Smart UAV Monitoring System for Parking Supervision

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Abstract. Unmanned Aerial Vehicles (UAVs), or drones, are used in the field of remote collection of images at the time of flight. They can also detect irregularities in vehicle parking and issue fines in case of parking violations. The parking monitoring system uses real-time visual information. In this paper, the proposed solution is for real-time monitoring of areas and detecting irregularities in-vehicle parking using a fleet of drones. In this study, a camera mounted on UAVs applies for taking pictures of public areas at predetermined points. For monitoring of area will be used Observer UAVs while for detection will be used, Inspector UAVs. Visual information collected with UAVs is used to detect irregularities in vehicle parking, while the processing of collected data is performed by an artificial neural network.

Keywords: Unmanned Aerial Vehicles (UAV) · Fleet of UAVs · Surveillance · Observer UAVs · Inspector UAVs · Convolutional neural networks · Deep learning · Tensorflow · Keras

1 Introduction

The increase in the number of vehicles in urban areas is one of the biggest problems that city administrations face today. The increase in the number of vehicles causes a problem of parking space. Very often, the public areas are used for parking the vehicles. One of the possible solutions is to monitor public areas with a fleet of Unmanned Aerial Vehicles to prevent this.

Unmanned Aerial Vehicles (UAVs) or drones have numerous applications in the urban world today. They can be used in various human life areas, for example, for delivery, surveillance, professional photography, traffic regulation, disaster relief, safety, and the list is growing daily. The term unmanned aerial vehicle has a broad meaning; it

D. Perakovic and L. Knapcikova (Eds.): FABULOUS 2021, LNICST 382, pp. 240–253, 2021.
https://doi.org/10.1007/978-3-030-78459-1_18

includes all UAVs, regardless of whether they are controlled remotely - RPAS (system of remotely piloted aircraft) or aircraft with a certain level of autonomy. The word unmanned aerial vehicle has the same meaning as the abbreviation UAS (Unmanned Aircraft System), which means combining an unmanned aerial vehicle and the system required to operate it [1–3]. Earlier, UAVs were mostly used only for military purposes until the advent of quadcopters, when they became increasingly popular and easily accessible to the civilian community. The drone industry began to develop rapidly, and there was room for many innovations and adaptations of UAVs to the common man. Today, UAVs are becoming increasingly popular. In the United States, the Federal Aviation Administration (FAA) has projected that the number of small hobby UAVs will increase from an estimated 1.1 million in 2017 to 2.4 million by 2022 [4]. UAVs can be classified into different types based on their design, size, cost, and flying mechanism. Among the existing types, quadrotors or quadrocopters are especially popular because of their simple design, small size, low cost, greater agility, and the ability to hover in place [5]. Low-cost quadrotors are increasingly used in various applications such as surveillance and monitoring, search and rescue operations, geographic mapping, photography and imaging, wildlife exploration and management, media coverage of public events, remote reading for agricultural applications, and air package delivery [6–9].

The potential application of UAVs is to address the problem of illegal parking in public areas. UAVs can monitor public areas, identify and locate objects (vehicles) parked in a public area. For the mentioned application of UAVs to become operational, it is necessary to create a system with UAVs that use Artificial Intelligence and Machine Learning algorithms. On that basis, we perform continuous monitoring of the public area. Designing a system architecture in which UAVs would fly predefined trajectories and coordinating a network of UAVs to cover urban areas is not an easy task.

This paper proposes a prototype model that solves the problem of observing and supervising UAVs' predefined trajectories and communication between UAVs in urban environments where there are static and dynamic obstacles. Finally, the paper presents a prototype system model with the application of the offered solution. We proceed as follows. Section 2 provides an overview of related works. The architecture of a proposed system for monitoring and identifying illegally parked vehicles in public areas is present in Sect. 3. Section 4 presents the implementation of the proposed system in a specific environment. The study was partially carried out in terms of recognizing the situation from images taken with UAVs. Finally, we present our conclusions and reference to future research in Sect. 5.

2 Related Work

The possible use of UAVs is to solve traffic problems in urban areas. Urban areas often consist of several square kilometers. To be able to monitor these areas, as well as due to the flight duration of commercial UAVs, it is necessary to use more UAVs for this task. Working in groups to perform tasks is often found in nature, such as swarms of bees, flocks of birds, herds of cattle, packs of wolves, and fish flocks. Each of the mentioned groups performs group work to perform tasks as efficiently as possible. By applying this analogy to UAVs, we can perform multiple chores in the shortest time [10–12]. However, using a fleet of UAVs to perform a task is only part of the problem. Secure coordination of many UAVs with their autonomy in performing tasks is a topic that has interested many researchers [11–13]. There are several algorithms in use for the automatic guidance of UAVs. The application of these algorithms allows UAVs autonomy [14–17].

To use UAVs in area detection and monitoring, we must first create a secure and reliable network in which drones can flyundisturbed and send images to base. The most often used networks for the communication of drones with the base are WiFi and LTE networks, whose security in data transfer is described in [18]. The application of homogeneous networks in drone communication is presented in papers [9, 19]. In addition to homogeneous networks, there is also a interest in heterogeneous networks, where papers [20–22] present the problems and advantages of using both networks to obtain the most reliable communication between UAVs and infrastructure, and UAVs with UAVs.

According to the research at Barry University [23], parking vehicles becomes a big problem because there is often a shortage of free parking spaces. The lack of parking lots often is caused by people's improper parking of their vehicles and unregistered vehicles parked in reserved places. The study explains how automated drone surveillance applies to detect unauthorized parking at Barry University.

A real-time motion coordination and collision system for the drone fleet is presented in [5]. The system uses UAV geographic locations to successfully detect static and moving obstacles as well as to predict and avoid them: (1) UAV-UAV collisions, (2) UAV-static-obstacle collisions, and (3) UAV-obstacle collisions in a walk. The proposed system's characteristic is the ability to predict the risk of collisions in real-time and find the best ways to avoid predicted collisions to ensure the entire fleet's safety. The presented system generates efficient UAV routes and is suitable for densely populated, i.e., flying zones in urban areas.

A scientific research data model for detecting empty street parking spaces in city road networks based on data provided by cameras located on the vehicle is presented in [24]. The convolutional neural network was trained and evaluated using images from a moving camera. After processing, the images are converted into appropriate matrices to save only useful information for detecting an empty parking space on the street. In terms of structural parameters and learning parameters, the optimized convolutional network gave predictions for detecting empty parking spaces on the street with an average accuracy of about 90%.

According to [25], the proposed system describes an unmanned aerial vehicle that detects a free parking space to guide car parking and to reduce parking attendants' workload. These experiments show that UAVs can detect free parking lots, but the software used in these experiments still needs improvement.

3 System Architecture

In the Smart UAV Monitoring system for Parking Supervision (SmartUAV-PS), UAVs operate to monitor an urban region to prevent illegal parking in public areas. The system is based on a centralized architecture. Due to the use of many UAVs in the system, their price will play a significant role in the complete system's value. We transferred all data processing to the Control Center, which we equipped with a high-performance server, to minimize the necessary equipment for UAVs. Furthermore, with commercial UAVs, the equipment on it plays a significant role in forming their price. Based on the fact that we have centralized data processing and the management of UAVs, we can call this system centralized.

Architecture of SmartUAV-PS consists of (see Fig. 1):

1 Fleet of UAV's
2 Communication system

  2a Gateways
  2b Network Infrastructure
  2c UAV docking stations

3 Control Center

  3a Control server
  3b Application server
  3c Datastorage

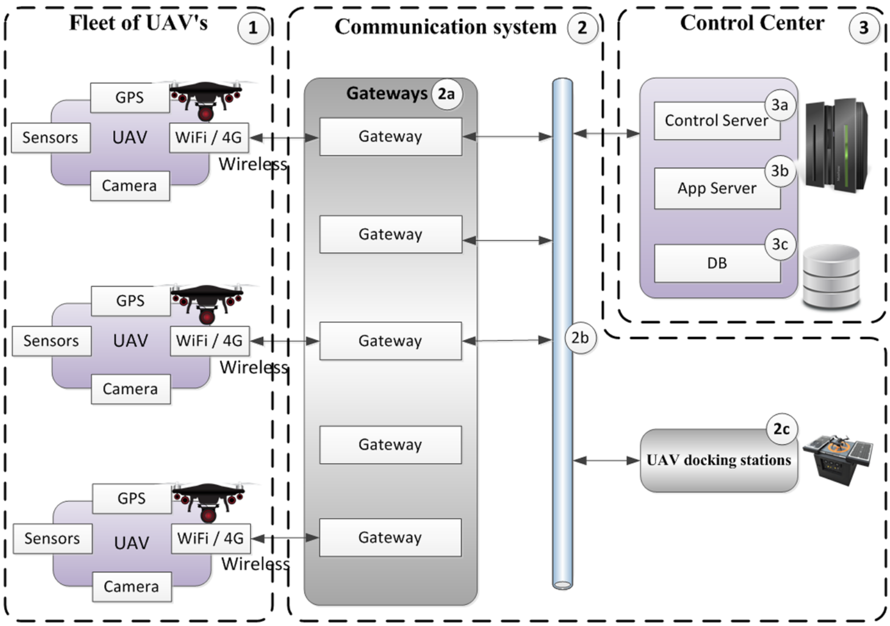

Fig. 1. Architecture of the system.

An explanation of Fig. 1 in more detail follows in the next sections.

3.1 Key Components of the System

A fleet of UAV's (1) refers to a group of three or more UAV's working together to achieve the same goal. The SmartUAV-PS consists of a fleet of UAV's that communicate with the Control Center to detect and identify improperly parked vehicles. The system is automated and operates with the help of Observer UAVs and Inspector UAVs. The Observer UAVs allow vehicle detection, while vehicle identification executes with the Inspector UAVs.

Observer UAVs

The purpose of Observer UAVs is an observation of public areas. A take-off of Observers performs according to a predetermined schedule. Observer UAVs move along defined paths, at altitudes of 30 to 70 m above the ground. On the one route, can be deployed several Observer UAVs. Those UAVs take in turns, one by one, and the time difference in starting the UAV depends on the number of UAVs deployed in a specific route. A higher altitude is necessary to avoid UAV detection and reduce the number of static obstacles while designing the UAV trajectory. Avoiding the detection of Observer UAVs is essential so that the vehicle owner would not drive the vehicle from the location when he sees the UAV. Observer UAVs take images of the monitored area's current state at the defined locations. After capturing images, the Observer UAV sends them via a wireless network to the Control Center. The Observer UAV continues its route to the next defined location, or if it is the end of the route, it flies to the UAV docking station where it has the battery recharge and flight report upload to the Control server (4). The Observer UAVs have the following configuration: GPS module, optional sensors for obstacle avoidance, Wi-Fi, LTE (4G) or both communication modules (depending on network infrastructure), and camera for image capturing and low latency image transfer. Additionally, the Observer UAVs should have support for route tracing.

Inspector UAVs

In the case of the suspect traffic situation, Inspector UAV is activated. Inspector UAV has the task of examining the location where the incident is detected. Using the location and route to the location data, the Inspector UAV goes to one or more inspection locations, where it takes video and image captures. He arrives at the position in a dynamically defined trajectory formed in the Control Center. When the Inspector UAV reaches the position, it descends to a height of 3 to 5 m above ground to perform a more detailed inspection of the location. Location snapshot records on SD storage. After finishing inspection at all defined areas, it returns to the UAVs docking station, where he uploads the data, repost logs, and recharge the batteries. The data collected with the help of Inspector UAV are used to initiate further forensic actions. The analysis of these data is proposed in the paper [26]. The Inspector UAV configuration is similar to Observer UAVs. Besides GPS, communication modules, and sensors, this type of UAV should support route tracing and camera (high resolution) for image and video capturing and SD storage for captured images.

Control Center

The Control Center (3) is the brain of the SmartUAV-PS. The elements of the Control

Center are: the Control server (3a), the Application server (3b), and Datastorage (3c). Besides UAVs' coordination, the Control server receives data from the UAVs, stores data in a database, performs analyses with machine learning algorithms, and performs further processing. It should have high data processing abilities to process images and process algorithms for defining UAV's routes.

The Control server should be with a high-performance data processing capability to process images in a reasonable time. The Control server, located in the Control Center, receives the Observer UAV data stores and processes it. If a situation is detected, it gives the instructions to the Inspector UAV to check the location. Based on the recording from the Inspector UAVs, the vehicle is identified in the Control Center based on registration plates to perform further processing.

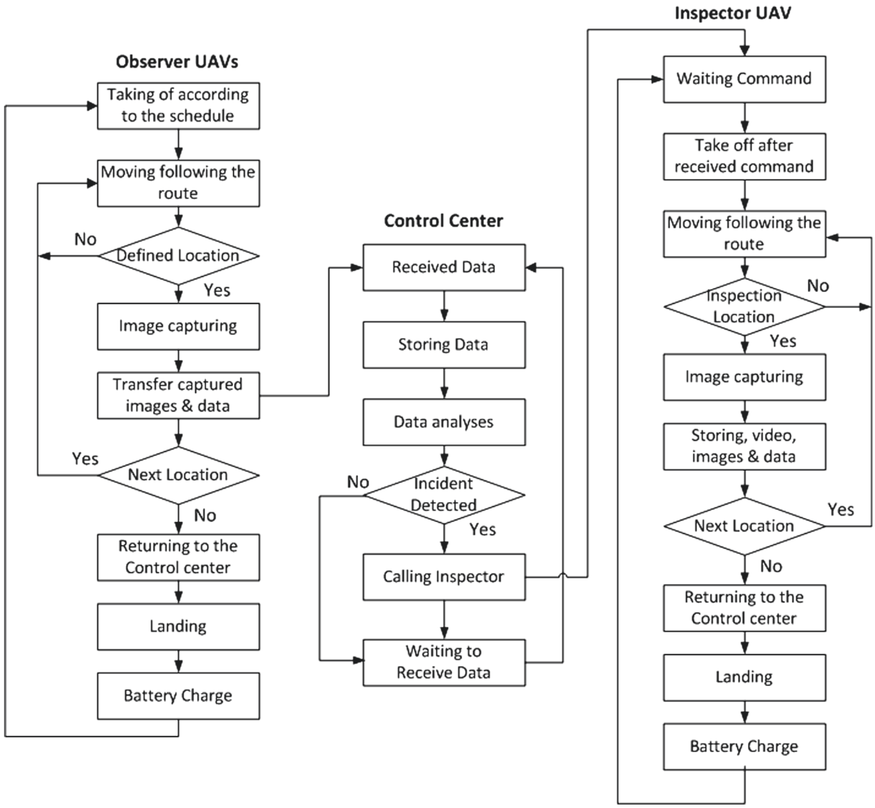

Fig. 2. Communication and operations of key system components.

Communication, relationships, and operations of the critical components of SmartUAV-PS through the algorithm are presented at Fig. 2.

3.2 Communication Components of the System

Generally, in multi UAV networks, there are two types of communication. These two networking modes are UAV-to-UAV (U2U) and UAV-to-Infrastructure (U2I). The design of the public areas monitoring and surveillance system is oriented as a UAV-to-Infrastructure (U2I) because communication between the UAVs manages with the assistance of a Control Server (3a) located in the Control Center (3) (see Fig. 3).

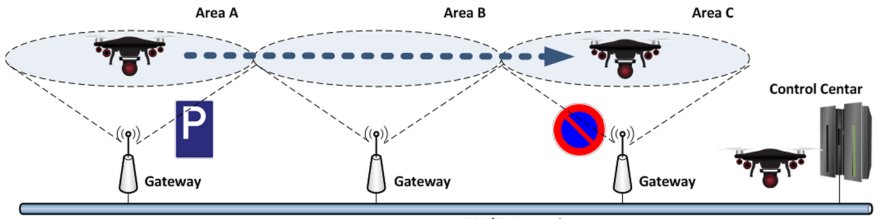

Fig. 3. The network infrastructure with the roaming UAVs.

The gateways (2a) have an essential role in maintaining UAVs' connection with the Control Center. Considering the UAVs' mobility, their aerial path in the urban environments with the numerous obstacles, the real image transfer from the Observer UAVs' to the Control Center is challenging. Also, considering the location of the system deployment and terrain configuration, the network infrastructure should have support for roaming in homogenous networks (only Wi-Fi, only LTE) presented in [22] or heterogeneous (hybrid) networks as presented in [20, 27]. To ensure as much reliable transfer of captured images as possible, support for MPTCP (MultiPath TCP), primarily on UAVs but in the rest of the system, should be considered.

The UAVs docking station (2c) is the place that is used for UAVs take-off and landing, battery charging, and communication with the Control Center (see Fig. 4).

The UAV docking station is a fully automated system that serves UAVs. The station is a precisely specified place for safe vertical take-off and landing of UAVs. In addition to this function, it should allow fast recharge of UAVs batteries, establish communication between the Control Center and the UAV, and maintain their airworthiness. It would be desirable for the proposed system to use static stations with a wired connection to the Control Center and electricity infrastructure.

3.3 Artificial Intelligence Components of Control Center

The image sent from UAVs to the Control Center is analyzed using the Convolutional Neural Network (CNN) to detect the suspect traffic situation in public areas. Role of CNN is to classify the traffic situation. The research described in this paper relies on previous research results[29, 30], as well as on a specific original case of classifying the traffic situations [31]. Compared to the previous research, the difference reflects the application of CNN in the context of a broader system that should provide Situational Awareness (SA) in the traffic environment. The broad definition of SA implies the case when an

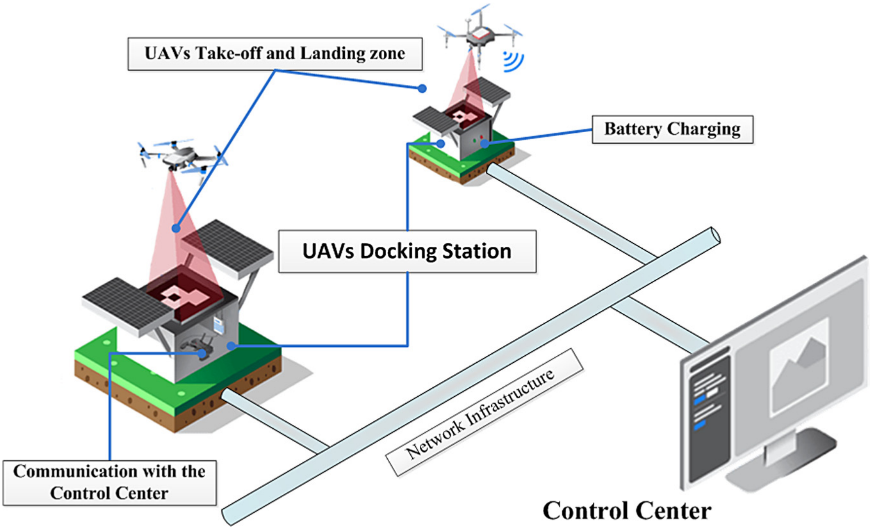

Fig. 4. UAVs docking station [28].

entity, whether human or machine, develops and maintains an understanding of events in the environment and the possible implications of those events. As in [32], SA has explored many operational contexts, including military settings, surface transportation, aviation, maritime, sport, healthcare/medicine, and process control. A generally accepted definition of SA comes from [33]: "perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status soon".

The same author also introduced a three-level model of SA [34]:

- L1, perception of the elements in the environment,
- L2, comprehension of their meaning,
- L3, projection of future system states.

Figure 5 shows a simplified three-level SA model, which includes only the elements relevant to this research.

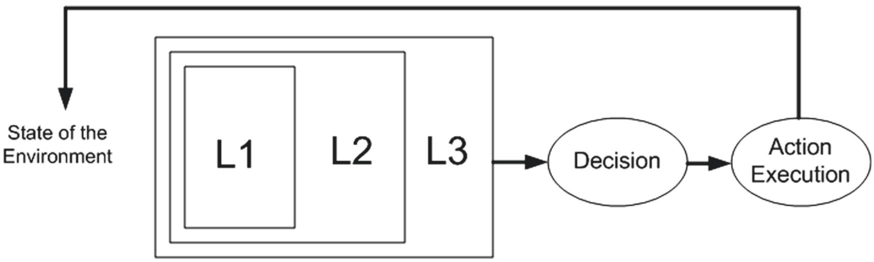

Fig. 5. Simplified three-level model of SA.

CNN application performs in L1, which is part of L2, and consequently L3, so it is primarily about the perception of objects in environment and less about the comprehension of their meaning. Projection of the future system states will be tackled in further investigations.

The initial results of the UAV application project in traffic control are presented in [31], specifically in the monitoring of particularly hazardous intersections in urban areas with properly or non-properly parked vehicles. Data were collected by recording a real situation using a camera mounted on UAVs. The experiments were conducted on a Tensorflow/Keras platform. The data sample was formed by image augmentation and was small in size: 40 images, classified into two classes: traffic situation OK/notOK. After multiple experiments, initial results were achieved by following CNN architecture:

1. Convolution2D (kernel = 64, kernel_size = (3, 3), activation = 'relu')
2. MaxPooling2D (pool_size = (2, 2))
3. Dense (164, activation = 'relu')
4. Dense (1, activation = 'sigmoid')

In previous experiments, images were down-scaled to 255-Gy 400p by 225p, but the learning process was pretty time-consuming. Given the high consumption of resources, we have conducted several case studies, and one of them is presented in the text that follows.

4 Case Study

The case study was conducted in the city of Doboj (Bosnia and Herzegovina). Doboj is a city under 100,000 inhabitants with many public areas. These areas usually are used as parking spaces. These irregularities in public areas are legally punishable and execute by the Communal Police department, which functions within the city administration. The area of the city of Doboj is 648 km^2, of which about 10 km^2 is the area of the city settlement of Doboj [35]. Because it is a large space, surveillance area needs to be separated into sectors. Separation into the sectors is defined considering UAVs' characteristics (max range, max flight speed, max flight length, battery capacity, etc.). In sectors, air corridors for UAVs based on precisely defined critical points would be formed. For our experiment, we chose Vojvode Mišića street in Doboj, where we defined five critical points to record for a case study. The image-taking points are determined based on the observed irregularities in public areas within this street and the Faculty of Transport and Traffic Engineering proximity, where Gateway's location is to achieve wireless communication with UAVs. For the recording, we used three DJI Mavic Air 2 commercial UAVs. Two UAVs were used as Observer UAVs, while one UAV uses as Inspector UAVs. UAVs trajectory was defined from the Control Center's to the observed street and back (see Fig. 6). Figure 6 was processed using the tools of the Google Earth application.

The chosen place for the Control Center is the building of the Directorate for Development and Construction of the City. That location is chosen for Control Center because it is in the center of the city zone and has all necessary infrastructure. This location of the Control Center is optimal for the implementation of SmartUAV-PS in the city of Doboj.

Fig. 6. Defined UAVs trajectory.

For the case study, we performed four flights according to a defined trajectory. Recording of images in defined points on this trajectory performs from a height of 5 to 30 m above the ground.

4.1 Results and Discussion

A previous case study showed significant problems with the use of UAVs, such as the impact of weather conditions, the problem of obstacles, the technical limitations of UAVs, and battery life. Nevertheless, the proposed concept is acceptable from the point of view of UAV operation and communication with the Control Center. Wireless communication using gateways and TCP/IP network infrastructure proved to be successful.

A special problem is collecting images because their number should be sufficient for the neural network's successful training. This is a significant problem because it is impossible to use at least three UAVs in a more extended period due to financial and safety reasons and legal regulations.

However, the previously proposed CNN architecture requires excessive resources: the accuracy on the training set was 0.90625, while the accuracy on the test set was 0.875. High time/memory consumption is not acceptable in applying the SA model, so the research presented in this paper refers to additional down-scaling of images. The system's rapid response is necessary because the UAVs' fleet on the circular path shown in the previous part of the paper will transfer the data to the server, where further training of CNN is performed. It is estimated that the system needs to react within a maximum of a few tens of minutes, so CNN training must be fast, given that drone cameras will collect a large number of images.

In previous applications, image sizes used for CNN training range from the recommended 32 by 32p, 96 by 96p, or 128 by 128p, to 512 by 512p. Of course, higher resolutions are possible, but these cases are rare. Also, it is possible to use more channels (e.g., 3 for RGB components), which further increases the training time. In this case, experiments were performed on grayscale images for the following resolutions: 32 by 32p, 96 by 96p, 128 by 128p, and 256 by 256p. Also, the number of epochs was varied, and the validation of the achieved result was performed using accuracy. Results are summarized in the following table (Table 1).

Table 1. Experiments summary

Id	Resolution/Epochs	Training set accuracy	Test set accuracy
1	32 by 32p 10 epochs	0.90625	0.625
2	32 by 32p 20 epochs	0.9375	0.75
3	32 by 32p 100 epochs	0.9375	0.875
4	32 by 32p 1000 epochs	0.96875	0.875
5	32 by 32p 2000 epochs	0.96875	0.875
6	96 by 96p 10 epochs	0.5	0.5
7	128 by 128p 10 epochs	0.9375	0.75
8	128 by 128p 2000 epochs	Out of resources	Out of resources
9	128 by 128p 500 epochs	Out of resources	Out of resources
10	128 by 128p 50 epochs	0.96875	0.875
11	256 by 256p 2000 epochs	Out of resources	Out of resources

Based on the result from the previous table, it can be concluded that the image resolutions from the training set higher than 128 by 128p are not suitable because the training time is too long (measured in hours/days) on the average/advanced hardware configuration. Lower resolutions remain, but it is evident that the maximum accuracy is 0.875. This clearly points us to the case of 32 by 32p and 100 epoch of training, although it remains to check the time of training in the case of a more extensive training set, which is one of the tasks of future research. Also, the accuracy of 0.875 is not so high. So there is an additional adjustment of CNN and a better selection of elements of the training set.

5 Conclusion

The paper presents the results of the experimental application and partial implementation of a new system concept for SmartUAV-PS. The aim was to propose a basic concept of a system that ensures scalability. The proposed system's scalability reflects in the centralization of UAVs control and the application of SmartUAV-PS in image processing and machine learning application.

It has been shown that it is possible to handle a fleet of UAVs on an experimental example. Several case studies have been undertaken, one of which is described in this paper and relates to UAVs use to identify illegally parked vehicles from images collected by UAVs. The recognition task is performed using the Convolutional Neural Network

(Tensorflow/Keras). It was concluded that the image's low resolution allows successful recognition on a small dataset: Training set accuracy was 0.9375 while test set accuracy was 0.875. It is clear that the achieved accuracy is not enough, so the system must be scalable.

The presented case study confirms the applicability of the proposed concept from the point of view of network infrastructure and UAVs' role. Namely, there are two roles that drones can play. Observers are in charge of recording situations, usually from a height. If an irregularity is noticed (using CNN), the Inspector drone will be sent to the location to take further action from a lower height. This concept allows saving resources in terms of minimizing the duration of the flight, the equipment needed (batteries, cameras, network equipment), but the main contribution relates to the possibility of centralized management of the entire process and scalability.

Centralization, in this case, has several advantages: it is possible to manage multiple fleets of drones operating simultaneously in different parts of the city, even in different cities, it is possible to share resources, as well as easy upgrades of hardware components. This also impacts further upgrading the system in terms of the number of UAVs, trajectories, and resources required to implement CNN.

From all the above, it is clear that it is necessary to improve the system and perform additional research and experiments in real conditions. Further research in this area will result in additional improvements based on various experimental scenarios of possible application. Regarding the system's software architecture, further work will be directed towards implementing a layered service-oriented architecture that will provide services for different devices, systems, and users. Improvement of the system's architecture could be a module for detecting irregular situations, in-vehicle parking, and traffic. Also, algorithms for routing UAVs may be the subject of further research. In future research, business models and new value chains for the offer of services based on the application of this system's results, on the principle of offering services on the principles of the IaaS paradigm, for smaller cities up to 100,000 inhabitants will be explored. Special attention will be on researching the security challenges of applying UAVs in urban areas.

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