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DEVELOPING THE GOOGLENET NEURAL NETWORK FOR THE DETECTION AND RECOGNITION OF UNMANNED AERIAL VEHICLES IN THE DATA FUSION SYSTEM

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This work reports a study into the possibility of using the GoogleNet neural network in the optoelectronic channel of the Data Fusion system. The search for the most accurate algorithms for detecting and recognizing unmanned aerial vehicles (UAVs) in Data Fusion systems has been carried out. The data processing scheme was selected (merging SVF state vectors and merging MF measurements), as well as the sensors and recognition models on each channel of the system. The Data Fusion model based on the Kalman Filter was chosen, integrating radar and optoelectronic channels. Mini-radars LPI-FMCW were used as a radar channel. Evaluation of the effectiveness of the selected Data Fusion channel model in UAV detection is based on the recognition accuracy. The main study is aimed at determining the possibility of using the GoogleNet neural network in the optoelectronic channel for UAV recognition under conditions of different range classes. The neural network for the recognition of drones was developed using transfer training technology. For training, validation, and testing of the GoogleNet neural network, a database has been built, and a special application has been developed in the MATLAB environment. The capabilities of the developed neural network were studied for 5 variants of the distance to the object. The detection objects were the Inspire 2, DJI Phantom 4 Pro, DJI F450, DU 1911 UAVs, not included in the training database. The UAV recognition accuracy by the neural network was 98.13 % at a distance of up to 5 m, 94.65 % at a distance of up to 20 m, 92.47 % at a distance of up to 50 m, 90.28 % at a distance of up to 100 m, and 88.76 % at a distance of up to 200 m. The average speed of UAV recognition by this method was 0.81 s

Keywords: GoogleNet, YOLO, neural network, Data Fusion, UAV recognition, optical channel, FMCW-radar

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1. Introduction

Drones (UAVs) pose a large-scale threat to the world community due to their great destructive capabilities and ease of use by intruders. Terrorist organizations and criminal groups can use drones for photo and video shooting of strategic objects, the development of technical and tactical actions and air strikes. The high destructive activity of drones is evidenced by terrorist attacks on the Abqak and Khurais oil refineries in Saudi Arabia on September 14, 2019.

In this regard, the development of technologies for detecting and eliminating dangerous drones without false positives is relevant in the scientific world. In practice, classical methods of combating UAVs as air targets (airplanes, helicopters) are often used. At the same time, even generally recognized radar, electro-optical, acoustic technologies are not able to achieve the desired accuracy. This is due to the relatively small size, small values of the effective scattering area, inconvenient for recognizing the speed of maneuvering drones. Also complicating the task is the need to detect the drone at safe distances for strategically important objects (from 1 to 3 km).

Separate use of sensors of the above-mentioned technologies does not make it possible to detect and recognize drones with a minimum of false alarms and the ability to measure radial velocity, azimuth, and angle. The solution to such complex problems can be Data Fusion using a neural network. Data Fusion involves combining data from sensors of different technologies. A key indicator in the choice of algorithm, recognition and classification model in Data Fusion channels (radar, acoustic, electro-optical, RF) is accuracy and speed. It is important to choose exactly the algorithm that is able to provide Data Fusion with the most progressive values of these parameters. To recognize and classify UAVs, it is proposed to use the GoogleNet convolutional neural network in the Optical-Electronic Channel Data Fusion.

2. Literature review and problem statement

Typically, drone detection systems include blocks for scanning and noise reduction, recognition, central processing, and real-time display of results.

In [1], the authors considered the ADS-ZJU drone protection system. In the heterogeneous sensing phase, three observation technologies are combined: audio, video, and data from RF sensors. At the same time, the radar technologies used by the authors are a problem in densely populated urban areas. The system reported in [2] combines several sensors to capture images and sound information about the environment in different directions. To recognize UAVs, the support vector machine (SVM) method is used.

In work [3], the SVM method was also used but a histogram of oriented arguments is preliminarily used in order to determine the specific features of the UAV and use them at subsequent stages of recognition. In [4], the use of SVM as a classifier was used along with the unification of dynamic optical streams from video cameras, taking into consideration the mobility of the UAV and the complexities of stationary surveillance. A similar approach to UAV systems, such as the ADS-ZJU system, was discussed in [5]. SVM is used to recognize UAVs in the cited works [1–5]. The merge algorithm consists of running multi-touch detection in parallel. All vectors are combined together to improve the merger of solutions. The localization phase follows the discovery phase. Namely, the direction of arrival (DOA) and the power of the received signal (RSS) are extracted from the received acoustic signals, video images, and radio frequency signals. The results show an accuracy of more than 90 % when combining data with 5 % false positives. At the same time, accurate localization under the global positioning mode, important technical parameters of the target (angular coordinates, radial velocity, distance) in these systems are unreliable. Under the operating conditions of such systems, it must be borne in mind that UAVs can be located at a distance of more than 100 meters from the measuring station for analysis and data processing. In such cases, the accuracy of recognition is markedly reduced.

In paper [6], the authors describe another approach that leverages the ability of deep learning neural networks to detect high-level and abstract functions from representations of raw data. Namely, three modes are used to detect UAVs, including thermal image data, visual data, and 2D radar data in the form of range profile matrix data, which are combined into a deep neural network (DNN).

Work [7] considers the possibility of detecting drones in real time in scenes with a static background. The detection of moving objects was based on background subtraction, and the classification was performed using a modified version of MobileNetV2, widely used by efficient convolutional neural networks (CNNs). This platform detects, tracks, and follows the drone within a range of its sensors using a pre-trained machine learning model.

In [8], the authors observed the flying drone using a fisheye camera. The drone was detected using three methods for classifying a convolutional neural network, the support vector method (SVM), and the nearest neighbor method. The results show that CNN, SVM, and nearest neighbor have overall accuracy of 95 %, 88 %, and 80 %, respectively.

In study [9], the authors in the framework of the competition for the detection and classification of drones and birds, proposed an algorithm based on YOLOv5. This convolutional neural network uses PANet extension and mosaic magnification to help improve detection of small objects. The authors trained a neural network with an air-to-air dataset with complex backgrounds and lighting conditions. The proposed approach achieved 0.96 recalls, 0.98 mAP 0.5, and 0.71 mAP 0.5:0.95 in 10 % of a randomly selected dataset from the entire dataset.

Work [10] describes the method of detection and classification of UAVs in real time using a single-stage detector YOLOv4. The maximum mAP (recognition accuracy) of 74.65 % is achieved at 4000 iterations. Further work of the authors is aimed at testing new versions of the YOLO algorithm. New versions are improved according to mAP and FPS criteria. The authors of [11] used the architectures Zeiler and Fergus, VGG16 for training and detection of UAVs. The results of the training dataset from five MPEG4 videos showed that VGG and Faster R-CNN are superior in accuracy. The authors of [12] used CNN and a recurrent neural network to recognize and classify the UAV's unique acoustic markers. The training dataset consisted of audio recordings of drones. YOLOv3 was used to detect and classify different types of drones [13]. The training dataset included 10,000 images and 150 epochs. The authors of [14] developed a drone detection system based on OpenCV, which achieved an accuracy of 89 % with a dataset of 2088 positive and 3019 negative examples. Paper [15] used YOLOv3 to improve detection accuracy and obtain more accurate bounding frames. Their experimental configurations were as follows: a 64-bit Ubuntu 16.04 operating system with a hardware configuration including an Intel Xeon E5-2630 v4 processor, an NVIDIA GeForce GTX 1080 Ti GPU model, and 11 GB of memory. The experiment was conducted on the Darknet platform.

In works [6–15], where data from optoelectronic sensors were processed (UAV recognition was made from photos and videos), two-stage detectors (R-CNN) and single-stage YOLO detectors were used. This type of detector allows for real-time recognition with an optimal FPS value but the average accuracy parameters of the UAV are relatively not high; for example, the average recognition accuracy of YOLOv5 is no more than 55 %.

Work [16] studies the features of the use of infrared thermal imaging cameras for the recognition of commercial UAVs of small sizes at night. As a result of the analysis of images obtained from the thermal imaging sensor, the greatest heating of the UAV is concentrated in the level of the battery mount, this is due to the fact that the motors are cooled by the air circulation of propellers. Due to the current conditions for displaying the target in the focus of the optoelectronic sensor, the detection range for quadcopters was only 40–45 meters, for the hexacopter – 102 meters.

In works [17–20], a three-dimensional point cloud organized by the LiDAR sensor system for detecting people, cars, and ships became the basis for the application of such technology for the recognition of mini/micro UAVs. Study [17] used two types of sensors, VLP-16 and HDL-64E. VLP-16 sensors are only suitable for distances of up to 10 meters; in the case of HDL-64E, the detection range increases to 35 meters. With a further increase in distance, the quality of detection decreases markedly.

Works [16, 17] proved the functionality of the use of infrared thermal imaging sensors and LiDAR sensors in detecting different types of UAVs at ranges from 10 to 100 meters but the issue of studying the accuracy of recognition relative to other flying objects (for example, birds) is considered only in perspective. The technology based on the construction of a 3D point cloud has prospects for application for recognition so far only for larger detection objects than UAVs. In work [18], on the basis of this technology, the accuracy of human detection was 93 % at a distance of 20 m. In [19], a car acted as the object of detection, and in [20] – a sea vessel.

Work [21] proposes a radar based on 5G for detecting a drone outdoors and indoors with almost 100 percent accuracy. In addition, the cost-effective machine learning system developed by the authors is able to localize the UAV with an accuracy of 75 % in real time. The applied method of 5G bistatic radar showed effectiveness only under indoor conditions, i.e. in a closed space (recognition accuracy is about 100 %, UAV localization accuracy is 75 %). As a result of research in open areas, the localization accuracy indicator decreased to 25 %, and the accuracy of classification and recognition of UAVs in the presence of other flying objects was not included in the research tasks.

In [22], the authors reported evidence of progress in the use of multi-input and output radar (MIMO) systems in detecting small drones at the Beijing Institute of Technology. The developed system used the DDMA method to achieve orthogonality in the transmission of radar signals. This format makes it possible to separate signals from each other due to the fact that each antenna of the array has its own Doppler offset. At the same time, it is more difficult for this radar to detect hovering drones compared to the FMCW radar because the scanning scheme limits the residence time of the radar illuminating a specific target. In addition, the micro-Doppler signature of the target is also difficult to obtain, in which case the effectiveness of classification methods may be limited due to the lack of such information, often used for automatic target recognition.

Work [23] reports the configuration of the system based on the MIMO OFDM radar, which can be used to detect drones and detect unmanned aerial vehicles (UAVs) in general. This radar is equipped with *PxQ* transmitting (*Tx*) and receiving (*Rx*) antennas using the signal model and the concept of a virtual antenna proposed in [24]. The detection range with a clear display of the UAV was only 27 meters.

In [25], the authors presented a demonstration sample of a radar with frequency modulation of continuous action (FMCW), operating in the X-band. The system is capable of detecting and tracking the DJI-Phantom 4 at a distance of up to 3 km.

In paper [26], Joshua Bernard-Coopera, Samiur Rahmana, Duncan A. Robertson investigated the features of the FMCW of four drones and the possibility of using them to distinguish models using machine learning methods, which makes it possible to determine the location and classify the drone. The authors developed several algorithms to automatically extract the strength of the microdoppler, the ratio of volumetric doppler to microdoppler, and the distance between HERM lines from spectrograms. Four models were classified with an accuracy of 85.1 %. A higher accuracy exceeding 95 % was achieved when training using fewer drone models.

Paper [27] reports the use of microdoppler signatures collected using radar systems operating on three frequency bands to classify and recognize drones with and without payload. Owing to the use of the KNN classifier with six functions, the authors managed to achieve a classification accuracy of 80.95 %, 72.50 %, 86.05 % for data collected in S, C, W bands.

Works [22–27] prove the effectiveness of using radar systems of various topologies for detecting UAVs and report the results of using classifiers to distinguish these objects by signs. However, to organize the recognition of UAVs solely by radar characteristics increases the likelihood of false alarms since in order to solve the problem of classifying UAVs from other objects with similar values of RCS (effective scattering area), confirming data from sensors of another type (acoustic, optical-electronic, radio frequency) is required.

Thus, our review of the scientific literature reveals the possibility of applying different technologies and approaches in the detection and recognition of UAVs. Works [10–14] showed the advantage of convolutional neural networks in comparison with other classifiers (SVM and KNN). However, to detect an object in these systems, either a video camera or individual images are used. At the same time, some systems have shown the advantage of using radar technology but not in urban environments. In this regard, the idea of combining radar and optoelectronic channels with the use of Data Fusion technology and the use of a convolutional neural network for the recognition and classification of UAVs was suggested. The main condition for the effectiveness of the introduction of this neural network into the MF model of the Data Fusion system will be the achievement of an average accuracy value of 90 %.

3. The aim and objectives of the study

The aim of this work is to develop and examine a UAV recognition system based on the GoogleNet neural network in the optoelectronic channel of the Data Fusion system. This will make it possible to determine the key qualitative characteristics of the neural network: accuracy and speed. These characteristics can be compared with the proposed algorithms from other works, as well as make a conclusion about the effectiveness of using GoogleNet in the optical-electronic channel Data Fusion.

To accomplish the aim, the following tasks have been set:

– to develop and train a neural network for UAV recognition;

– to study the capabilities of the neural network in the structure of Data Fusion.

4. The study materials and methods

ISAR (Inverse synthetic-aperture radar) images obtained at the National Laboratory for Radar and Surveillance Systems (Pisa, Italy) as a result of testing the LPI-FMCW mini-radar in the laboratory prove the ability to determine a number of characteristics of the UAV by the radar method (Fig. 1).

The LPI-FMCW radar is tuned to the X band with a carrier frequency of 9.6 GHz, a bandwidth of 300 to 500 MHz, with a transmission power of 33 dBm. Such characteristics made it possible to obtain on ISAR noticeable microdoppler markers of six UAV blades (three on the left and three on the right). Microdoppler bird signatures also record the flapping of birds' wings. This fact makes it possible to use microdoppler properties as functions for the classification of UAVs and birds. While the hexacopter and quadcopter are more noticeable due to their blades, then the flying wing of drones against this background is less selective. In this regard, the radar system and the optoelectronic detector are integrated into a single Data Fusion model (Fig. 2).

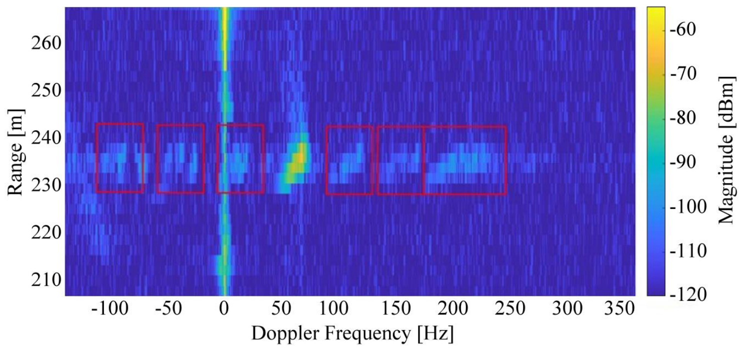

Fig. 1. Image of the hexacopter by radar with reverse synthetic aperture

Data Fusion is a technology that makes it possible to better design autonomous systems. Specifically for protection systems against unmanned aerial vehicles (drones), the best quality of the system is achieved by combining radar and optical-electronic channels. In accordance with the structural scheme (Fig. 2), the recognition algorithms differ in the optical and radar branches. In the radar region, the dynamic characteristics of objects, namely microdoppler signatures, are analyzed. The study is based on the analysis of work of the second branch – the optical channel. To organize the operation of the optical channel, a Tiandy PTZ camera is used with a maximum range in the daytime up to 2000 meters, and at night up to 1000 meters. Preliminary, the camera is used to create a database using video footage of UAV flights. The video material is sent to the MATLAB application (USA) and is divided into frames, which are a set of data in addition to photos and images of drones and birds from open sources. In addition, the camera is used to record data for checking and testing a convolutional neural network. For this purpose, images of UAVs and birds are formed, recorded by the camera at different distances from the location of the camera. These distances are divided into 5 classes:

– class 1: to 5 m;
– class 2: from 5 to 20 m;
– class 3: from 20 to 50 m;
– class 4: from 50 to 100 m;
– class 5: from 100 to 200 m.

The task of developing an application for training, testing, and checking a convolutional neural network is implemented in the environment of the MATLAB computer-aided design system. A special database was prepared for training a convolutional neural network, consisting of objects of recognition and classification (photo, video).

5. Results of a study on the possibility of using GoogleNet to recognize drones in the Data Fusion system

5. 1. Results of neural network development

It was decided not to create a new neural network for the recognition of drones but to use transfer learning technologies on a ready-made neural network. Transfer training makes it possible to optimize the network, ready to learn new features. Thus, by changing GoogleNet, you can organize your own neural network to solve specific problems.

The GoogleNet neural network implements methods to reduce the computational load and ensure high performance through the use of Inception modules [28]. The module is represented by a combination of convolutional blocks 3×3, 5×5, 1×1. This makes it possible to use several filters in parallel, which increases the number of operations when moving from one layer to another. Due to 1×1, the depth of the image decreases, and the quality of work is maintained at a high level. This principle is used to solve various problems, including object recognition [29]. UAVs and birds were chosen as objects of classification. For this purpose, materials from the open sources Kaggle.com, Roboflow, Google were used. We also added video footage of UAV flights, which was produced by an IP PTZ camera. As a result, it was possible to construct a database for the «drone» class in the form of 27,500 pictures and, for the «not a drone» class, 14,200 pictures. This material is enough to organize the classification process between the two classes.

Transfer learning based on this neural learning is easy to implement in MATLAB R2020a [30]; the structure in the current version of the software includes 144 layers (Fig. 3).

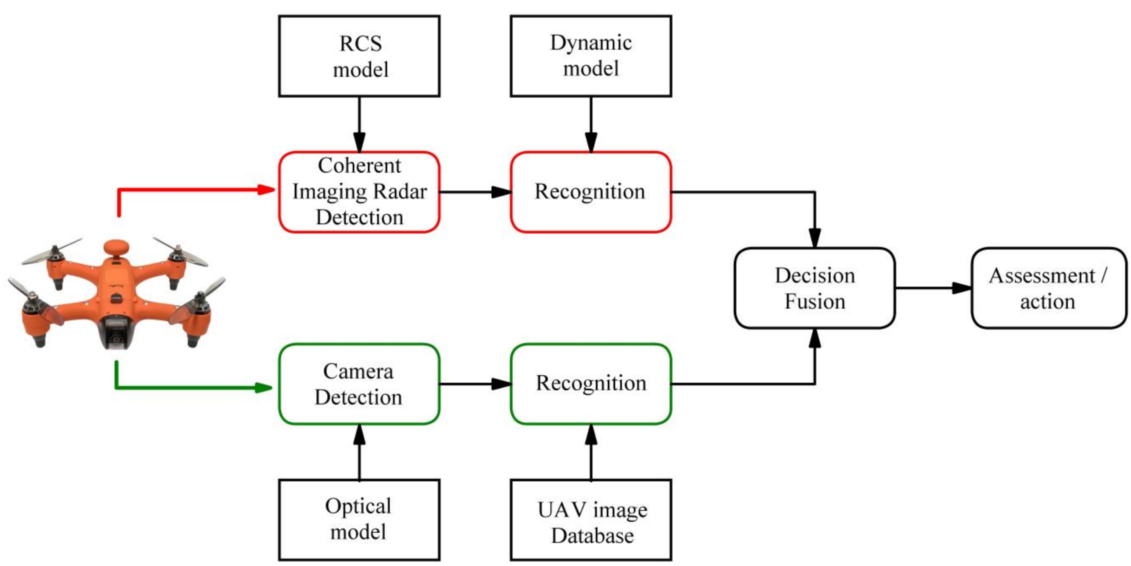

Fig. 2. Flowchart of the proposed drone detection system

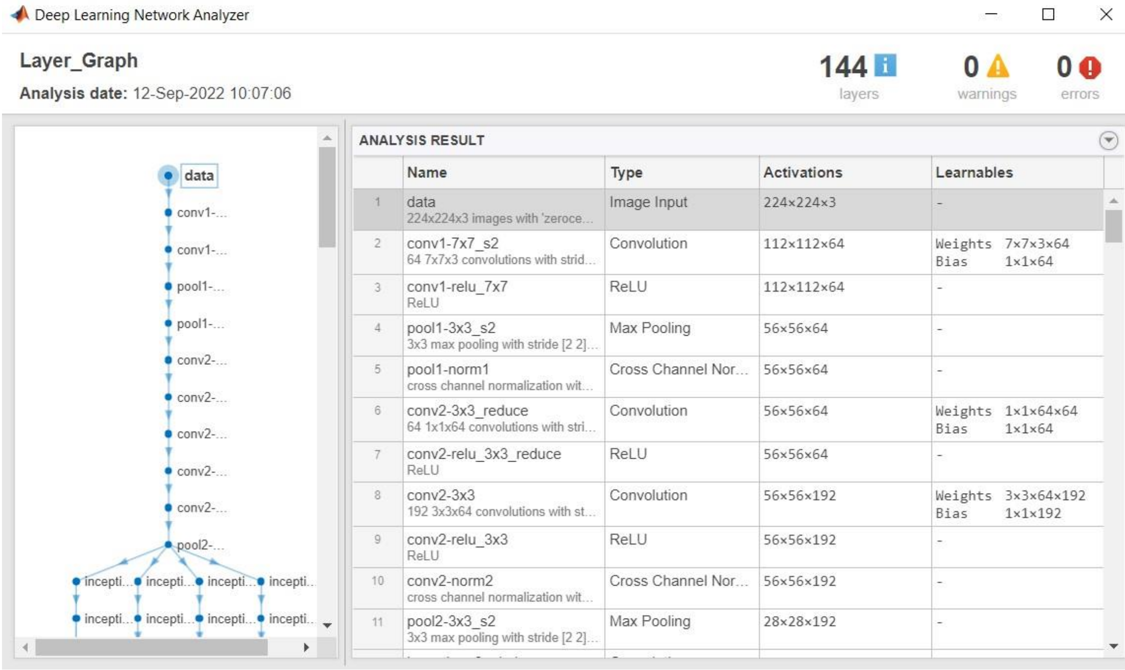

Fig. 3. Diagram of the GoogleNet convolutional neural network (built in MATLAB R2020a)

Thus, MATLAB was used to develop an application for training, validation, and testing of the GoogleNet neural network. The development of an application with an artificial neural network for the recognition of drones by the optical-electronic channel Data Fusion includes the following steps:

– loading the database;

– download of a pre-trained network (GoogleNet);

– correction of the last layers;

– increasing the number of images to prevent retraining (augmentation);

– training;

– network testing.

To download the files, they were previously divided into a training set and a test set. To this end, the code script uses the imageDatasore() function, which requires to specify the path to the folder where the files are stored. After this procedure, using the splitEachLabel (Dataset, 0.7) function, the database is split in a percentage of 70 % of the files – training, 30 % – validation.

The pre-trained network is loaded using the command «net==googlenet». The neural network was trained after preliminary adjustment of the parameters for selecting training options (stochastic gradient descent method, sgdm is selected), the size of the mini packet (10), the maximum number of epochs (6), the learning speed (0.0003), the frequency of verification (248). Fig. 4 shows a chart of training progress for 6 epochs.

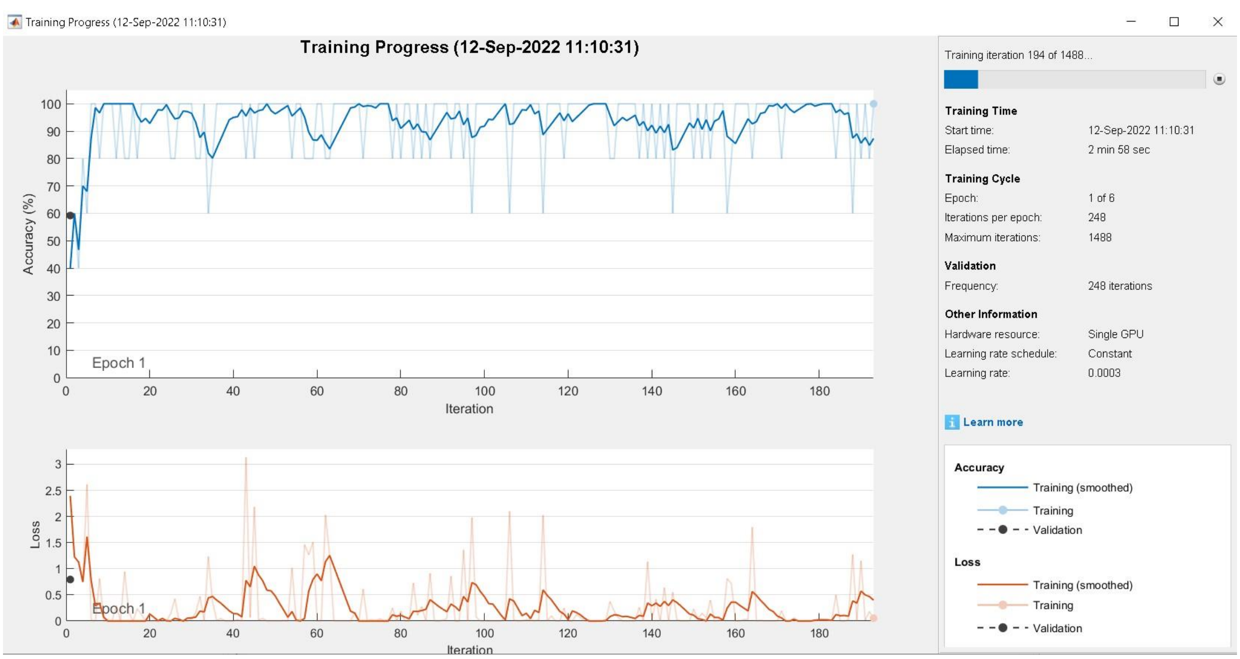

Fig. 4. Demonstration of neural network training progress

The process of testing the neural network is performed using the imresize and classify functions, which are used to convert the size of images into the format of training data and to classify images. The program code is executed in training files. m and test_network. m. The first file reflects the stages of loading the database, pre-training GoogleNet, setting up the last layers, augmentation, and training of the network, the second file – testing. The program displays the test result indicating the image of the object, class, and the probability of belonging to the class. Fig. 5 shows an example of displaying the result of testing a neural network using images of different classes (drones/not drones).

In order to improve the quality of the experiment, increase the convenience in the selection of initial data, transfer training, verification, and recognition of images obtained from the optical camera, an application was developed using the MATLAB App Designer plugin. The GUI Application Interface (Fig. 6) for the experiment includes explanatory pictures demonstrating the concept of a neural network in the Data Fusion optical channel; three main buttons are built-in as well:

– «Search for targets» – uploading drone images to the input of the developed neural network, in accordance with five range classes relative to the point of observation (blue button);

– «Train a neural network» – training a neural network when expanding the database by adding new images to the classes «drones» and «non_drones» (green button);

– «Recognition» – the launch of an experimental process of recognizing images obtained from an optical camera (red button).

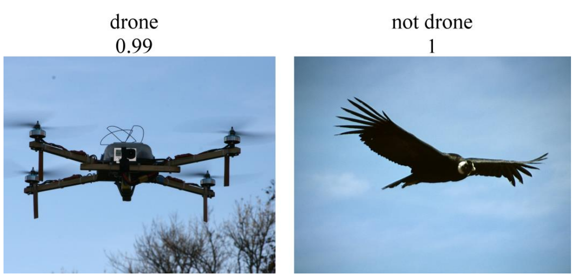

Fig. 5. Example of testing a trained neural network for object classification

Fig. 6. Experiment application GUI

After the training process, a neural network was obtained, ready to conduct research on the recognition of drones/UAVs in accordance with five classes of range to the optoelectronic IP PTZ camera.

5. 2. Results of investigating the possibilities of the neural network in the structure of Data Fusion

With the help of a PTZ camera, a dataset of 75 images from 5 range classes was prepared. Data transmission and storage was carried out using the method described in [31]. The objects of detection were UAVs from the laboratory «Assembly of drones» (RSE «Palace of Schoolchildren», Petropavlovsk, Republic of Kazakhstan). Experimental flight tasks were carried out on UAVs DJI Inspire 2, DJI Phantom 4 Pro, DJI F450, DU1911 (designed by RSE «Palace of Schoolchildren»). These images were not included in the training database, otherwise it violates the purity of the experiment.

The test results in the form of a diagram of the probability of object recognition are shown in Fig. 7.

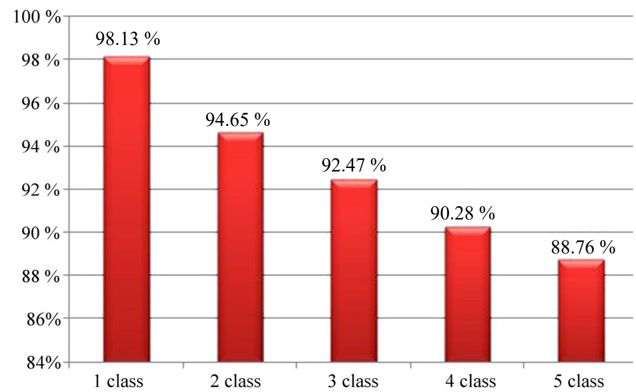

Fig. 7. Diagram of the probability of recognition of the drone by the developed neural network in accordance with five classes of distance to the target

According to the results of the study, the neural network in images where the object was at a distance of no more than 5 meters from the optical camera is able to recognize drones with a probability of 98.13 %. A slight decrease in the probability of object recognition was found as the UAV moves away from the camera, which is confirmed by the results obtained:

– probability of recognition for class 2 – 94.65 %;
– for class 3 – 92.47 %;
– for class 4 – 90.28 %;
– for class 5 – 88.76 %.

Additionally, to determine the time spent on UAV recognition by the method of «video from a PTZ camera – dividing the video into frames (jpg files) through the MATLAB script using the stract function – GoogleNet processing», separate tests were carried out. As a result, in 2 minutes of continuous acquisition of files from the PTZ camera, 148 images were processed. Consequently, the average speed of recognition of UAVs by this method is 0.81 seconds. This figure is 4764 times slower than the best speed reading YOLOv5. Therefore, such an algorithm is far from the characteristics of real-time operation.

6. Discussion of results of drone recognition by the GoogleNet neural network in the Data Fusion system

The task of developing a neural network was completed successfully. This is proved by the fact that the neural network is trained without retraining errors and successfully processed all incoming data during testing and verification (Fig. 4). According to the results of investigating the capabilities of the GoogleNet neural network in the recognition of UAVs in the Optical-Electronic Channel Data Fusion at five range classes, the average recognition accuracy was more than 90 % (Fig. 7). This indicator is higher than that of convolutional neural networks in [10–14]. The decrease in recognition accuracy by 10 % (from range class 1 to 5) is due to a deterioration in the quality of the image obtained with the PTZ camera due to an increase in distance. In addition, with an increase in the distance from the camera to the UAV due to the need to use zoom, the viewing angle of space decreases, which limits the recognition capabilities. However, on the other hand, if you configure the radar channel in the Data Fusion system to detect the target with the provision of indicative data on the location of the UAV for the optical-electronic channel, then the problem of narrowing the search angle can be partially avoided. At the same time, if the accuracy parameter (the average value for range classes of 90 %) meets expectations, then the detected value of the processing speed (4764 times slower than YOLOv5) proves the impossibility of processing data in real time.

Owing to our study, the idea of combining two classifiers was formed: the developed recognition model based on GoogleNet and a detector to solve a more complex problem – determining the presence of a drone or UAV payroll. The solution to this problem is able to confirm or refute the danger of a target that has fallen into the field of view of the Data Fusion system. One can use more advanced models YOLOv7, YOLOR, YOLOX to solve this problem, which are better in qualitative parameters than YOLOv5 reported in [6]. This can be implemented at the level of the optical channel using the following sequence of actions:

– collection of a database of various variants of the payload of quadcopters, UAVs of the «flying wing» type for training the GoogleNet neural network;

– collection of a data set for training the neural network YOLOv7/R/X;

– training and testing of GoogleNet and YOLOv7/R/X;

– testing of a new algorithm: connecting YOLOv5 to an optical camera for target recognition (drone, birds), video recording, video splitting into frames, payload type recognition.

Thus, the neural network, developed as a result of transfer training based on GoogleNet, is able to recognize drones with a probability of more than 90 % under conditions of a range of up to 200 meters to the target. It is determined that the system is not able to work in real time with a high FPS. Therefore, to recognize the payload of drones, it is preferable to use the developed neural network in conjunction with YOLOv7/R/X.

The low speed of data processing as a result of research can be associated with the use of a computer of average performance. It is planned to explore the possibilities of recognizing drones by the GoogleNet neural network in the Data Fusion system using a high-performance computer. Nevertheless, due to the fact that the speed of data processing as a result of research showed too low results, it is unprofitable to use this algorithm at the practical level as a central block of target recognition.

It is more efficient to use the developed convolutional neural network as an additional block of high-precision recognition of air targets when the basic algorithms YOLO and R-CNN are not able to guarantee reliable processing results.

It is planned to continue research of the GoogleNet neural network in the Data Fusion system for the possibility of recognizing the presence or absence of the overall payload of UAV. This is due to the fact that the existing methods of recognition (radar, acoustic, radiofrequency methods, optoelectronic two-stage detectors) are not effective in performing this task.

7. Conclusions

1. The neural network was obtained by transfer training of the GoogleNet neural network. To train the neural network, frames from experimental flight tasks of unmanned aerial vehicles were used. Such data for training increase the accuracy of classification and create conditions for the qualitative application of the neural network in the recognition of real objects. Using the App Designer MATLAB application allowed us to eliminate the possibility of errors in the process of transfer training and testing of the neural network associated with the «manual» writing of MATLAB code to add new files for the test and training set. The «visibility» of the developed application significantly increased the convenience in processing the test results.

2. The results of investigating the capabilities of the GoogleNet neural network in the recognition of UAVs in the optical-electronic channel Data Fusion at five range classes showed an average recognition accuracy of more than 90 %. The parameter of the processing speed of incoming frames (4764 times slower than YOLOv5) proves the unsuitability of this model in real time with high FPS. It is preferable to use the developed neural network in conjunction with YOLOv7/R/X to solve a more important problem in the optical-electronic channel Data Fusion: determining the presence or absence of additional suspended cargo in UAV.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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