obtained by setting $z = e^{j2\pi f_D T}$,

$$H(fD) =(1-z^{-1})|_{z=e^{j2\pi f_D T}},$$

$$=1-e^{-j2\pi f_D T},$$

$$=e^{-j\pi f_D T}(e^{j\pi f_D T} - e^{-j\pi f_D T}),$$

$$=2je^{-j\pi f_D T} sin(\pi fDT),$$

The concept of a cascaded two-pulse cut-off choke to create higher order filters can be extended to an N-pulse canceller obtained by a cascaded N-1 two-pulse cut-off choke. Thus, it becomes a more general transfer function of an N-pulse compensator.

$$H_N(z) = (1 - z^{-1})^{N-1} .$$

In the process of information extraction, there are a variety of time-frequency

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analysis tools that can be used to highlight important features for further inspection and classification of possible objects. One of the most popular methods is the short-time Fourier transform (STFT), which involves applying the Fourier transform to small parts of the received signal. Other methods such as Cadence Velocity Diagram (CVD) are also key features, which are entirely based on spectrogram estimation, i.e. STFT squared modulus. Also of note are tools such as the Wigner–Ville distribution, which, using correlation techniques, can show how a signal's energy is distributed over both time and frequency.

Below is the definition of STFT, which is one of the most common methods:

$$X[k] = \sum_{t=0}^{N-1} x[t]\omega[t - \tau]e^{-2\pi k\frac{t}{N}} \, where \begin{cases} k \in 0 \cup \mathrm{N}: \mathrm{k} < \mathrm{N} \\ \tau \in 0 \cup \mathrm{N}: \tau < \mathrm{N} - \mathrm{M} \end{cases}$$

In the STFT equation, where k and t represent frequency and time, respectively, x[t] is the target signal, w[n] is a window function of length M, and N is the number of samples, we obtain a complex vector described by amplitude and phase depending on frequency and time. The spectrogram, as a typical method for estimating the micro-Doppler signature, is the result of the STFT.

Although STFT is a powerful tool, it has its limitations, including fixed resolution. The choice of window has a large effect on the representation of the signal: a narrow window gives good time resolution but poor frequency resolution; a wide window, on the other hand, provides better frequency resolution but degrades time resolution.

There is a trade-off between time and frequency resolution that can be explained by the Nyquist criterion for sampling. Decreasing the sampling rate (fs) will increase the frequency resolution, but you will need to increase the window size (M), which will decrease the time resolution. Alternatively, increasing M will improve the frequency resolution, but again decrease the temporal resolution.

4.2.3 Peculiarities of using deep learning in object recognition systems

Object recognition is a technique used in computer vision to identify objects in images or videos. This process is an important component of deep and machine learning algorithms. Compared to humans who can easily recognize objects, scenes and details in photos or videos, the goal is to teach a computer to perform similar tasks by understanding the content of images.

There are a variety of approaches to object recognition, but recently deep and machine learning methods have become the main trends in this field. Both methods learn to recognize objects in images, but they differ in their performance. In particular, deep learning technologies such as convolutional neural networks (CNNs) have become popular for object recognition.

Deep learning models, such as CNN, are used to automatically learn the characteristic features of objects for their identification. For example, CNN can tell the difference between cats and dogs by analyzing thousands of training images. There are two approaches to object recognition using deep learning: training a model from scratch, which requires a large data set and building a network architecture, and off-the-shelf model tuning, which uses existing models and tunes them for a specific recognition task.

Using a pre-trained deep learning model is a popular approach in most deep learning applications. This process uses a transfer learning method where an already tested model is fine-tuned. Typically, you take an existing network, such as AlexNet or GoogLeNet, and train it on new data that contains classes that were previously unknown. This method is less expensive and can lead to faster results because the model has already been trained on a large number of images.

In comparison, the standard machine learning approach to object recognition involves selecting features for each image and assembling a collection of images (or videos). For example, a feature extraction algorithm can extract edge or corner features to distinguish between classes in a dataset. These features are added to a machine learning model that analyzes and classifies new objects.

Achieving an accurate object recognition model will likely require the use of a variety of machine learning algorithms and feature extraction techniques that provide many combinations. Using machine learning for object recognition allows you to flexibly choose the optimal combination of features and classifiers for training, achieving accurate results with minimal data.

The comparison between machine learning and deep learning for object recognition depends on the specific task and application. Machine learning can be effective, especially when it knows which image characteristics are best used to separate object classes.

A key consideration when choosing between machine and deep learning is the availability of a powerful computer and the amount of images to train on. If the answer to any of these questions is "No", then a machine learning approach may be the optimal solution. Deep learning usually works better with a large volume of images, and using a graphics processing unit (GPU) helps reduce the time it takes to train a model.

In reality, the object recognition functionality consists of three sub-functionalities or stages, the implementation of which does not necessarily have to be interconnected. These steps can be performed by different subsystems, using different tools and approaches. The main thing in this approach is to provide a convenient communication format between subsystems, allowing you to choose the most optimal tool for the implementation of each stage without being tied to a specific technology stack. These three stages are:

• Detection (detection) - finding the object in the image.

• Recognition - recognition, obtaining information about the detected object.

• Identification (identification) – recognition of object details, information extraction. Object detection and Object recognition Viola-Jones method

This algorithm is considered key in recognizing a face, its individual elements and emotions. Developed in 2001 by Paul Viola and Michael Johnson, it remains the foundation for face and other object recognition, including real-time use.

The operation of the algorithm is based on five main principles:

1. Image in integral representation:** Using the integral representation matrix, the size of which corresponds to the size of the original image. This allows you to quickly calculate given parts of the image using a linearly proportional integral image calculation time.

2. Using Haar features:** Haar features, adapted from the idea of Haar wavelets, use rectangular pieces to identify certain features in an image. These features are

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quickly calculated and used for object recognition.

3. Use of boosting:** The procedure of sequentially building a composition of machine learning algorithms, where each subsequent algorithm compensates for the shortcomings of the previous ones in the composition.

4. Classification of features:** All features fall into the classifier, which returns a boolean variable (true or false). This classifier divides objects into certain classes based on defined features.

5. Using cascades of features:** Using a group of features to discard parts of the image where the required object is not found. The cascade of features serves as a basis for building a system for highlighting complex objects.

This algorithm is considered efficient and fast, especially for face and other object recognition in real time. This allows you to get the ability to recognize objects even in real time. The Viola-John method is one of the best in terms of the ratio of recognition efficiency / speed. Also, this detector has an extremely low probability of error in face detection and identification. The algorithm works well and recognizes the details of the object (such as facial features) even at a small angle, 11 up to about 30 degrees. At an angle of inclination of more than 30 degrees, the percentage of detection drops sharply. And this does not allow the standard implementation to detect the turned face of a person at an arbitrary angle, which greatly complicates or makes it impossible to use the algorithm in modern production systems, taking into account their growing needs. A detailed analysis of the principles underlying the Viola Jones algorithm is necessary. The functionality of this method searches for objects and their details using the "scanning window" method. The algorithm of the scanning window with signs looks like this:

• there is a researched image, the scanning window is selected, the features used are selected;

• then the scanning window begins to move sequentially across the image with a step of 1 cell of the window (suppose the size of the window itself is 32 x 32 cells);

• when scanning the image in each window, approximately 200,000 options for the location of features are calculated, due to changing the scale of features and their position in the scanning window;

• scanning is performed sequentially for different scales;

• not the image itself, but the scanning window is scaled (the size of the cell changes);

• all found features go to the classifier, which "makes a verdict". In the search process, it is simply unrealistic to calculate all the signs on low-power desktop PCs. Therefore, the classifier should respond only to a certain, necessary subset of all features. It is absolutely logical that it is necessary to train the classifier to find individuals from a given subset. This can be done by training the computer automatically.

4.3. Practical aspects of implementation of object recognition systems in UAV operation

4.3.1. Selection of hardware and software for implementation of recognition systems. Preparation of training sets for training recognition models

The proposed AirGuardian complex consists of an unmanned vehicle and a ground station, which was developed on the basis of Obuda University. The complex includes hardware and software, such as an autopilot (AERObot), a tracker station antenna and a ground control station. This ensures optimal interaction of modules.

The main goal of AERObot research is to develop a general autopilot capable of controlling various designs of flying machines without recalculating a complex mathematical model. Keywords include unmanned aircraft, navigation, ground control stations, virtual cockpits, and flying wings.

The AirGuardian complex takes into account such criteria as compactness, automatic self-calibration before flight, autonomous tracking of UAVs and multi-user server-client architecture with various capabilities. Also provided are full mission recording and playback functions, support for specially calibrated AERObot maps and compact wireless sensor electronics.

AirGuardian was created to answer the following criteria: tracker antenna unit:

1. Compact unit without any other conductive module

2. Automatic self-calibration before flight

3. Autonomous tracking of UAVs

4. Connecting software for ground control

5. Server-client architecture for multi-user use with different capabilities (navigator, observer, mission planner and pilot)

6. Full mission recording and replay features

7. Support for calibrated AERObot maps (embedded hardware and software)

8. Compact, small electronics with non-conductive sensors

9. Modular design with a slot to achieve a specific program task

10. Universal communication interface for using both wireless (various RF modems) and wired (FTDI USB)

11. The autopilot can store at least 200 waypoints, aircraft parameters and functions in non-volatile memory

12. Fully autonomous operation (telemetry problems do not affect the flight)

The electronics of the ground system are located in the antenna tracker. The main task of the tracker is to provide radio frequency (RF) communication with the unmanned aircraft (UAV) using directional high-loss antennas, as well as wired communication with the ground control PC. The tracker also has a built-in GPS, which allows not only to track the UAV from one position, but also to use it as a mobile ground station. The tracker has two degrees of freedom with multiple rotations at the right angle.

Ground control software is based on a client-server architecture. The server is connected to an antenna tracker that provides telemetry and camera data. It can handle serial ports or TCP/IP packets. Multiple clients can connect to the server from one or more PCs. The server also transmits telemetry over Wi-Fi, allowing AirGuardian Mobile (smartphone version) to access mission data.

Users primarily use client software to communicate with the server over TCP/IP over wired or wireless networks. Clients have authentication that gives them the appropriate permissions (pilot, navigator, observer, and administrator). They can only see data relevant to their tasks. For example, a pilot can remotely control a UAV using the front-facing camera, but cannot change waypoints or altitude like a navigator can. The client interface is customized for each new role.

This software has great scaling capabilities. It can be used as a multi-station system with one dedicated server and multiple role-based clients, or as a single, low-cost laptop with an administrator role. AirGuardian can also record and replay missions in real time. Multilayer maps and 3D satellite images can be imported for mission planning.

To create and further apply neural networks, it is necessary to have a suitable set of data at one's disposal. This information usually includes special markers that indicate the expected results. Such a dataset is divided into three main categories: training data, validation data, and testing data.

The training data is the actual data set used to train the model, i.e. to adjust the weights and biases in the case of a neural network. The model "sees" this data and learns from it. Validation data are used to evaluate the effectiveness of this model [8]. In real situations, this data is used to fine-tune the hyperparameters of the model. The model periodically reviews this data, but does not learn from it. The validation results are used to update hyperparameters at the higher level. So validation, set in a certain way, affects the model, but indirectly.

The test data set serves as the gold standard for model evaluation and is used only after the model is fully trained (using the training and validation sets). The test set is usually well prepared and includes carefully selected data covering different classes that the model might encounter in the real world.

Since the amount of information is limited, the question arises about the efficient distribution of the available data for efficient training and testing of the neural network. This depends on the total number of instances in your data and the model you are training. Some models require a large amount of data for training, so they are optimized for large training sets. Models with a small number of hyperparameters can be easily tested and tuned, so the size of the validation set can be reduced. However, for models with many hyperparameters, it is optimal to use a large validation set. The split ratios between training and validation data are determined for each specific use case and are subjective.

4.3.2 Stages and methods of improving recognition accuracy. Testing and evaluating the effectiveness of the developed system on the example of specific tasks

Improving the quality of recognition accuracy can be done at the architecture level, thanks to the modification of existing blocks and/or the creation of blocks with new functionality. When training convolutional networks, convolutional filters also isolate boundaries. However, after passing through many layers of convolutions on the lower layers of the encoder, the boundaries of the object become blurred. This paper uses the assumption that in applied problems, the contour of the object can often be found by changing the gradient. Since the boundaries of the object need to be accurately known in the tasks, the additional separation of the contours should improve the performance of the network.

The input data is an input image of dimension c*w*h, where c is the number of channels (for RGB images c=3), w, h are width and height. The contour selection operator returns feature maps of dimension w*h, which are fed to the network decoder.

Detection of contours in the image is possible with the help of Kenny, Roberts, Pruitt, Sobel operators. The study analyzed the effectiveness of these operators. The use of Kenny and Sobel operators was recognized as the best in terms of accuracy. However, the Sobel operator has advantages such as simplicity of implementation, which affects processing speed, and easy integration with convolutional neural networks.

For convolution of the input image, the Sobel operator uses 2 matrices:

$$Sx = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}; \; Sy = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}. \tag{3.1}$$

The use of matrices (3.1) made it possible to effectively isolate contours for those

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objects whose boundaries are close to the X axis (the X axis is directed to the right) or the Y axis. In addition, you can use convolution matrices of the form:

$$Sd_1 = \begin{pmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{pmatrix}; \; Sd_2 = \begin{pmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{pmatrix}. \tag{3.2}$$

Matrices (3.2) make it possible to effectively isolate contours close to diagonals.

Thus, the following convolution operations can be defined:

$$\begin{aligned} Gx &= Sx * A, \\ Gy &= Sy * A, \\ GD_1 &= Sd_1 * A, \\ GD_2 &= Sd_2 * A, \end{aligned} \tag{2.6}$$

де Gx, Gy, Gd1, Gd2 — results of convolution along axes and diagonals,

Sx, Sy, Sd1, Sd2 — Sobel matrices (3.1), (3.2),

A – input image, passed as a matrix of pixel values.

The resulting image is obtained by combining the results:

$$G = \frac{1}{2}\sqrt{Gy^2 + Gx^2 + Gd_1^2 + Gd_2^2}, \tag{3.3}$$

G — final image;

Gy, Gx, Gd1, Gd2 — results of convolution along axes and diagonals.

The results of applying the concatenation of all component mappings to the Sobel operator with the direct result of its calculations (3.3) provide better results than using only the Sobel operator.

Thus, after applying all operations, the following set of matrices is obtained:

$$Out = [G, Gy, Gx, Gd_1, Gd_2]. \tag{3.4}$$

In the future, the implementation of Out calculations will be called a Sobel block.

As a rule, input images are not single-channel images (black and white), but two-channel or more (for example, RGB images). The Sobel operator is applied to each channel independently. For example, for an RGB image, 15 channels will be obtained, which will be reproduced by a set of matrices OutR, OutG, OutB.

Modification of the architecture of deep learning networks

In this work, research was conducted on the U-Net and FPN networks, DeepLab

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v3 and PSPNet. The elementary layers of these networks are convolution, activation, concatenation, pooling, addition, and upsampling.

To present the modified architecture, let's introduce the concept of a block, noting beforehand that the dimension of the image in the general case is defined as:

$$Shape = W * H * C, \qquad (3.5)$$

W - image height,

H - image width,

C - the number of image channels.

We define a block as a group of elementary layers of a neural network that processes input data of fixed dimensions only in width (W) and height (H).

In the figure, the repetition of the blue block emphasizes the copying of data from the output of the encoder block to the corresponding decoder block. The raw input image is fed to the encoder and further undergoes standard processing. In the proposed architecture, only a few upper (last) blocks of the decoder are modified. Forced definition of contours (highlighted in yellow) and their concatenation with the corresponding encoder blocks have been added to these blocks. Studies have shown that the best results are provided by the use of the proposed method on the last 2-3 blocks.

In addition, a modification of the FPN network was proposed, which is also a deep learning network, but unlike the U-Net network, it has a different decoder structure.

The modification of the FPN network is shown in Figure 3.1. The main difference is that the signal after the Sobel block passes through a 3*3 convolution layer.

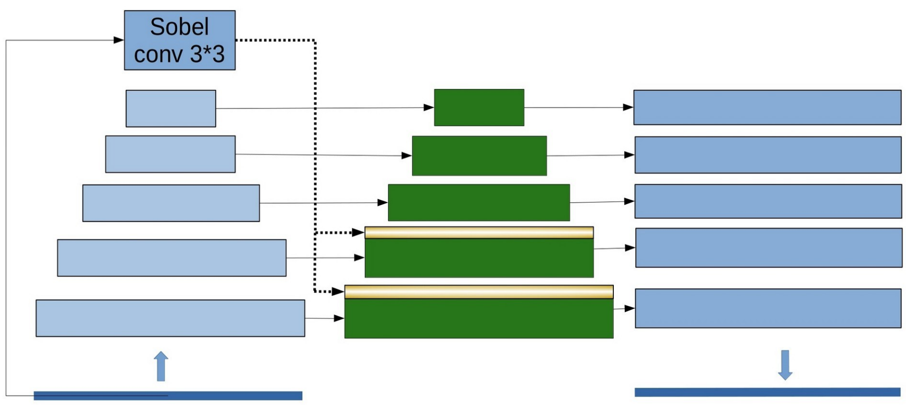

Fig. 3.1. - Modernization of the FPN network

Since the dimensions of the layers in height and width do not match, it is necessary to reduce the result to the appropriate dimension. The network decoder block has dimensions:

$$Shape = (W / k ; H / k) \tag{2.10}$$

W, H – width and height of the input image, respectively, k – block number from the end.

The pooling layer reduces the dimensionality of the Sobel block output by a factor of k.

In addition to the considered U-Net and FPN networks, other convolutional networks were also used in the research: PSPNet and DeepLab v3. Since these networks have a different decoder structure, the result of the Sobel block was proposed to be concatenated with the output of the encoder block (bottleneck) (Figure 3.2). Additionally, the output after the pooling layer was passed through the convolution layer.

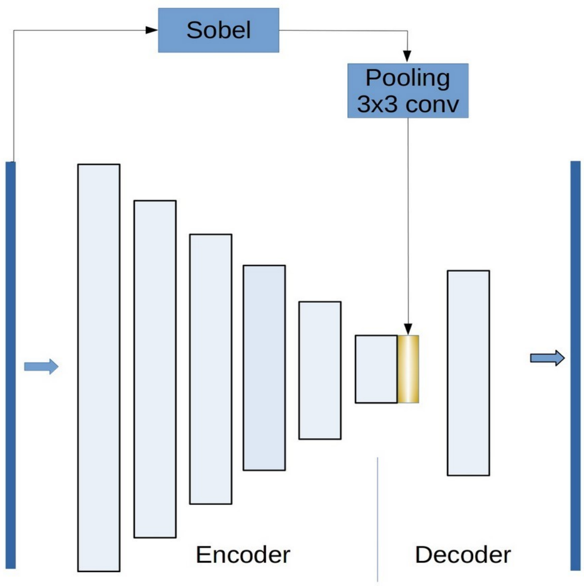

Fig. 3.2. - Implementation of the Sobel block in the DeepLab v3 and PSPNet networks

Modification of networks is implemented in the Python language on the Keras framework using the segmentation_models library.

The detection range of targets with smaller ESRs is determined by formula (1.3):

$$\sigma ц1 = 0.1 \text{ m2}$$

$$R1 = \sqrt[4]{\frac{P_{pr} \cdot (G^2 \cdot \sigma ц1 \cdot \lambda^2)}{(4 \cdot \pi)^3 \cdot P_{pr\_min}}} = 2.5 \cdot 10^3 \text{ m}$$

$$\sigma ц2 = 0.07 \text{ m2}$$

$$R2 = \sqrt[4]{\frac{P_{pr} \cdot (G^2 \cdot \sigma ц2 \cdot \lambda^2)}{(4 \cdot \pi)^3 \cdot P_{pr\_min}}} = 2.287 \cdot 10^3 \text{ m}$$

$$\sigma ц3 = 0.05 \text{ m2}$$

$$R3 = \sqrt[4]{\frac{P_{pr} \cdot (G^2 \cdot \sigma ц3 \cdot \lambda^2)}{(4 \cdot \pi)^3 \cdot P_{pr\_min}}} = 2.102 \cdot 10^3 \text{ m}$$

$$\sigma ц4 = 0.01 \text{ m2}$$

$$R4 = \sqrt[4]{\frac{P_{pr} \cdot (G^2 \cdot \sigma ц2 \cdot \lambda^2)}{(4 \cdot \pi)^3 \cdot P_{pr\_min}}} = 1.406 \cdot 10^3 \text{ m}$$

$$\sigma ц5 = 0.005 \text{ m2}$$

$$R5 = \sqrt[4]{\frac{P_{pr} \cdot (G^2 \cdot \sigma ц5 \cdot \lambda^2)}{(4 \cdot \pi)^3 \cdot P_{pr\_min}}} = 1.182 \cdot 10^3 \text{ m}$$

Figure 3.3 shows the change in the radar observation area in accordance with the reduction of EPR targets. At the same time, the probability of correct detection and false alarm remained unchanged.

Therefore, a clear understanding of the appearance of the radar and the technical characteristics necessary to solve the task is impossible without experimental evaluations of observability (EPR) of objects of interest. The obtained EPR estimates for small UAVs, on the basis of which the detection limits of promising radars can be calculated, are able to count on the creation of mostly cheap radars for controlling UAV flights, for example, over urban areas. Experimentally measured EPRs have a value of about 0.1 m^2. Available models of UAVs can be detected by radar at distances of approximately 3-5 km, which is enough to ensure the safety of protected objects and mass events.

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Table 3.1 – Change in range with decreasing EPR of targets

ESR σц, m^2	Range R, km
0,1	2,5
0,07	2,287
0,05	2,102
0,01	1,406
0,005	1,182

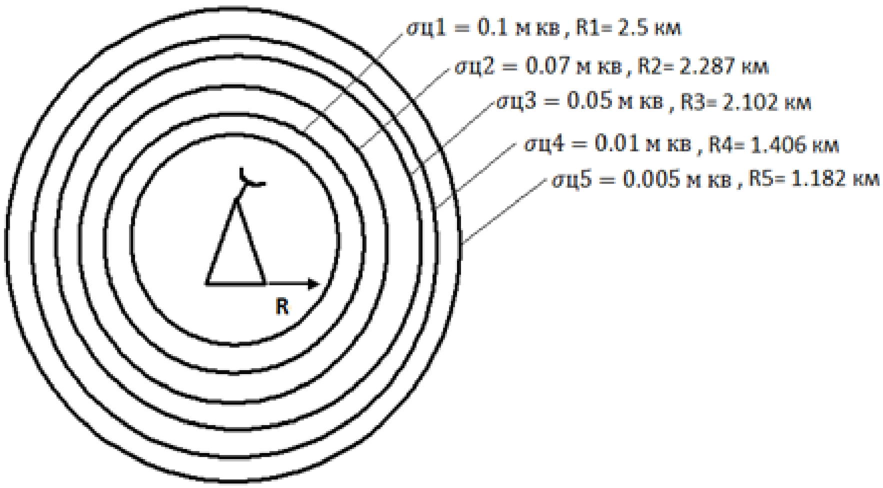

Fig. 3.3 — Radar viewing area

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Conclusions

By 2026, the global market for unmanned aerial vehicles (UAVs) is forecast to grow significantly to $34.5 billion, with annual growth of 32%. Due to the decrease in cost and the increase in the availability of UAVs for consumers, there is a rapid increase in the amount of images obtained with the help of these devices.

The solution to this dynamic lies in the application of artificial intelligence (AI) and computer vision in the field of UAVs. New technological advances allow computer vision models to perform the tasks of image classification and object detection with impressive efficiency, comparable to or even exceeding human capabilities, in fractions of a second.

UAVs are used in a variety of industries, including animal population tracking, reforestation monitoring and livestock tracking in natural resources, as well as security, intelligence and surveillance, as well as being used by emergency services to search for survivors and deliver medical supplies to remote areas.

To optimize the processing of received data, AI performs it directly on embedded devices located close to the source of collection, instead of sending data to the cloud. The result of such an approach could be the development of an AI system for UAVs that is capable of identifying any object it is trained to recognize, be it animals, people, or ordinary objects. This method promises to be more cost-effective, safer and more accurate than traditional image analysis methods, providing benefits that outweigh the costs of development and implementation.