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DIGITAL MODEL OF AUTOMATED UNMANNED AERIAL VEHICLE WITH EDGE COMPUTING APPLICATION FOR RAILWAY RECONNAISSANCE

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Abstract. In the last decade, unmanned aerial vehicles have been widely used in various civil and military field operations. Most modern drones are manually controlled by an operator and require decision making, which requires experience gained through training, which is time consuming and expensive, and even with experienced operators, the human factor can never be excluded. In this paper, an algorithm for an automatic flight mode of unmanned aerial vehicles without an operator's participation has been developed. The proposed algorithm has been considered in the military reconnaissance of railways using edge computing and computer vision approaches to recognise railroads and moving trains for simulated and real cases as well as send report data to the web platform. As a result, the head of the operation received information about the number of carriages and Global Positioning System coordinates of the recognised train to make the necessary decisions.

Keywords: Drone, military intelligence, image processing, tracking of the railroad, robotics simulator.

1. Introduction

Modern unmanned aerial vehicles (UAVs) are widely used in the world for many applications, from delivering packages to performing combat missions on a battlefield. The most common civil task for UAVs is reconnaissance and searching for missing people over a large area [1]. Reconnaissance with the application of UAVs often uses Full Motion Video to embed spatial information in a video file and ensure the compatibility with standard geographic information system environments [2]. In military operations, drones are still applied for reconnaissance of enemy positions, weapon stores and military equipment as well as to provide tactical support and humanitarian aid [3]. Modern conflicts have shown that the use of transport infrastructure by enemies, particularly railways, is critical to the provision of combat units participating on the front lines. Therefore, it is quite important to conduct a reconnaissance of the railway [4] to detect moving trains with weapons, heavy equipment, and enemy forces.

However, among the frequently encountered technical problems in using UAVs are poor navigation and a high vulnerability to jamming and spoofing [5]. In addition, the travel routes optimisation [6] and minimisation of the data refreshment rate [7] are quite critical issues in UAV reconnaissance. The former could be solved by applying the ant colony algorithm [8] and the latter by adding a few drones with a genetic algorithm to observe a point of interest [9, 10]. Nevertheless, the human factor is a key parameter when performing a reconnaissance operation using UAVs [11].

To minimise the impact of the human factor, we proposed to automate the process of UAV flight and detection of reconnaissance targets. The application of artificial intelligence (AI) to solve the automation problem is widespread around the world. For instance, the AI-based controller for the quadcopter Parrot Bebop 2 showed a high performance and allowed image processing to detect or track targets in real-time [12]. The most used UAV object detection method is YOLO. For example, Sungtae Moon applied the YOLOv5 model, adding the filter pruning method, and as a result, he achieved 40 % parameter reduction as compared to the base model [1].

This study aimed to develop an automated flight algorithm for the UAV and detection method of railroad and moving trains for military reconnaissance, and then send the Global Positioning System (GPS) coordinates of detected targets to the head of the operation for decision making.

Properties	**Mavic 2 Pro**	**Mavic Air**	**Global Hawk**	**ScanEagle**	**Lancaster Hawkeye**	**Phantom Vision 2**
Price	1 499 USD	799 USD	93 000 000 USD	100 000 USD	10 000 USD	1 300 USD
Flight duration	31 minutes	20 minutes	28 hours	24 hours	45 minutes	25 minutes
Operating altitude	8 000 meters	4 000 meters	18 288 meters	5 943.6 meters	121.92 meters	Less than 121 meters
Speed	72.42 kmph	67.59 kmph	574.53 kmph	91.73 to 111.01 kmph	40.23 kmph	40.23 kmph
Weight	0.9 kg	0.43 kg	14 628.3 kg	22 kg	1.36 kg	1.27 kg

Table 1. Specifications of reconnaissance drones.

1.1. Related works

UAVs often use computer vision methods to detect and inspect the railway infrastructure. For example, Milan Banic applied a Gaussian filter to reduce image noise from the background and used a double threshold to determine the boundaries of the rails [13]. Nevertheless, considering the results of the processed images, it can be seen that not the entire length of the railway was recognised based on the proposed algorithm. There were unrecognised areas of railway infrastructure closer to the horizon and to the observer. Convolutional Neural Network (CNN) based on U-Net network [14] and Deep CNN methods are also commonly used to track the railway and identify vegetation as obstacles along the railway path [15]. In addition, one of the alternatives for railway recognition is sleeper detection based on the Region-based CNN approach [16]. The method based on the RSNet network has shown the best results in railway recognition, reaching 0.973 dice coefficient and 0.94 jaccard [17]. Despite that, all considered methods above require powerful computing resources and discrete graphics cards for complex calculation and object recognition.

The next step is to recognise a train. For instance, to solve the problem of detecting traffic jams and recognising crowds of people to assist traffic police, drones with the YOLOv5 model were used. However, the authors noted that the process of recognising small targets was complicated [18], and it should also be noted that the approach consumes significant computing resources and energy of the device. In order to overcome these disadvantages, some researches used edge computing [19, 20]. The experimental results of the study using edge computing significantly optimised the wireless network bandwidth and improved scalability without compromising the accuracy of the results and latency [21, 22].

2. Materials and methods

Webots R2023b has been chosen as the 3-dimensional robot simulator [23, 24] to develop an automated flight algorithm for UAV, as it has a wide scope of applications, allows programming the controller, contains a large library of robots and tools for their design, maintains a large number of widely used programming languages, and it is a cross-platform software.

As the programming language for the development of the railway and moving trains recognition algorithm, Python has been chosen, as it has advanced and free libraries in the field of computer vision. Thingspeak has been used as a web-based reporting platform since it supports graphical visualisation.

Furthermore, we have proposed a general scheme of the system with a description of the reconnaissance process and object recognition of a railway.

2.1. Robot simulator and flight UAV algorithm

From the existing robot base of Webots, DJI MAVIC 2 PRO has been chosen as the UAV for military intelligence gathering. The DJI Mavic 2 PRO has the most optimal weight, wind tolerance, and flight duration among the reconnaissance drones. The general specification of reconnaissance drones is presented in Table 1.

The drone and designed railway tracks are shown in Figure 1.

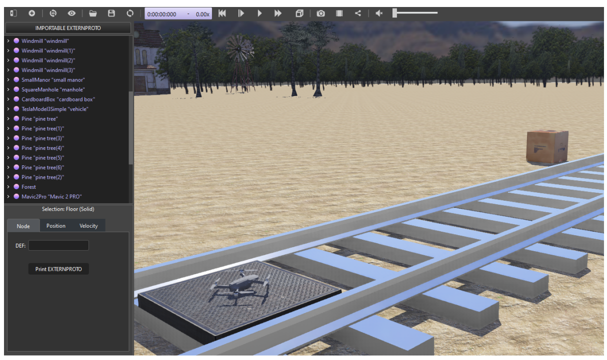

Figure 1. Mavic 2 pro and railway in Webots.

The DJI MAVIC 2 PRO drone comes with a built-in GPS module, a camera, a gyroscope, and lidars. The programming language C was used to develop the drone controller. During the operation of the UAV, the start of the motor, GPS module, camera, gyroscope, and lidars were initialised. The built-in object detection method was used to recognise the railway and the train in the simulated environment. The object recognition process is discussed in the next subsection. After detecting the railway, the drone ran an algorithm for following the recognised railroad track with the transmission of GPS coordinates in the console. That process is presented in Figure 2.

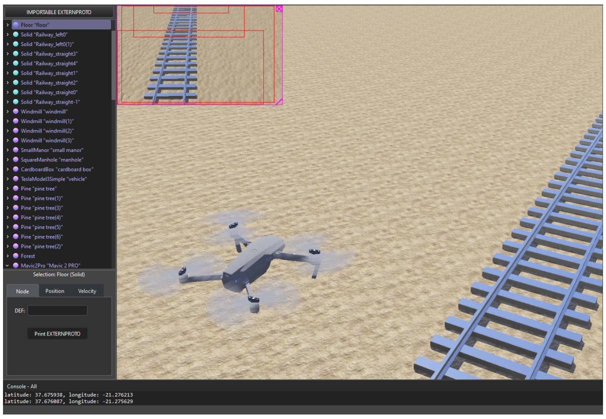

Figure 2. Railway tracking using UAV and GPS coordinates transmitting.

The sections of the detected railway are marked with red rectangles, and there is a console with GPS coordinates at the bottom of the program window.

In the case of detecting a train, the drone provided information about GPS coordinates to the head of the operation and marked the train with a green rectangle, as illustrated in Figure 3.

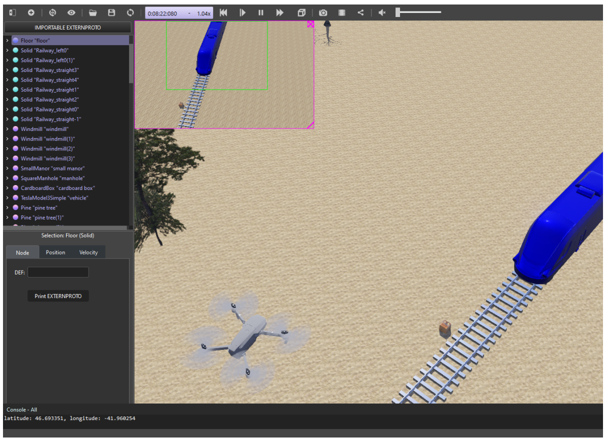

Figure 3. The case of detecting a train in Webots.

2.2. Object detection

To recognise objects, the OpenCV, Numpy, Matplotlib and Skimage libraries of the Python programming language have been used. Figure 4 demonstrates a flowchart of the object detection process.

The result of applying "Equalise Hist" is shown in Figure 5.

At the first stage, the colour image was converted into a grey scale image via "COLOR BGR2GRAY".

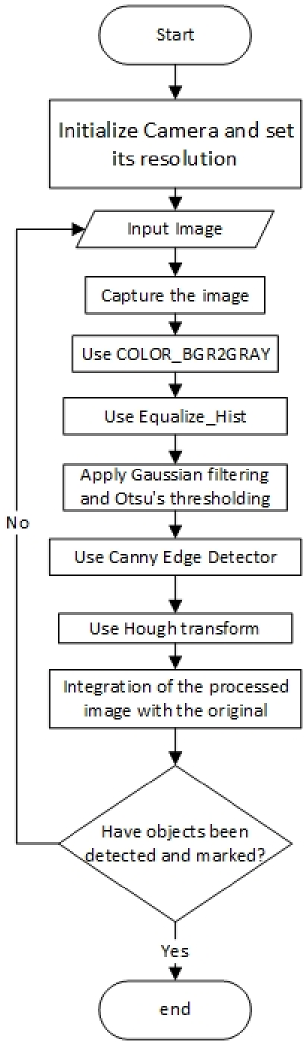

Figure 4. The flowchart of the object detection process.

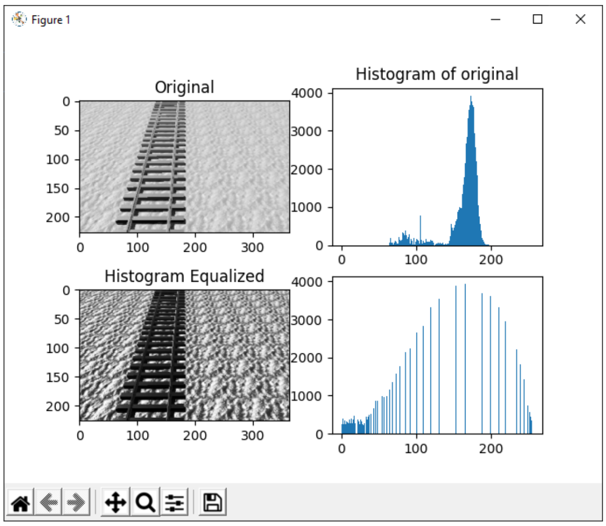

Figure 5. Equalise Hist image.

Then "equalise hist" has been applied to improve the contrast in the image to stretch out the intensity range. The next step was to use Gaussian blur to

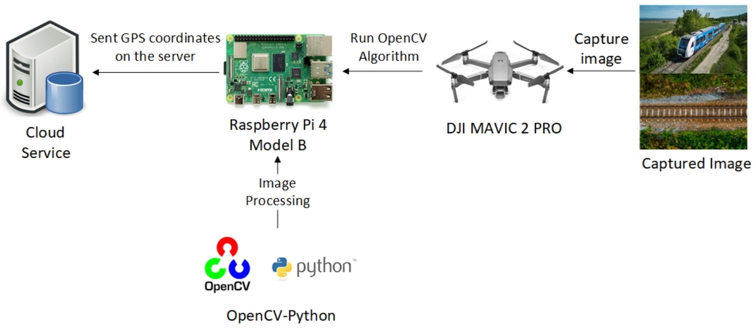

Figure 6. The concept scheme of military reconnaissance by UAV.

reduce image noise and detail. Otsu's thresholding has been applied to the obtained result to separate an image into two classes, foreground and background. Further, Canny Edge has been used to locate sharp intensity changes and to find object boundaries in the image. Hough transform has been applied to the final result for detecting simple geometric shapes and lines in images. And, finally, the Hough lines have been combined with the original image.

2.3. General scheme

Figure 6 shows a concept scheme of military reconnaissance by UAV of a railway track to represent the process for a real model.

The DJ MAVIC 2 PRO transmits GPS coordinates and the camera captures an image of the train and railways, which are then processed by Raspberry Pi 4 Model B (RPi). Computer vision libraries and frameworks have been deployed on the RPi [25, 26]. The results are transmitted to the head of the reconnaissance operation or a cloud server.

3. Experimental results

Returning to the process of object recognition, it is necessary to consider the results of image processing of each stage according to the flowchart shown in Figure 4. The obtained result of converting the image into a grey scale is demonstrated in Figure 7.

To provide a clearer explanation, based on the image provided below, it is evident that the pixels are clustered around the centre of the available range of intensities. The purpose of Histogram Equalization is to expand this range.

A comparison of the Global Thresholding, Otsu's Thresholding and Otsu's Thresholding after Gaussian Blur are presented in Figure 8.

In the case of global thresholding, we have selected a threshold value arbitrarily. However, the Otsu's method eliminates the need for manual selection by automatically determining the threshold value. Gaussian Blur allowed to get rid of the noise created by the desert sand.

The Canny edge detector is a commonly employed technique in computer vision for identifying areas of significant intensity variation and detecting the

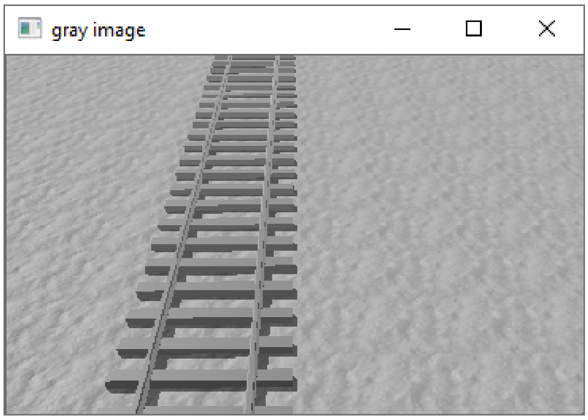

Figure 7. Converting the original image into COLOR BGR2GRAY.

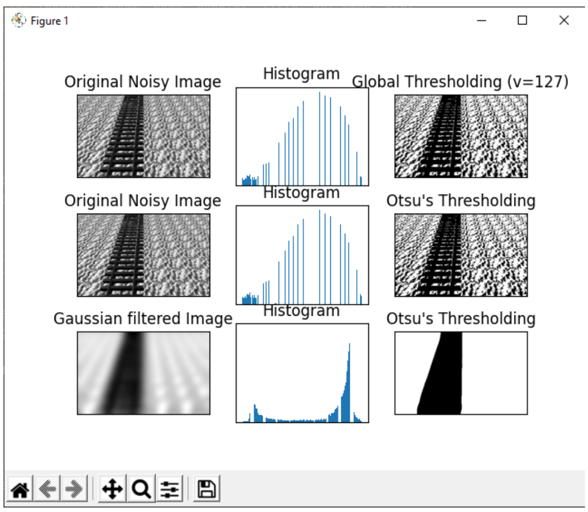

Figure 8. A comparison of the Global Thresholding, Otsu's Thresholding and Otsu's Thresholding after Gaussian Blur.

boundaries of objects within an image. With this technique, the boundaries of the railway section were determined. The applied canny edge detector to the Otsu's Thresholding after Gaussian Blur and the final result of railway detection after Hough Lines is presented in Figure 9.

The Hough Line Transform is a transform used to detect straight lines. The Hough Lines have been

(a). Canny Edge Detection

(b). Hough Transform

Figure 9. Canny Edge Detector and Hough Transform over the original image layer.

pasted into the original image.

Thereby, the UAV is able to recognise the railroad and trains. The results can be seen in Figure 10.

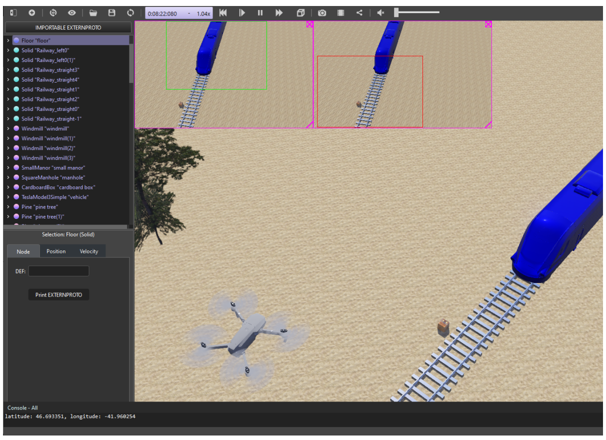

Figure 10. UAV detects the railway and train.

It is also important to consider the railway and train recognition algorithm based on a real UAV footage taken from open sources [27]. The recognition algorithm for the real case is slightly different from the simulated case due to the huge amount of vegetation in the background, which is shown in Figure 11.

The original image is converted to an HSV image

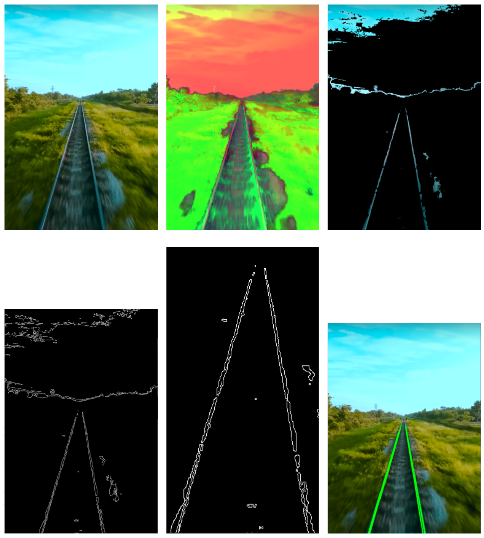

Figure 11. The recognition process of the railway for a real case.

and forms a mask to highlight the pink-magenta hue to recognise the railway. Next, we followed the standard steps from the previous algorithm, using the Canny Edge Detector and Regions of Interest to display the area of the image with the railroad, and applied the Hough Line Transform to detect straight lines.

YOLOv4-tiny has been used for train detection since it supports mobile devices like Raspberry Pi and consumes less computing power than other models. Table 2 shows the benchmarking results for mobile devices, such as Raspberry Pi 4, Jetson Nano, and Rock 5 [28, 29], in frames per second.

The result of train recognition is shown in Figure 12.

Figure 12. The recognition process of the train for a real case.

The mean average precision (mAP) for train recognition is 96.67 %. The graph of loss function versus iterations during training is shown in Figure 13.

It should be noted that as the distance to the carriage increases, the mAP decreases. Table 3 shows the mAP for the various distances between the observer and the target object.

Thanks to edge computing, the operator and head of the operation received information through the web

Model	Size	Objects	mAP [%]	Jetson Nano, FPS	RPi 4, FPS	Rock 5, FPS
NanoDet	320×320	80	20.6	26.2	13.0	36.0
NanoDet Plus	416×416	80	30.4	18.5	5.0	24.9
YoloFastestV2	352×352	80	24.1	38.4	18.8	65.4
YoloV2	416×416	20	19.2	10.1	3.0	20.0
YoloV3	352×352 tiny	20	16.6	17.7	4.4	15.0
YoloV4	416×416 tiny	80	21.7	16.1	3.4	22.4
YoloV4	608×608 full	80	45.3	1.3	0.2	1.5
YoloV5	640×640 small	80	22.5	5.0	1.6	12.5
YoloV6	640×640 nano	80	35.0	10.5	2.7	20.8
YoloV7	640×640 tiny	80	38.7	8.5	2.1	17.9
YoloV8	640×640 nano	80	37.3	14.5	3.1	16.3
YoloV8	640×640 small	80	44.9	4.5	1.47	9.2
Yolo×	416×416 nano	80	25.8	22.6	7.0	28.5
Yolo×	416×416 tiny	80	32.8	11.35	2.8	18.1
Yolo×	640×640 small	80	40.5	3.65	0.9	7.5

Table 2. Benchmark comparison for various mobile devices and computer vision models.

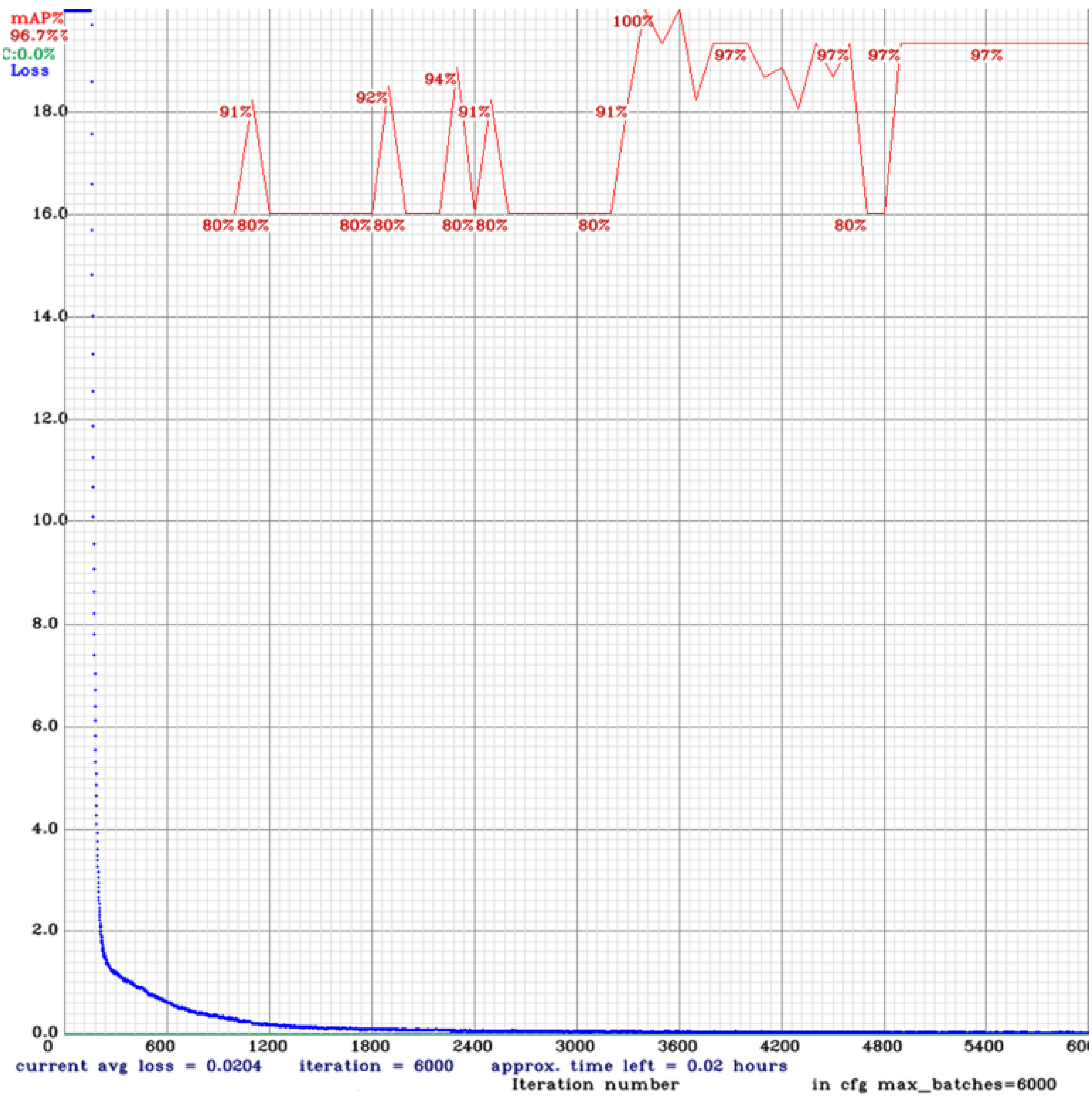

Figure 13. The loss function versus iterations during training.

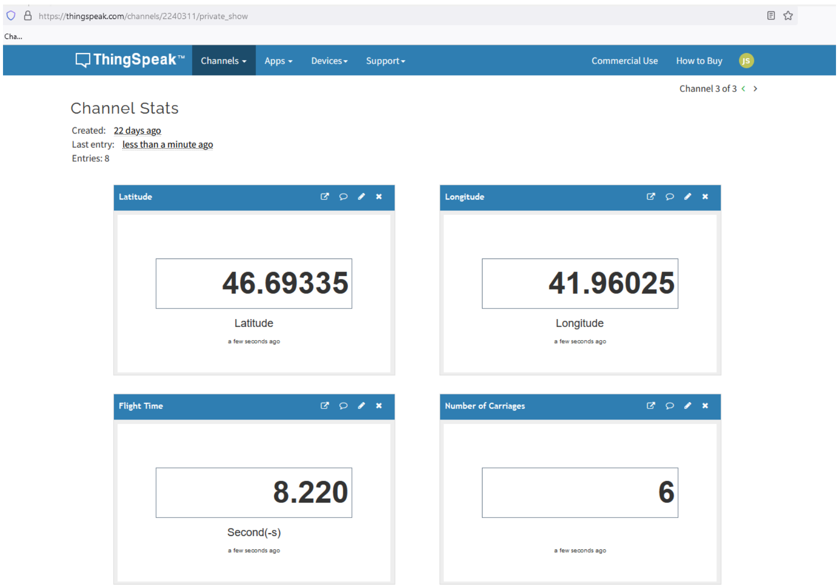

Figure 14. The report on the web platform ThingSpeak.

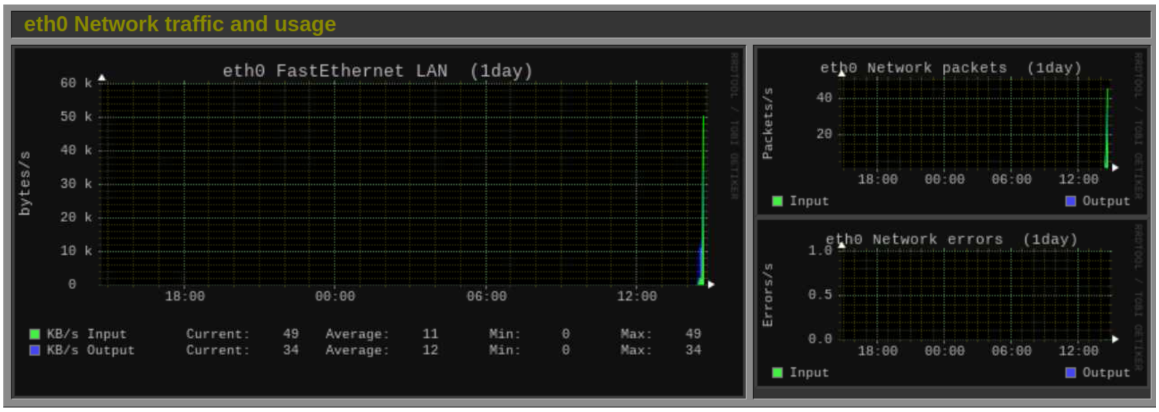

Figure 15. The network bandwidth in the 'MonitoriX' web application'.

Distance, meters	mAP, per cent
3–7	51.27
7–15	98.19
15–75	90.33
over 75	less than 63.41

Table 3. Dependence of the mean average precision on the distance to the object.

platform ThingSpeak about the latitude and longitude of the recognised train, the number of carriages, and the flight time in seconds. The interface of the analytic platform service, channel, widgets, and report are shown in Figure 14.

As can be seen from the report results, 6 carriages for transporting people were recognised, the UAV's flight time was 8.22 seconds, coordinates of the detected train: latitude – 46.69335 and longitude – 41.96025.

The use of edge computing made it possible to optimize network bandwidth, reaching 13 kilobytes per second or 33 packets per second without errors during data transmission (Figure 15).

Thus, the application of edge computing reduces the load on the server, allowing data to be processed on the spot and transfer the final results to the server for reporting and decision making.

4. Discussion

Thereby, the application of edge computing has contributed to the optimisation of network bandwidth, in contrast to cloud computing, which requires at least 1.5 megabits per second for video streaming [25]. As a result, the proposed algorithm reduced the load on the server and also allowed it to perform other tasks. However, it should be noted that frames per second readings on the Raspberry Pi will be significantly lower than on workstations and personal computers. Comparing the mAPs of our study, it is worth noting that very good results were obtained compared to the accuracy of 35.3 % for the GBS-YOLOv5 [18] and 95.6 % for the all-in-one YOLO [30].

5. Conclusions

This study has introduced an automated flight algorithm for unmanned aerial vehicles (UAVs) and a detection method for identifying railroads and moving trains for simulated and real cases. This research allowed the transmission of the UAV flight time, GPS coordinates, and the number of detected targets to the operation leader. Additionally, the algorithm proposed in this study aims to reduce the time and financial resources required for operator training, while also minimising human error. Moreover, the scheme of military reconnaissance by UAV has been proposed for the simulated and real cases.

As a suggestion for future research, this study could be expanded to include features, such as recognizing types of civilian carriages and armoured trains, and adding an infrared camera for night reconnaissance. The development of a similar system based on an FPGA is being considered to increase the recognition speed.

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