Unmanned System Technologies

Fadi Al-Turjman *Editor*

Unmanned Aerial Vehicles in Smart Cities

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Unmanned Aerial Vehicles in Smart Cities

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ISSN 2523-3734 ISSN 2523-3742 (electronic)
Unmanned System Technologies
ISBN 978-3-030-38711-2 ISBN 978-3-030-38712-9 (eBook)
https://doi.org/10.1007/978-3-030-38712-9

This Springer imprint is published by the registered company Springer Nature Switzerland AG.
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Sometimes you can find words to fill in a 200 pages' book, but you can't find a word to thank somebody without whom the book itself wouldn't be realized. Thanks to my wife and my little stars, my great parents and my best friends. Thanks to all who standby and realized this incredible work.

And remember, flying was realized mainly with the imagination.

Fadi Al-Turjman

Preface

We are living in an era where the Internet of Things (IoT) is becoming a global platform for computation and the interaction between humans and machines while at the same time performing several critical tasks.

Artificial intelligence and drones have been considered as a complementary package towards realizing the emerging smart city paradigm in the IoT era. From this perspective, it is essential to understand the role of these significant components that will provide a comprehensive vision for the worldwide smart city project in the near future. It is also essential to consider the emerging drones-based intelligent applications for better lifestyle and more optimized solutions in our daily life.

The objective of this book is to provide an overview of existing smart city applications while focusing on the issues/challenges facing the use of drones. The main focus is on drone-based intelligence aspects that can help in realizing such paradigm in an efficient way. Artificial Intelligent (AI) techniques and new emerging technologies such as IoT accompanied by critical evaluation metrics, constraints and open research issues are included for discussion. This conceptual book, which is unique in the field, will assist researchers and professionals working in the area to better assess the proposed smart city paradigms, which have already started to appear in our societies.

Hope you enjoy it...

Nicosia | Fadi Al-Turjman

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About the Editor

Fadi Al-Turjman received his Ph.D. in computer science from Queen's University, Kingston, Ontario, Canada, in 2011. He is a full professor and a research center director at Near East University, Nicosia, Cyprus. Prof. Al-Turjman is a leading authority in the areas of smart/intelligent, wireless, and mobile networks' architectures, protocols, deployments, and performance evaluation. His publication history spans over 250 publications in journals, conferences, patents, books, and book chapters, in addition to numerous keynotes and plenary talks at flagship venues. He has authored and edited more than 25 books about cognition, security, and wireless sensor networks' deployments in smart environments, published by Taylor & Francis, Elsevier, and Springer. He has received several recognitions and best papers' awards at top international conferences. He also received the prestigious *Best Research Paper Award* from Elsevier Computer Communications Journal for the period 2015–2018, in addition to the *Top Researcher Award* for 2018 at Antalya Bilim University, Turkey. Prof. Al-Turjman has led a number of international symposia and workshops in flagship communication society conferences. Currently, he serves as an associate editor and the lead guest/associate editor for several well-reputed journals, including the *IEEE Communications Surveys & Tutorials* **(IF 22.9)** and the Elsevier Sustainable Cities and Society **(IF 4.7)**.

A Comprehensive Review on the Use of AI in UAV Communications: Enabling Technologies, Applications, and Challenges

Fadi Al-Turjman and Hadi Zahmatkesh

1 Introduction

Artificial intelligence (AI) is being used to improve technologies because of its great capability to deal with big data and complexity as well as speedy and high-accuracy processing. There are different AI algorithms that can be employed in various areas such as medicine, engineering, finance, and computing, to just name a few. These algorithms include machine learning (ML), artificial neural network (ANN), genetic algorithm (GA), particle swarm optimization (PSO), pattern recognition, etc. Together with robotics which have the capability of self-organizing [1], self-learning [2], and self-reproducing [3, 4], AI can be utilized to make machines smarter, meaning that it provides the ability for the machines to do intellectual tasks similar to what human beings can perform. In recent decades, robots have been smart machines that utilize their AI abilities and smartness to perform intellectual and smart tasks. Among all the robot-based infrastructures, unmanned aerial vehicles (UAVs) are considered as one the most promising solutions regarding the development of smart environments. UAVs are becoming more and more popular due to their functionality, adaptability, availability, and low cost. They have been successfully used in agriculture [5], security and surveillance [6], military applications [7], and transportation [8], to just name a few. UAVs are small, compact, and remotely operable and, therefore, have their specific uses. In recent years, UAVs

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_1

are being used more and more for telecommunication applications [9, 10]. However, due to the limitations of processing power and flying time, onboard processing for intelligent telecommunication applications is a challenge.

In this chapter, the use of AI in UAV communications is comprehensively discussed. Moreover, we overview the applications of UAV and discuss various applied communication protocols and technologies in UAV-assisted IoT era. We also introduce the communication architecture for the UAVs which specifies how information is transmitted between a UAV and the ground BS or between UAVs. In addition, we provide a summary of the design factors for utilizing AI in UAV communications in order to ensure an efficient and reliable system and acceptable quality of service (QoS). Finally, we discuss some open research issues associated with AI-based UAV communications in the IoT environment.

The rest of this chapter is organized as follows. Section 2 discusses the applications of UAVs in the IoT era. Applied communication protocols and technologies for UAV-assisted IoT systems are overviewed in Sect. 3. Communication architecture for the UAVs in the IoT era and their various components are presented in Sect. 4 in order to help to understand its architecture and mechanism. Section 5 discusses various design factors and requirements for the AI-based UAV communications and provides several classification and image-based techniques that are used for UAVs. Section 6 discusses some open research issue. Finally, Sect. 7 concludes this chapter.

2 Applications

The use of UAVs is rapidly growing in several application domains including intelligent transportation systems (ITSs), agriculture, wildlife preservation, disaster control, security and surveillance, remote sensing and geology, healthcare, military, education, and smart cities. These applications are briefly described in the following subsections.

2.1 Intelligent Transportation Systems (ITSs)

The use of UAVs has recently opened up new opportunities for various applications in ITSs such as automatic collection of traffic data [8]. In this regard, it is crucial for many applications to detect vehicles and extract traffic patterns in an accurate way. Unlike most of the conventional traffic monitoring devices which show traffic conditions at fixed positions, some UAVs can cover a traffic network or a continuous part of a road instead, so it requires less units to control a single section of a road [11]. Moreover, UAVs, as an infrastructure with high mobility, can provide quick evaluation and identification of accident locations where a number of static sensors are located for emergency purposes [8, 12]. In addition, UAVs have lower operating cost compared to manned aircrafts, and can fly near to the ground, and, therefore, can respond better in bad weathers [8].

2.2 Agriculture

In recent decades, the development of UAVs has provided opportunities for remote sensing in agriculture. One of the most common applications of UAVs is precision agriculture which is widely defined as a system in such a way that the management process is done at the right time and the right place as well as with the right intensity [13]. Moreover, due to the advantages of UAVs including ease of operation and high flexibility, they can provide a way to extract phenotypic information of various crops in farms quickly and precisely [5]. Agricultural UAVs are also important in areas where ground-based systems have difficulties in performing farming operations [14]. Although agricultural UAVs have revealed important advantages and features in practice, their level of AI still requires to be optimized and enhanced in various aspects such as data collection, management mechanisms, and safety factors [15].

2.3 Disaster Management

One of the most important use cases of UAVs is in emergencies such as disaster management [16]. UAVs play an important role to reduce the negative effects of disasters by providing necessary assistance to the rescue operations. They can have access to disaster areas where it is impossible or unsafe for humans to gather information for search and rescue in the disaster events. In addition to that, UAVs can carry medical equipment to the damaged areas without human interventions [17]. Moreover, UAVs, due to their flexibility and mobility, can be used as flying base stations (BSs) to provide wireless coverage to the devices in disaster areas for the purpose of rapid service recovery after the disasters [18].

2.4 Security and Surveillance

In the recent decade, UAVs have become an important technology to implement security and surveillance system due to their reliability and effectiveness [6]. For example, UAVs equipped with camera can be utilized in traffic surveillance to monitor roads and collect traffic information in order to improve the road's safety [19]. This information is the basis for traffic control and management, as well as transportation planning. Moreover, UAVs can fly in dangerous conditions such as very bad weather conditions or evacuation conditions to obtain surveillance data in real time [20].

2.5 Remote Sensing and Geology

In recent years, UAVs have been increasingly used for agricultural remote sensing due to their suitability and low cost as well as high operational efficiency [21]. For example, high-throughput phenotypic platforms assisted with UAVs, using remote sensing technology, can significantly make the collection of crop trait data easier. They can be utilized to gather data on temperature, canopy reflectance, biomass of maize, etc. [22, 23]. Moreover, UAVs equipped with global positioning system (GPS) are able to provide georeferenced imagery in order to map a region with high resolution [24]. It has been utilized more and more in small-scale remote sensing tasks because of its high robustness, flexibility, and low cost under various weather conditions [25].

2.6 Healthcare

UAVs are a revolutionary technology for the future of the healthcare sector by acting as wireless relays (WRs) to enhance connectivity with ground wireless networks [26]. They can collect and process information in real time by connecting the current network infrastructures such as body area networks (BANs) with remote servers and clouds. Moreover, UAVs can be utilized to pick up standard blood tests and deliver routine test kits so that the workloads and travel time of medical staff will be significantly reduced [27]. In addition, UAVs have been utilized to discover health hazards such as radiation and prediction of cancer risk [28]. For example, in [29] UAVs equipped with photogrammetry software with high resolution have been used to precisely access and predict the risk of cancer in agricultural areas due to the high level of copper concentrations.

2.7 Military

In the last decade, UAVs have attracted too much attention from both industry and academia especially due to their importance and possibilities in military applications [27]. UAVs improve accessibility and connectivity for military applications [30]. For example, they can be armed with live video communication to weapons or ground troops to protect the lives of military soldiers. Moreover, UAVs can be equipped with gyrostabilized electro-optical and thermal infrared camera to be utilized by military forces for the target acquisition and reconnaissance and surveillance-related tasks [31]. Besides the payloads for military purposes, they are also suitable for civil applications such as border security and search and rescue in emergencies.

2.8 Smart Cities

UAVs are expected to be utilized for several applications in smart cities as the number of flying UAVs is dramatically increasing [32]. They are estimated to play an important role in smart cities in various applications such as agriculture, transportation, and medical and environmental monitoring [33]. For example, growing concerns related to air pollution as the largest environmental health risk in large cities require the development of efficient technologies to control and enhance air quality in smart cities [34]. In this regard, UAVs equipped with low-cost microsensors can be used to provide several advantages for air pollution monitoring in smart cities [35]. Other applications of UAVs for smart cities such as agriculture, traffic monitoring, environmental monitoring, etc. have already been discussed earlier in this section. These applications can provide cost-effective services to help fulfill the goals of smart cities [36].

3 Applied Communication Protocols and Technologies

In the IoT era, communication technologies connect various smart objects together to provide smart services. In UAV-assisted networks, the UAV nodes should operate using low power while noisy and lossy communication links are present. Examples of communication protocols used for the UAV-assisted networks in the IoT environments are Wi-Fi, Long Term Evolution-Advanced (LTE-A), WiMAX, ZigBee, Long Range Wide Area Network (LoRaWAN), and 5G.

Wi-Fi is one of the most common access networks for providing connectivity to IoT devices within a range of up to 100 m [37, 38]. Two different modes of operation called infrastructure mode and ad hoc mode are provided by all versions of Wi-Fi communication technology (IEEE 802.11a/b/g/n/ac) which can be utilized for the communication among UAVs and between a UAV and the ground BS. For example, the study in [39] shows better performance of UAV-assisted IoT networks utilizing IEEE 802.11ac in terms of throughput when compared to IEEE 802.11n. However, it is required to conduct more research to better understand such a behavior. In addition, most commercial UAVs are designed to be tested by Wi-Fi signals to permit people to utilize their own smart device to control the UAV [40]. As the sustainability of AI relies on the access to huge amount of data, it can grow more quickly by building its intellectual capacity using data collection and analysis. Moreover, Wi-Fi is one of the main Internet access technologies where mobile users can rely on wireless services according to the contextual data such as location services. Therefore, by the integration of AI and Wi-Fi technology, data from the Wi-Fi can be sent to the cloud where it can be analyzed by the AI which in turn provides reliable, predictable, and measurable wireless operations.

LTE is a technology which is based on Global System for Mobile communication (GSM) and Universal Mobile Telecommunications System (UMTS) and used for high-speed data transfer between mobile devices [41]. LTE-A is the enhanced version of the LTE which provides lower latencies and higher throughput as well as improved coverage. Cellular infrastructure such as 4G LTE and LTE-A can be utilized to design a monitoring architecture for streaming real-time video surveillances from UAVs to a control center [42] in and around environments consisting of several macro cells and small cells [43, 44]. Such an architecture may result in timely action in the prevention of disaster and crime [42]. On the other hand, AI is an enabler for cellular networks to deal with the 5G standardization requirements [45]. For example, in [46], statistical regression and machine learning algorithms are utilized to evaluate the problem of performance prediction in LTE small cells. The results reveal that the AI-based learning approach can achieve very high-performance gains.

WiMAX is another alternative technology for communication of IoT devices in the UAV-based networks. Communicating devices on UAVs may use WiMAX technology which is a standard based on IEEE 802.16e to increase the size of the service area and the number of available communication channels among service providers. WiMAX can provide data transmission and Voice over IP (VoIP) services and guarantee the possibility of communication with people having a smart device ready to receive emergency messages [47]. UAVs can be equipped with various devices allowing them to take part in the network as nodes and to route the traffic of the network properly. In addition, it is crucial to predict the traffic of WiMAX networks in order to analyze its performance and provide better network management. In this regard, AI-based approaches such as ANN can be utilized to forecast the performance of the WiMAX network by using the minimum and maximum number of online users [48].

ZigBee is a communication technology which is based on IEEE 802.15.4 and provides low-power consumption and low data-rate communication. It was designed for wireless sensors and controls allowing smart IoT devices to communicate within a range of around 50 meters [49]. IEEE 802.15.4 can be used for the communication between UAVs and fixed ground sensors where short-range communication is required such as in smart agriculture and smart farming [50]. Moreover, the combination of AI techniques and ZigBee technology can be utilized in various applications and scenarios. For example, it can be used to enhance and optimize the services offered by libraries [51].

LoRaWAN is a low-power, low bit-rate, and long-range wireless technology for the IoT which is expected to overcome the connectivity problem of millions of smart IoT devices in the next decade [52]. LoRaWAN can be used as the communication protocol between UAVs and the ground BSs due to its advantages over other communication technologies such as low-power consumption and long range [53]. LoRaWAN can be cost-effective with some AI techniques that do not necessitate lots of parallel work between the nodes. Moreover, LoRaWAN can serve as an important foundation for the AI machine learning [54], while AI would have various effects on the operators such as in network architecture and big data analysis. In addition, AI-based approaches such as ANNs can be integrated with LoRaWAN technology to estimate its propagation [55] as they are less computationally demanding and more precise compared to deterministic and nondeterministic algorithms, respectively [56].

5G is the next generation of wireless networks which is expected to provide extremely low latency and high data rates as well as ubiquitous coverage for the IoT smart devices [57]. The use of UAVs as flying objects in the next generation of wireless networks has recently attracted too much attention from both academia and industry [58]. One of the most promising solutions for 5G networks in terms of energy efficiency and cost is flying platform [59]. For example, UAVs can be integrated to act as drone BSs in order to improve coverage and connectivity [60], or capacity [61], of the networks in 5G era. They offer the flexibility of integration in fast cellular deployments and provide high data rate with low transmit power because of their efficient line-of-sight (LoS) capabilities [59]. Therefore, 5G is one of the most important communication technologies used for the UAV-assisted networks in the IoT era. Moreover, in the UAV-assisted communications, AI-based solutions can be proposed to address the security and privacy issues in 5G networks [62, 63]. In addition, 5G networks and AI, when combined with UAV systems, can communicate with the location of people, bicycles, and vehicles in real time and, therefore, reduce the chance of collisions and accidents.

4 Communication Architectures

This section introduces the communication architecture for UAVs which specifies how information is transmitted between a UAV and the ground BS or between UAVs. The architecture can be classified into centralized vs. decentralized communications.

In the centralized architecture as shown in Fig. 1, all UAVs are connected to a central node called ground BS. In this architecture, UAVs are not connected to

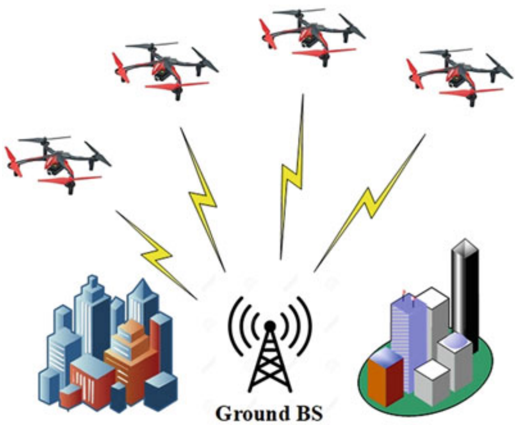


Fig. 1 Centralized UAV architecture

each other directly. Instead, each UAV sends/receives command and control data directly to/from the ground BS. In addition, the ground BS is responsible for the communication between two UAVs. This results in a relatively long delay for the information to be transmitted between two UAVs since the data has to be routed through the ground BS. Moreover, UAVs in the centralized architecture require to have advanced radio transmission devices with high transmission power since the communications between UAVs and the ground BS are often long-distance communication [64]. This is not suitable for small or medium UAVs because of their size and payload restrictions. In addition, if the ground BS encounters failures, the whole UAV network will be down. Therefore, the centralized architecture is not a strong and robust architecture.

Unlike the centralized architecture, UAVs can directly or indirectly communicate with each other without the help of the central node or the ground BS. The decentralized communication architecture can be classified into three categories: UAV ad hoc network, multigroup UAV network, and multilayer UAV ad hoc network.

UAV Ad Hoc Network In a UAV ad hoc architecture as shown in Fig. 2, each UAV takes part in data forwarding for other UAVs in the network. In this architecture, only one UAV is connected to the ground BS and acts as a gateway to relay information between the ground BS and other UAVs. This can significantly increase the coverage area of the network. The gateway UAV requires one radio for the communication with the ground BS and one for the communication with other UAVs in the network. This architecture is more practical for medium- or small-sized UAVs as the flying UAVs are relatively close to each other, and, therefore, the radio transmission devices can be lightweight and low cost. However, all the UAVs

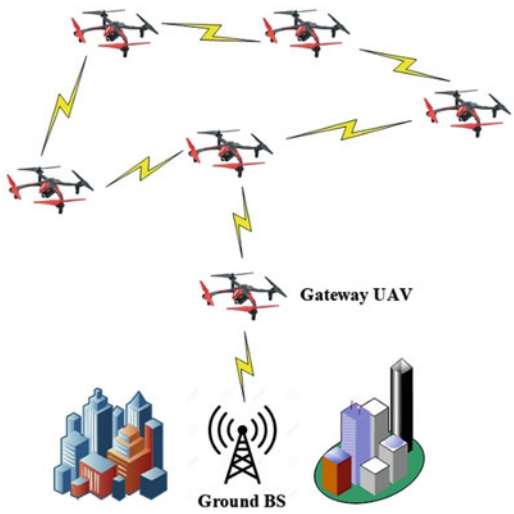
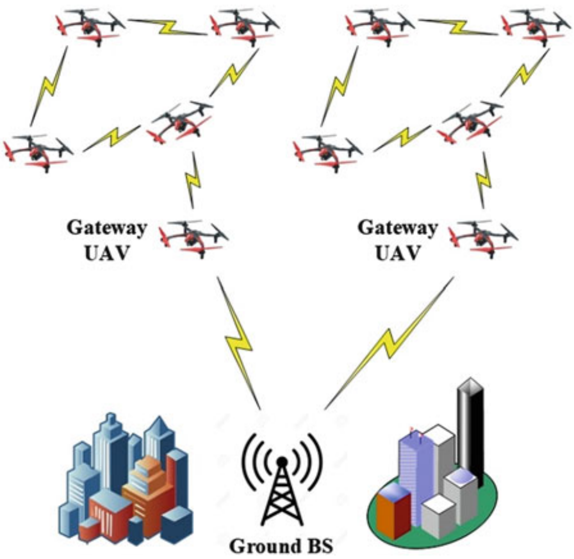


Fig. 2 UAV ad hoc network architecture

Fig. 3 Multigroup UAV network architecture



need to have similar mobility patterns such as heading directions and speed in order to ensure connectivity of the entire network. Therefore, this architecture is suitable for a group of similar UAVs tasks such as continuing surveillance actions [65].

Multigroup UAV Network A multigroup UAV network is a combination of the centralized architecture and UAV ad hoc network. As shown in Fig. 3, a group of UAVs and its respective gateway UAV form a UAV ad hoc network which is connected to the ground BS. The communication within the same group is performed through the UAV ad hoc network discussed earlier in this section, and the communication between two different groups is conducted through the gateway UAV and the ground BS. Please note that this communication architecture is appropriate when there are a large number of UAVs having different communication and/or flight characteristics. However, this communication architecture is not still a robust architecture because of its semi-centralized nature of communication.

Multilayer UAV Ad-Hoc Network Multilayer UAV ad hoc network consists of multiple groups of heterogeneous UAVs as shown in Fig. 4. It is a communication architecture where the gateway UAVs of different groups of UAV ad hoc networks are connected to each other. Moreover, only one of the gateway UAVs is directly connected to the ground BS which handles the communication for data that are destined to the ground BS. The communication between two UAV groups is handled by the gateway UAVs and does not need to be conducted through the ground BS. This significantly reduces the communication and computation load in the ground BS. The multilayer UAV ad hoc network is a robust architecture, as it does not have a single point of failure.

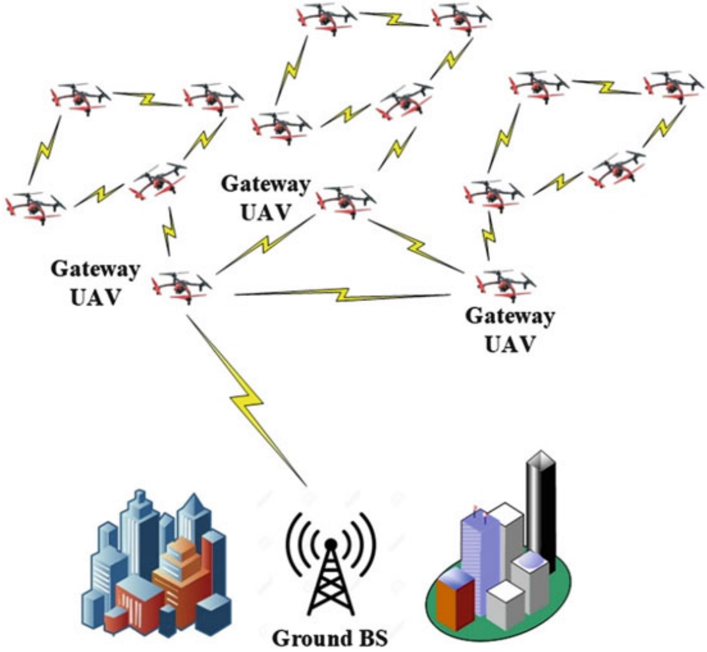


Fig. 4 Multilayer UAV ad hoc network architecture

4.1 UAV Components

In this section, various components of a UAV are discussed which help to understand its architecture and mechanism to create an enabling environment in order to ensure that resources and time are saved in the daily business engagements. We classify these components into subcategories as primary and secondary. Primary components are the most important components in designing the UAV, and secondary components are those that are less important compared to the primary components but still are significant in designing an efficient UAV.

4.1.1 Primary Components

Battery The battery is a part of the UAV that enables all the required actions and reactions. Without the battery, the UAVs have no power to fly. Different UAVs have different battery requirements. For example, small UAVs require smaller batteries because of the limited power requirements. On the other hand, bigger UAVs need bigger batteries with more capacities in order to provide power to all the functions of the UAV. The pilot can monitor the performance of the battery using a monitor on the UAV that provides the battery information.

Camera Cameras are basically one of the main components of a UAV. They help in taking images from above which provides an important use of the UAVs. Some UAVs have built-in cameras, while for other UAVs, it is possible to attach various camera types available in the market.

GPS Module GPS module is a very important component which is responsible to provide latitude, longitude, and elevation points of the UAV. It helps the UAV to fly longer distances and control specific places in the environment. It also helps to return the UAV safe to the controller even if it loses the connection to the controller.

Flight Controller This is basically the motherboard of the UAV. Flight controller is responsible for all the commands issued to the UAV. It interprets inputs from the GPS module, receiver, and sensors. It is also responsible for the control of the UAV and the regulation of motor speeds by the electronic speed controller. In addition, flight controller controls the autopilot mode and other autonomous functions in the UAV.

4.1.2 Secondary Components

Propellers The propellers are normally placed in front of the UAV and are different in terms of size and material used in making them. Some of them are made of plastic, which is suitable for smaller UAVs, but on the other hand, carbon fiber is used for the manufacturing of the more expensive propellers. They are responsible for the motion and direction of the UAV.

Solar Panel Due to the battery limitation of the UAVs, adding a lightweight and renewable energy source such as solar panel can significantly improve the efficiency and extend the flight time of the UAV. Moreover, it can eliminate the need to recharge the battery of the UAV from a power grid. This can make the UAV ideal for traveling in long distances without returning back to the ground.

Transceiver The transceiver is a unit responsible for transmission and reception of the radio signals to/from the UAV. The transceiver uses a radio signal in communication with the UAV during the flight. Each radio signal has a standard code that helps to differentiate it with other signals in the air.

5 Applied AI

In this section, design factors and requirements of AI-based UAV communications are comprehensively discussed. We also discuss various important features of the AI-based models in UAV systems. Moreover, we investigate online vs. offline processing of the UAV images.

5.1 Design Factors and Requirements

Utilizing AI in UAV communications requires special attention to ensure that there is an efficient and reliable system and acceptable quality of service (QoS). The important design factors regarding the use of AI in UAV communications are briefly discussed in this section. We divide these factors into two main categories: hard design factors and soft design factors.

5.1.1 Hard Design Factors

The design factors of the AI-based UAV systems are addressed in this section from the hardware perspectives. The hardware of the UAV affects the operability and efficiency of the imaging process. The main hard design factors are as follows.

Power Supply and Physical Structure The power supply and the aerodynamics of the UAV determine the airtime of the device. The power supply is an important unit of the UAV as it acts as a power-generation and conditioning system. It takes the electrical input and converts it to the required output. Moreover, the physical structure of the UAV can significantly affect the speed and the battery lifetime of the UAV. Therefore, it is important to use the UAV with appropriate power supply and physical structure based on the specific requirements and applications in order to improve the efficiency and operability of the entire system.

Motors and Control Mechanism The motors or rotators as well as the motor controllers also determine the airtime and speed as well as the lift capacities of the UAV. Depending on the application, different types of motors can be used in UAVs. This ensures that the motor can provide sufficient output with energy effectiveness in cases where it is required for the drones to have long-hour flights or to be used for a very short time.

Sensors and Interfaces Various sensors (e.g., camera and temperature sensors), actuators, and interfaces are required for online or offline image processing. The sensors can sense various environmental parameters, and in case of any abnormalities, a camera, which is connected to its specific interface, can take an image, which can be processed online or offline. Therefore, it is important to utilize the appropriate sensors and interfaces for the efficient image processing purposes.

Localization, Mapping, and Path Planning If the UAV is autonomous in nature, it will have a built-in localization and mapping algorithm. Using various cameras and sensors such as laser scanner, the position of the UAV can be estimated, and the 2D/3D map of the environment can be constructed. The input data can be taken from depth cameras. Moreover, the appropriate mapping will enhance the robustness and accuracy of the localization [66]. In addition, mapping supports various basic requirements of the autonomous navigation such as path planning and obstacle avoidance.

Communication System In order to transmit and receive data, there must be an established communication system for the UAV. The employed sensors in UAVs differ in terms of the used communication protocols. They can be categorized into short-range wireless communication technologies such as ZigBee, Bluetooth, and Wi-Fi and long-range low-power wide-area networks (LPWANs) including LoRaWAN (low-power WAN protocol for the IoT), Narrowband IoT (NB-IoT), Sigfox, and LTE-A. Therefore, communication system is an important design factor in order to have an efficient and reliable UAV system with acceptable level of QoS.

5.1.2 Soft Design Factors

This category of the design factors considers software aspects of the UAV systems as well as the processing of data obtained through the sensors using AI models. Depending on the objectives for the UAV images (e.g., classification, object detections, segmentation), several factors may be looked at when considering the network architecture that has to be used. Several classification and image-based techniques are used for UAVs. Some of these methods are discussed as follows, and a summary is presented in Table 1.

Bayesian Networks Bayesian networks are probabilistic graphical models that use Bayesian inference to calculate probabilities. Bayesian networks can be used for the classification of images in aerial surveillances. For example, in [67], the authors present an automatic vehicle detection mechanism for aerial surveillances using

Table 1 A summary of the image-based techniques used for UAVs using AI models

Ref.	Algorithm	Idea
[67]	GA in fuzzy images	Vehicle extraction
[68]	ANN with multiple particle collision	Determining UAV position estimation alongside GPS
[85]	CNN	Species detection, image processing (counting and tracking)
[86]	Deep CNNs with SVM	Species detection and image processing for detecting and counting cars
[72]	Graph-based K means clustering with SLIC algorithm	Mangrove ecosystem classification
[73]	K-means clustering with graph-cut (KCG)	Aerial rice yield estimation
[74]	Linear regression	Estimating forest canopy fuels and structure
[78]	Deep CNNs with naïve Bayes preprocessing	Ship detection from high resolution UAV images
[79]	KNN, decision trees, extra tree, and comparison of these methods	Classification of terrain images
[80]	RF object-based image analysis	Accurate and timely detection of weed
[81]	GA in fuzzy images	Vehicle extraction

dynamic Bayesian networks in order to design a pixel-wise classification technique for vehicle detection. Moreover, the relations among neighboring pixels in an area are also maintained in the proposed method in the process of feature extraction. Therefore, these features contain both pixel-level and region-level information. The authors reveal the accuracy and adaptability of the proposed framework for detection in different aerial images.

Artificial Neural Network (ANN) ANN is an interconnected group of nodes which represent artificial neurons. It can be used for the edge detection process in an image matching system using aerial images taken in flight time, as well as the aerial geo-referenced images in order to estimate the position of UAV where the Global Navigation Satellite System (GNSS) fails to respond [68]. ANN can be classified into supervised, unsupervised, and reinforcement learning.

1. **Supervised learning (SL):** In this category, given a dataset of labeled data, the network is trained to classify the data into the given labels. For example, in [69], supervised learning is used to provide initial training data set for an effective on-road vehicle recognition based on the image data obtained from the UAVs as traffic data collection devices. Then, the proposed approach uses an online learning- and tracking-based approach to enhance the precision of vehicle recognizer.
2. **Unsupervised learning (UL):** In this category, given a dataset of unlabeled data, the network groups similar data together through statistical analysis and outputs them in clusters. For instance, in [70], an unsupervised learning algorithm is used to evaluate and propose a practical technique for deployment of several UAVs. This technique is not limited to a fixed set of positions and is based on the concept of electrostatic forces to locate aerial BSs in a continued 3D space.
3. **Reinforcement learning (RL):** RL is the training of machine learning (ML) models to make a sequence of decisions. In this algorithm, an AI agent is used to learn about the environment and figures out which actions to perform in order to produce maximum rewards. For example, the study in [71] presents a vision-based landing supervision of UAVs using reinforcement learning algorithm to generate appropriate commands for UAV landing in various situations.

K-Means Clustering K-means clustering is an unsupervised ML algorithm that divides an image of N pixels into M clusters where the value of M is fixed [72]. The clusters provide a way to group the pixels, which is dependent on their values in the image. For example, the study in [72] uses K-means clustering and simple linear iterative clustering (SLIC) algorithms to segment the images taken from a camera placed on a UAV from a mangrove ecosystem in Fiji. Similarly, the authors in [73] propose an image processing method using K-means clustering and graph-cut algorithms to segment the rice grain areas. The results of the experiments show the accuracy of the proposed UAV image-based grain segmentation approach in estimating rice yield.

Linear Regression (LR) Given a set of training examples, LR is an approach for supervised learning that fits a linear function into a group of numeric input–output pairs. It is utilized to predict a quantitate response B from the predictor variable A such that there is a relationship between A and B. The study in [74] shows the possibility of using UAV images as a way to estimate the forest canopy structure and fuels in a forest in the USA. The authors use simple LR models to test the relationship between the field-measured variables and the UAV image derived. The results indicate the accuracy of the proposed approach in estimating a number of items such as canopy height, canopy cover, and tree density in the forest.

Naïve Bayes Classifier (NBC) The NBC is based on the Bayes probability theory which can dynamically classify data based on its posterior probability and can provide accurate performance [75]. It can be used in various fields for different purposes such as classifying documents [76], detecting Internet intrusion [75], and carrying out health surveillances [77]. Moreover, the study in [78] proposes a method for ship detection using high-resolution images obtained from UAVs. The authors use a deep neural network auto-encoder in order to extract features automatically for the set of discrete NBC. The results reveal that the proposed method outperforms the previous methods.

K-Nearest Neighbors This method of classification allows a single point of data to find its nearest neighboring data cluster and assign that class to the data point. For example, the study in [79] presents an approach to classify terrain images taken from a UAV into five different types: car park, green zone, building, canal, and road. The authors use K-nearest neighbor together with two other classifiers called decision tree and extra tree. In order to cover the area of interest, the process stitches groups of four images to form large field-of-view images. The images are then divided into grids which are manually labeled as one of the mentioned terrain types.

Random Forest (RF) In AI, a decision tree is a tree where each node represents an attribute, each link represents a decision, and each leaf represents an outcome. RF is a group of classification trees where each decision tree uses a subset of variables and training samples chosen by a bagging method, whereas other samples left are utilized to test the effectiveness of the RF performance using cross-validation techniques [80]. In [80], the authors propose an approach for vegetation mapping based on UAV remote sensing using RF and texture analysis. An RF containing 200 trees is utilized to classify 2 selected UAV images in the area. The results reveal that the UAV provides an ideal approach for urban vegetation mapping. Moreover, RF performs better than the traditional maximum likelihood classifier in terms of object-based image analysis.

Genetic Algorithm (GA) This evolutionary algorithm uses methods of population, breeding/crossover, and mutation in order to find the global optimum solution in a given data. For example, the study in [81] develops an approach to identify and extract vehicles from UAV images. First, a segmentation algorithm based on fuzzy c-partition is employed to segment the color UAV imagery. Then the GA is used to cluster the color space data point in order to achieve the optimal color segmentation. The obtained results show the effectiveness of the proposed approach in terms of positional accuracy and visual effect.

Deep Learning (DL) DL is a part of ML techniques based on ANNs. There are different deep learning approaches such as convolutional neural networks (CNNs) that have been used in various applications including object detection, image classification, and recognition tasks. CNNs are broadly applied in image classification due to their ability to handle large datasets with higher accuracy compared to the traditional approaches [82]. Moreover, CNNs are able to implement nonlinear decision functions [83] and can automatically learn characteristics from the large datasets by using the organization of multilayers of neurons [84]. For example, in [85] the authors propose a method using deep CNNs to count and monitor animal species through video recording taken from UAVs. In addition, the study in [86] presents a solution to the problem of counting and detecting cars in UAV images. The authors use a deep CNN system as a feature extraction tool and combine it with a linear support vector machine (SVM) to classify the area under study into "no-car" and "car" areas. The results reveal the effectiveness of the proposed approach in terms of accuracy and computational time.

Deep networks can be classified into generative and discriminative architectures. Generative architecture as shown in Fig. 5 includes deep belief network (DBN), deep Boltzmann machine (DBM), and deep autoencoder (DA). Moreover, discriminative architecture can be classified into convolutional neural network (CNN) and recurrent neural network (RNN). Simple descriptions of each architecture are presented as follows.

Generative Architecture

- **Deep belief network (DBN):** This is a multilayer class of deep neural network that has connections between the layers, but not between individual units in a single layer. DBN can be used as a classifier for detecting and classifying the micro UAVs to recognize the signature patterns produced by utilizing a Doppler radar-based approach [87].
- **Deep Boltzmann machine (DBM):** DBM is an undirected version of the DBN. In DBM, nonlinear hidden variables are structured in multiple connected layers

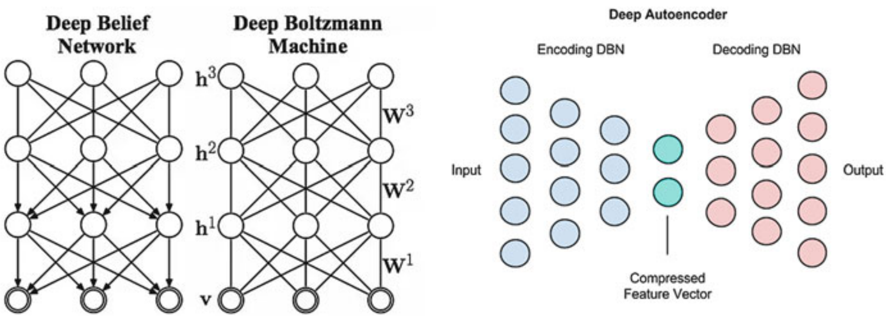


Fig. 5 Deep belief network (DBN), deep Boltzmann machine (DBM), and deep autoencoder (DA) structures [90]

such that variables in one layer can concurrently contribute to the states or probabilities of variables in the next layer [88].

- **Deep autoencoder (DA):** A DA is a generative architecture composed of two symmetrical DBNs that typically have four to five shallow layers. DA is a kind of unsupervised learning algorithm that performs data self-recovery training based on the value of the target input and output being equal. It reduces the loss function by training to figure out a set of network parameters [89].

Discriminative Architecture

- **Convolutional neural network (CNN):** This is the most utilized feedforward neural network architecture that uses a variation of multilayer perceptrons in order to classify complex data. This DL approach can be used in various applications such as image classification [82].
- **Recurrent neural network (RNN):** RNN is a type of network where the output from the previous step is fed as input to the current step. It is useful for data changing over time, equipped with a feedback loop mechanism. RNN proved to provide more precise segmentation results by utilizing related data-dependent characteristics automatically [91].

The combination of CNN and RNN can be applied to UAV images of various applications such as in flooding areas for precise semantic segmentation of meaningful object borders with end-to-end learning [91]. This in turn results in detection of flood areas with high accuracy from a large UAV dataset.

5.2 Features

In this section, we discuss the most important features and criteria used to train AI algorithms that are utilized in UAV communications.

In [92], the authors designed an intelligent proportional–integral–derivative (PID) controller based on the radial basis function neural network (RBFNN) in order to control the longitudinal attitude of a small UAV based on the complexity and nonlinear features. RFBNN control algorithm is fast and easy to operate and can approximate any nonlinear functions. Therefore, it can be easily utilized in UAV flight control system. The study in [93] utilizes the application of RL to the derivation of control rules for the flight control of a UAV. The authors use the features of height and positions controllers for training the AI algorithm in the UAV communications.

In [94], a support vector regression (SVR) approach is proposed for the adaptive control of a UAV based on the input–output feedback linearization approach. The approach is trained using the maximum tolerable error and the regularization parameter. The results reveal the effectiveness of the proposed method compared to other techniques such as neural network (NN) algorithm.

The authors in [95] propose a nonlinear autopilot for quadrotor UAVs according to the feedback linearization. It is then compared to an autopilot that has been learned by RL using fitted value iteration concerning performance and design effort. The study in [96] proposes a framework for combining RL and cooperative planner techniques in order to improve the accuracy and policy of the cooperative planner while reducing the sample complexity of the learner. In [97], the authors present a mechanism based on extreme learning machine (ELM) for learning the stored digital elevation information. This is performed to carry out an estimation or map building for the navigation of UAVs without the need for GPS. The ELM training algorithm is applied to significantly speed up the rate in a way that the network learns about the previous available maps. The results show better mean square error performance of the training algorithm compared to other approaches.

In [98], the authors propose an approach based on CNN to safely drive a UAV in the streets of a city. Based on the features of complexity and processing time, the model learns to move by considering the movement of bicycles and cars in the city which follows the traffic rules. Moreover, the study in [99] describes a system that navigates a small UAV autonomously through dense forest environments to avoid collisions with trees. The approach teaches a controller that needs mapping of camera images to a set of features which can be utilized by the training algorithm. These features include optical flow, Radon transform statistics, and structure tensor statistics.

The study in [100] proposes an ML-based system for weed mapping in precision agriculture based on the images provided by UAVs. The study considers a broad range of features such as geometrical, statistical, spatial, and texture based in order to train the AI algorithms. A summary of the mentioned studies and their most important features and criteria used to train AI algorithms in UAV communications is presented in Table 2.

Table 2 A summary of the studies and the most important features and criteria used to train AI algorithms in UAV communications

Ref.	Algorithm	Features	Learning type
[92]	RBFNN	Complexity and nonlinearity	Supervised learning
[93]	Learning automata	Height and positions controllers	Reinforcement learning
[94]	SVR	Maximum tolerable error and regularization parameter	Supervised learning
[95]	Markov decision process	Fitted value iteration	Reinforcement learning
[96]	CNAC, CSarsa	Accuracy	Reinforcement learning
[97]	ELM	Speed	Supervised learning
[98]	CNN	Complexity and processing time	Supervised learning
[99]	Imitation learning	Optical flow, radon transform statistics, and structure tensor statistics	Supervised learning
[100]	Object-based image analysis	Geometrical, statistical, spatial, and texture-based features	Supervised learning

5.3 *Online Vs. Offline Classifications*

Currently, the processing workflow of UAVs in most cases is based on the image post-processing since the processing power of the UAVs is limited. The system takes the UAV images and then processes them in a workstation. However, there are great interests in using real-time image processing solutions which can be done by using cloud computing [101, 102]. Cloud-based platforms can improve the availability of data processing performance without investing on high-performance computers or server infrastructure [103]. The processing techniques can be categorized to offline vs. online processing techniques.

In offline processing, the approach processes the already recorded videos or captured images by the UAVs. It is enabled by utilizing more complex and computationally demanding algorithms and, therefore, provides better results compared to real-time processing. Some of deep learning tools for offline image processing on CPU are Neural Network Toolbox in MATLAB and OpenCV dnn module which supports TensorFlow and Torch.

On the other hand, some applications such as traffic monitoring and target tracking in military purposes require real-time processing and feedback from the sensors for the UAV images. Some of the tools for online processing in graphics processing unit (GPU) are OpenVX standard with Neural Network Extension and OpenCL standard and Torch.

The study in [103] utilizes real-time data processing object detection from the UAVs based on cloud computing for future anti-collision systems and georeferencing. The results reveal that the real-time data processing can be useful to track changes precisely. Moreover, in [104], the authors developed an edge computing and sensing system for the UAVs which is compatible with deep learning frameworks. They also proposed a real-time localization and obstacle detection technique which is used to control the UAVs locally without depending on the link to a ground BS. The results show the autonomous navigation feature of the UAV by considering a predefined path with the location error of less than 10%.

6 Open Issues

In spite of the rapid development that has been achieved and several research activities carried out in recent years regarding the use of AI in UAV communications, there are still open issues and research challenges that need to be carefully taken into consideration. Some of these research issues are outlined in this section.

6.1 Wireless Challenges

One of the most challenging issues regarding the use of UAVs in IoT era is related to wireless connectivity especially for the scenarios related to ITSs. For example, UAVs can provide a fast report when an accident happens and can act as speed cameras and flying units to monitor accidents, provide road safety, and control road traffic. In this regard, UAVs can be equipped with different sensors to send various types of data to other UAVs and vehicles. In such scenarios, each UAV can transmit a specific part of the data to other vehicles instead of transmitting the whole data file. This in turn results in lower power consumption and faster data transmission for each UAV. In this regard, deep learning based on spectral clustering can be applied to group the UAVs into various clusters for transmission of data based on the type of sensors, and location of the UAVs, as well as the number and location of vehicles in the network [62].

6.2 Security

In various applications of UAVs such as ITSs, a group of UAVs can perform the necessary tasks better in comparison with a single UAV. However, the data sharing among them can be prone to adversarial machine learning (AML) attacks in such a way that an attacker can join the group and change the data which may result in collisions as well as odd movements. In this regard, AI-based solutions such as federated learning can be applied so that each UAV can receive the common task that has to be performed by the UAV group from the BS and enhance the learning model for accomplishing the necessary tasks according to the collected data. Therefore, each UAV can summarize the changes in the learning model and share it with other UAVs in the group [62]. This can help to mitigate the risk of AML.

6.3 UAV Autonomy

UAV autonomous operations are crucial for the development of various military and civilian applications. They would enable safe navigation without (or with little) human supervision. However, UAV systems have significant flight tolerance restrictions which limit the weight, size, and power consumption of the payload [105]. These restrictions limit the necessary capabilities for the UAV autonomous operations. In addition, onboard processing is used for various UAV operations such as when the available bandwidth is limited or when the huge amount of data have to be transmitted. Therefore, it is crucial to carry out research in the design of computing devices with low power consumption, especially GPUs.

6.4 Deep Learning Challenges

Deep learning algorithms have been broadly applied within the architecture a UAV system such as in feature extraction systems which require great computational resources. It is still difficult to integrate these resources on onboard UAVs which require off-board processing and great communication capabilities. In addition, in most cases, the current computational resources available are not compatible with online processing which in turn limits the applications where the reactive behaviors are required [105]. Therefore, it is beneficial to perform research into the design of more efficient deep learning architectures.

7 Conclusions

The integration of AI and UAVs is considered as one of the most promising solutions regarding the development of smart environments as they can be utilized to enhance technologies and to deal with complexity and big data, as well as to provide high accurate and speedy processing. In this chapter, through a comprehensive investigation on the use of AI in UAV communications, we discussed the applications and communication protocols of the UAV-assisted IoT systems and provided various design factors and requirements which ensure an efficient and reliable system with acceptable QoS. Moreover, we overviewed several classification and image-based techniques that are used for UAV communications in the IoT era. Finally, we outlined some open issues and research challenges that need to be carefully taken into consideration in this area.

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UAVs Healthcare Applications, Communication Protocols, Deployment Strategies, and Security Challenges

Zaib Ullah, Fadi Al-Turjman, and Leonardo Mostarda

1 Introduction

The fast, potent, and dynamic maneuverability nature of UAVs has placed its significance in many real world applications from military to civilian use. The affordable manufacturing cost, evolution in UAVs energy harvesting mechanisms, perfecting joint optimization issues of UAVs, e.g., trajectories, and data collection, etc. and increasing payload capabilities have made it a potential and vital tool of any society. The aforementioned evolving imperative features of UAV have led to a surge in its use for commercial activities, and this growth is expected to continue in the near future [1–4]. The UAV is making its place in the healthcare industry, entertainment sectors, power lines and oil rigs monitoring, next-generation telecommunication industry, forest monitoring, search and rescue operations, and construction industry. The Third Generation Partnership Project (3GPP) is playing a vital role in the smooth and steady social integration of UAVs. The primary objectives of 3GPP are to establish strong and durable connections between UAVs and cellular networks providing companies. The 3GPP has launched its study item that focuses on various UAVs related issues ranging from existing UAVs challenges, needs, possible opportunities, and its integration to LTE and next-generation communication, e.g., 5G and beyond [3].

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_2

In this chapter, we discuss the recent advances in UAVs application from a healthcare perspective, development in UAVs communication protocols, the UAVs deployment strategies and their impacts, and the UAVs performance from the security perspective and finally we discuss existing challenges and future research trends.

2 UAVs Application in Healthcare: A Brief Overview

In this section, we focus on the recent developments regarding UAVs application in the healthcare industry. We also consider the UAVs role and proposed techniques in improving the healthcare of livestock.

The authors in [5] have proposed UAVs utilization for body area networks (BANs). They have designed an architecture to use UAVs for collecting data from BANs efficiently and securely. In the proposed paradigm, a UAV simultaneously interacts with many BANs using the concept of wake-up radio (WuR) communication. The performance of proposed architecture has been analyzed by throughput and delay metrics in different proposed scenarios. The authors [6] have presented various applications of UAVs in medical fields, challenges, and possible solutions. UAVs played a significant role in healthcare activities during Haiti and Nepal earthquakes in 2010 and 2015, respectively. In this regard, the National Aeronautics and Space Administration (NASA) designed and tested UAV-based system to transport necessary medical pieces of equipment in rural Virginia. The "Doctors Without Borders" association employed UAVs for the transportation of tuberculosis (TB) test samples to the far-off parts of the country. Likewise, in Malawi, the UAVs are being used in eradication efforts of the human immunodeficiency virus (HIV), a big threat to people lives in the country. Similarly, in Rwanda, blood products and necessary medicines are transported by UAVs with the joint help of GPS and Rwanda's Telecommunication. In [7], the author has investigated the types of medical supplies, suitable for transportation in urban areas. Their findings suggest that lightweight, low volume, highly demanded, and least risky medical goods should be transported through UAVs in an urban environment. The authors in [8] have focused on UAV's role and performance in the blood delivery system. UAVs called Zipline have accomplished more than 4000 blood supply missions and are currently delivering approximately 20% of Rwanda's blood supply to far-flung areas of the country. Similarly, another UAV company called Matternet, operating in various cities of Swiss has flown 1800 blood supply and pathology specimens missions. By equipping UAVs with temperature-controlled compartments, its capacity of carrying temperature-sensitive medicines will be achieved. In [9], the authors conducted a sort of survey to study the opinion of Swiss people regarding UAV's role in the healthcare sector. The analysis affirmed that UAVs utilization for diagnosis purpose inside hospitals is of high concern while its use for delivery and emergency purposes is supported by the patients and employees. In [10], the authors proposed a technique based on a partially observable Markov decision process (POMDP). The primary idea is to design a UAV trajectory in such a way that the zone with the highest number of victims should be highly prioritized. The authors applied the proposed techniques to presume three different case studies namely nuclear disaster at Fukushima, the South Sudan refugee camp, and tornado destruction in Brazil. The proposed technique achieved successful coverage of the affected zones within an auspicious time. In [11], the authors proposed a UAV-based paradigm consisting of two models for patients with chronic diseases in rural areas. In the first model, the set covering mechanism is used to find the optimum number of UAVs center positions while the second model is based on a multi-depot routing problem, dealing with cost-effective UAV selection for medicines delivery and returning with patient blood samples and medical kit. The authors developed a cost–benefit mechanism to analyze the performance of UAV-aided healthcare services.

In [12], the authors proposed an idea of using UAVs to count and monitor by scanning the area of livestock. Animal species are video recorded in a specific area via UAVs and the attained number of images are analyzed for the track record of the species. In [13], the authors have proposed an idea of how to monitor and safeguard the health of livestock using agriculture UAVs surveillance. In this patent, the authors have provided a very detailed discussion and precise techniques of using UAVs to observe the livestock and identify their health conditions based on their body's thermal temperature. In the proposed idea, UAVs traverse over feedlots, monitor and analyze the health of individual livestock based on core body temperature, and pass the real-time information to control room for further processing and actions.

3 UAVs Communication Protocols and Technologies

In this section, we discuss various communication protocols and recent efforts that have attempted to establish the most reliable and stable communication between UAV to UAV (U2U) and UAV to Ground nodes (U2G), etc.

The authors in [14] proposed an innovative protocol known as the Iterative Sub-channel Allocation and Speed Optimization Algorithm (ISASOA). The objectives of the proposed protocol are to establish communication links between UAV-UAV (U2U)and UAV-Network(U2N) and maximizing the uplink sum-rate using the joint optimization problem of subchannel allocation and UAV flying speed. To efficiently solve the NP-hard problem, the authors divided the scenarios into three sub problems, i.e., UAV speed, U2U, and U2N subchannel allocation. The simulation results conclude that the proposed protocol performance is superior to the benchmark greedy algorithm. In [15], Johnston et al. proposed a hybrid MAC protocol based on features like contention and reservation. In this protocol, contention over available channels takes place using CSMA protocol in a random-access manner. Once an available channel is occupied, remaining users stop their further attempts to acquire it for communication. This technique of reserving channels for communication improves throughput and delay over existing standard MAC protocols. In [16], the authors proposed an idea of facilitating vehicles traveling in the coverage zone of an airborne UAV. According to the proposed technique, a traveling vehicle is first identified and its communication capabilities are assessed based on its identity. An optional communication request is initiated by the UAV to the aforementioned vehicle and the vehicle can accept or reject it. Based on accepting UAV requests, UAVs can forward predetermined information either from the surrounding vehicles or other relevant sources. In [17], the authors proposed a medium access control (MAC) protocol for WSN-UAV, known as Advanced Prioritized MAC(AP-MAC) to offer an efficient and high throughput in a dense network environment. The performance of AP-MAC protocol has been evaluated analytically using a 3-dimensional Markov chain and validated by corresponding simulations. In [18], the authors proposed a joint optimization approach based on deployed sensors wake-up schedule and UAV trajectory such as to enhance the sensor's energy efficiency and ensure a reliable UAV data collection. The numerical results confirm the efficient performance of the proposed technique. In [19], the authors proposed a delay-tolerant MAC protocol known as UD-MAC for UAV networks. The UD-MAC protocol takes advantage of UAVs returning towards the destination that are discovered through Control and Non-Payload Communication (CNPC) links. The returning UAVs collect data from UAVs along its returning trajectory. Simulation results show that the proposed approach significantly improves channel access when compared with the existing benchmark protocol. In [20], the authors proposed a radio frequency (RF) based sensors wake-up approach for data transmission to airborne UAVs. The performance efficiency of the proposed approach is experimentally evaluated and compared with the traditional duty cycle based mechanism. The authors in [5] proposed a technique to establish a wireless connection through IEEE 802.11n between two devices such that the wireless access point is attached to the flying machines. The authors conducted various experiments to analyze the efficiency of IEEE 802.11n at 2.4 GHz and 5 GHz. The data rate based performance evaluation shows that the proposed technique is slightly better at 5 GHz than at 2.4 GHz. In [21], the authors designed an algorithm to enhance the data transmitting rate from sensor nodes to UAV. The proposed optimal algorithm is based on dynamic programming and is known as DPBA. According to this paradigm, the authors have jointly considered the bandwidth allocation and energy assignment to enhance the entire transmission rate while assuring the data rate of individual sensor nodes in respective time slots. The simulation results based comparative performance of DPBA is superior to benchmark protocol, i.e., ERAA (equal resource allocation algorithm). In [22], the authors formulated a novel scheme to optimize the network energy consumption. To maximize network throughput, a mechanism was devised to minimize redundant data transmission. Sensor nodes are categorized into different clusters(frames) inside a UAV coverage zone and assigned a priority level based on their locations. Lower contention window values are assigned to high priority clusters to gather maximum desired data while high contention window values are assigned to frames of least priority. This approach optimizes packet loss from sensor nodes and reduces overall packet collision. The authors proposed a novel routing protocol based on the preceding mechanism to minimize the distances between transmitting and receiving nodes. The simulation results show that the shortest distance between the sender and receiver leads to improved channel quality and energy efficiency.

4 UAVs Deployment Techniques

UAVs aerial deployment is one of the significant issues faced by UAV's industrial and academic experts to highly benefit from the immense potential of UAVs. The random and deterministic (controlled) deployments are the two primary approaches, adopted in UAVs deployment. In the following, we briefly explain the aforementioned deployment strategies and their significance in area coverage, network connectivity, and network lifetime.

4.1 UAVs Random Deployment

In this technique, UAVs are randomly deployed in an area of interest without following any sort of deployment protocol. Most often such kind of UAVs deployment takes place in applications related to earthquakes affected zones, forest monitoring, rescue operations, etc. to maximize the surveillance capabilities, irrespective of the UAVs energy consumption.

4.2 UAVs Controlled Deployment

In this approach, UAVs are deployed in a given area according to some predefined approach. The UAVs deployment could be uniform or precisely arranged in clusters formations, depending on the nature of the application. The deterministic UAVs deployment approach is highly useful in applications that need careful considerations of UAVs coverage, optimum data collection from the ground nodes, high energy efficiency, UAVs acting as aerial BSs and relay nodes, UAVs acting as Jamming nodes, and taking part in covert communication. The deterministic UAVs network deployment topology plays a significant role in various mission-critical applications.

Coverage Area
Due to the fast and dynamic movements of UAV, its significance in area coverage is highly regarded in many applications. To enhance the efficiency of UAVs in terms of area coverage, different approaches have been investigated [23, 24]. For example,

the authors in [24] investigate different altitude levels for UAV placement to offer maximum radio coverage.

Network Connectivity
Network connectivity is a term widely used in WSNs and IoT to enable steady data communication across various existing nodes in a network. The deterministic deployment of UAVs plays an important role in network connectivity to maximize data throughput, energy efficiency and avoid the energy hole problem in UAVs networks.

Network Lifetime
Since airborne UAVs are supported by fixed-battery power and are prone to energy efficiency issues that can prove fatal to mission-critical applications. Different approaches including wireless power charging, protocols to optimize the use of onboard resources, defined duty cycle based data collection, and trajectory optimization, etc. are being used to develop the deterministic movements of UAVs to enhance the UAVs network lifetime.

5 UAVs Security Aspects and Issues

UAV's security from physical and communication perspectives is one of the most significant aspects of UAVs' industrial evolution. In the following, we discuss numerous studies and attempts to improve the UAV's security and efficiently handle miscellaneous possible hindrances that affect its social integration.

In [25], the authors have considered two different use cases of UAVs, operating as BS and an ordinary node while ensuring the security of data communication. Further, they testify the security techniques at physical layers and validate their performance through a numerical method. In [26], the authors proposed a complex scenario where a UAV acting as BS (UAV-BS) can securely transmit data to many receiving BS with the help of supporting jammer UAV, in the presence of a various eavesdropper. The authors designed a non-convex optimization problem based on UAVs trajectories and transmission power of UAV-B and UAV-J to improve the average secrecy rate at receiving different BS. The proposed problem is solved using a successive convex approximation mechanism and iterative algorithm. The results of the proposed technique show significant performance in the given scenarios. In [27], the authors have studied different issues related to UAV's communication from a physical layer security perspective. The UAVs LoS channels are prone to malicious attacks from ground nodes due to their high altitude and similarly, UAVs can also be used for malicious intentions, acting as jamming nodes for terrestrial communication and eavesdroppers. To efficiently handle such kind of scenarios, the authors have provided innovative solutions supported by a numerical explanation.

In [28], the authors studied the effect of congestion over the UAVs network and proposed an innovative optimized fruit fly routing protocol (OFFRP) to efficiently deal with such situations. The performance and effectiveness of the proposed protocol are analyzed and compared with the existing benchmark protocols.

In [29], the author's primary focus is to study possible security vulnerabilities of UAVs and to provide viable countermeasures. For this purpose, they have considered two UAVs namely, the Parrot Mambo FPV exposed to FTP service and de-authentication intrusions and Eachine E_{010} is open to custom made controller and radio frequency (RF) replay interruptions. This article outlines a detailed discussion and possible countermeasures to nullify the preceding attacks over UAV's communication.

Ursula et al. [30] studied UAV's communication from interference, handover, mobility, and cyber-physical intrusions perspective. The primary mottoes of their investigations are to address the security vulnerabilities and challenges during UAVs assisted multimedia streaming and UAV-based transportation. The authors proposed and validated the artificial neural network (ANN) based approach to ensure safe and secure UAVs communication in real-time. In [31], the authors have formulated a non-convex, joint optimization problem based on UAV's trajectory and transmission power of the legitimate node. In the proposed scenario, there exist two-way communication, i.e., from UAV to ground node (U2G) and ground node to UAV (G2U), subject to a potential eavesdropper on the ground. The objective is to maximize the average secrecy rate of G2U and U2G communication during a defined flight time of a UAV. The problem is efficiently solved by using successive convex optimization and block coordinate descent techniques, and its comparative performance to benchmark protocols are validated by the corresponding simulation results.

The authors in [32] formulate a UAV's covert communication scenario in a restricted zone and provide a possible solution to materialize it. In the proposed scenario, a UAV covertly transmits a message to Bob, a legitimate receiver while trying to avoid the warden. To enhance the efficiency of covert communication, a joint optimization problem of UAV's trajectory and transmit power is proposed to improve the average covert transmission rate from UAV to Bob. The problem is solved by using a successive convex approximation algorithm and its significance is verified by the comparative performance to existing benchmark techniques.

6 Challenges and Future Research Directions

There are many challenges in the evolution of UAVs and to become a constituent entity of the society. In the following, we discuss different emerging issues and challenges that affect the UAVs growth and in the next subsection, we focus on the recently adopted research trends that try to improve the existing issues faced by the UAVs industry.

6.1 Challenges

- One of the primary and most significant issues is the security of the collected data. Due to the lack of onboard high-level encryption mechanisms, the hackers can access UAVs data and manipulate its contents. To safeguard the UAVs collected data, various image optimization techniques like data fusion, stitching of aerial images, etc. need to be implemented.
- The UAV's regulations are in the evolution phase and some nations have not even initiated to formulate UAVs legislations inside their countries. The absence of UAVs regulation could be a potential threat to the civil aviation industry of any country. The nations should initiate a user-friendly UAVs registration mechanism to better facilitate UAVs evolution and avoid all possible threats.
- One of the main challenges that limit UAVs operations is its data processing and long-range communication capabilities. Coping with the aforementioned issues will enable UAVs beyond the line of sight (BLoS) movements and will contribute to the steady growth of UAV-based industry.
- During UAVs surveillance, precise identification of many vehicles traveling at the same time is also one of the challenges and various image processing based efforts are underway to perfect it.
- The collision avoidance or the "enemy avoidance problem" is also one of the real issues that restrict the true autonomous nature of UAVs. To equip UAVs with absolute collision avoidance characteristics and realize UAV swarms, advanced artificial intelligence (AI) and machine learning (ML) based techniques are needed to be designed.
- The airborne UAVs identification and designing more robust and effective mechanisms to counter malicious UAVs is one of the critical issues in the evolving UAVs industry.
- With the passage of time, the number of UAVs adoption for recreational, commercial, and surveillance purposes will exponentially increase, developing UAV-based scalable networks would be need of time.
- The wind speed and harsh environment have a high impact on the movements of airborne UAVs. An experimental study is needed to assess the precise impact of preceding factors over UAVs flights and define standard limitations from the UAVs weights and challenging environment perspectives.
- To enable high data throughput at IoT devices and enhance UAVs efficiency, joint optimization of mutual locations of UAVs, intended IoT devices, and the amount of caching data is needed. A study and measurement campaign of UAV to UAV channel, UAV to the ground node and UAV control links during vertical take-off and landing in harsh weather conditions, varying temperatures, and in the presence of a smooth and uneven shaped structure is highly needed to enable commercial and emergency UAVs operation. To ensure the data privacy of airborne UAVs, use cases of blockchain technology should be investigated.

6.2 *Future Research Trends*

- The AI, ML, and most importantly deep reinforcement learning (DRL) are playing a significant role in the design of advanced, autonomous aerial BS. Different AI, ML, and DRL based approaches are currently being investigated to solve problems like joint optimization of UAVs trajectory and duty cycle of deployed ground nodes, joint optimization UAVs battery capacity, sensing processing and trajectory, and many UAV-based applications, e.g., precision agriculture, vehicles tracking, covert communication, UAVs swarm optimization, collision avoidance problem, etc.
- Millimeter-wave (mmWave) communication-based technology can be employed in existing UAV networks to offer high data. However, the swift mobility of UAVs causes various issues (e.g., fast variation in UAVs channel, frequent handovers, mmWave blockage, etc.) that are currently under investigation to enable UAVs for next generation communication.

7 Conclusion

We investigated ongoing, contemporary research accomplishments by the research community in academia and industry. In this work, we offered recent developments regarding UAVs applications in the healthcare industry that can improve the health quality, particularly in the underdeveloped countries where the roads infrastructure is weak. Further, we studied the newly developed communication protocols to make UAVs communication links more stable and reliable, and UAVs deployment techniques to enhance the coverage area, network connectivity, and network lifetime. We offered an in-depth study of different issues and challenges regarding UAVs security from covert communication, jamming, and physical threats perspectives. Most importantly we provided an in-depth discussion of existing UAVs challenges that affect the pace of UAVs evolution and recent research trends that try to improve the preceding issues.

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Machine Learning Applications for Internet of Flying Vehicles in Case of Critical and Environmental Cases

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1 Introduction

Owning to the fact that Internet of Things (IoT) has emerged as a significant advancement for communication and mobile networks [1], it has converged technologies in terms of information processing, networking, and controlling intelligent technologies [2].

Recently, researchers are increasingly interested in smart city behaviors, such as pedestrian drivers and traffic, city resources, and environment known as Internet of Vehicles (IoV) [3]. IoV is divided into two architectures known as vehicle networking and intelligence. The networking consists of vehicular ad hoc network (VANET), vehicle telematics, and mobile Internet. Intelligence refers to the deep learning, cognitive computing, swarm computing, artificial intelligence, etc., whereas the integration of driver and vehicle together uses network technologies [4]. Hence, IoV is a new paradigm focusing on the intelligent integration of humans,

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_3

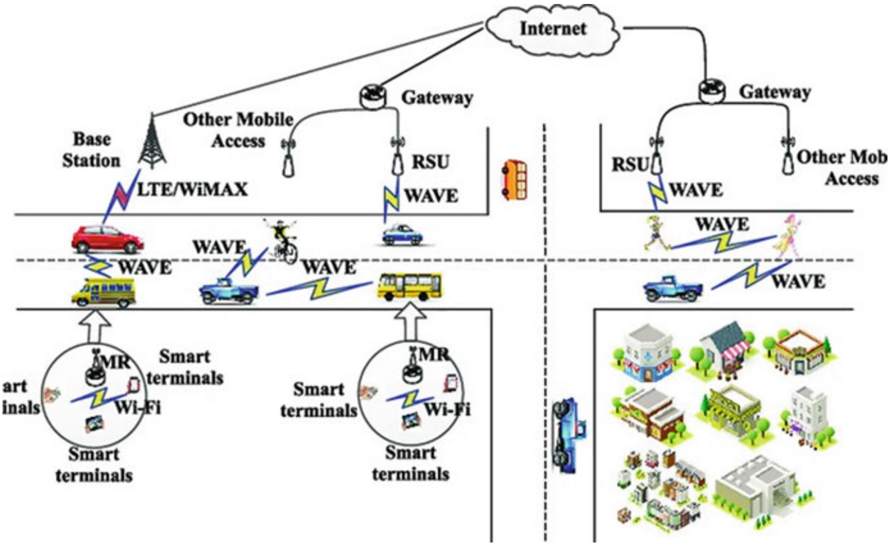

Fig. 1 IoV network architecture

vehicles, things, and environments. Figure 1 presents the general IoV architecture discussed in literature.

With increasing number of vehicles being connected to IoT in smart environments, a need for better communications and interconnectivity among these vehicles due to their mobility has emerged [5]. Within this context, unmanned aerial vehicles, known as drones, have attracted a lot of attention where a new novel paradigm known as Internet of Flying Vehicles (IoFV) becomes part of the IoV [6].

Due to the high mobility of drones or IoFV, they can be used to provide many applications, such as military services, health and rescue operations, service delivery, and pollution and disaster forecasting [6]. Although security and privacy issues are concerned and limited number of suggestions are being made, popularity and usage of IoFV have increased under the concept of open and integrated network system IoV which is composed of multiple users, multiple vehicles, multiple things, and multiple networks. This concept is highly manageable, controllable, and operational [4]. General IoFV devices (drones where they are known as UAVs) and applications are presented in Fig. 2.

IoV is the integration of humans and vehicles, where it interconnects humans within and around the vehicles, intelligent systems on vehicles, and various cyber-physical systems in virtual environments combining sensors, mobile devices, and vehicles.

Machine learning is a popular scientific field that includes the application in many multidisciplinary fields. In more than two decades, artificial intelligence (AI) has evolved in humans' daily lives in order to perform different problems [7]. Machine learning (ML) techniques, which are the part of AI, have been developed

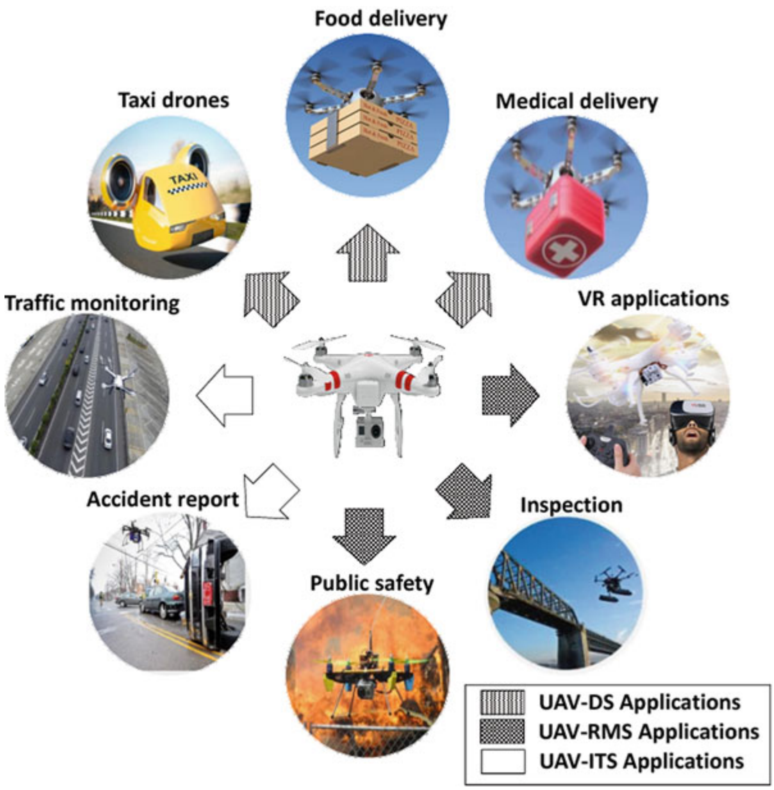

Fig. 2 Applications of drones

as problem-solving tool with capabilities of prediction, classification, and optimization [7]. Within this concept, ML techniques are divided into supervised and unsupervised algorithms. Although both supervised and unsupervised algorithms have many different existing algorithms, back-propagation neural networks, support vector machines, decision trees, support vector regression, long- and short-term memory are the most preferred.

As stated above, the IoT provides an interconnection between various devices as well as humans. Since IoT includes device-to-device, machine-to-machine, and machine-to-people communications, many useful and different applications have emerged. These applications include smart traffic monitoring, self-driving cars, collection of data from smart healthcare devices, and many more. Therefore, different intelligent algorithms have been applied in order to solve challenging tasks [8].

Due to high mobility of drones, they can be used to provide a lot of applications; however, there are many challenging issues to overcome. These challenging issues comprise not only the technical issues, such as battery lifetime, but also regulation issues that are associated with problems like security and privacy issues in both human and machine sides [6]. One of the ways to overcome technical challenges is developing different ML algorithms which are suitable for drones.

In this chapter, recent developments in ML will be critically analyzed. A ML algorithm will be suggested for IoFV, and limitations will be discussed as well.

As stated in [4], IoV can be defined as an integrated network which connects people within and around vehicles, intelligent systems onboard vehicles, and different communication infrastructures in urban environments. This research tries to detect vehicles in images and videos. It deploys a dataset from Udacity in order to train the developed machine learning algorithms. Support vector machine (SVM) and decision tree (DT) algorithms have been developed for the detection and tracking tasks.

The rest of the paper is designed as follows: Sect. 2 presents existing popular ML algorithm in the literature as well as ML algorithms suggested for IoV and IoFV. Section 3 explains detailed description of the proposed design and its evaluation strategy. The conclusions and future works are summarized in Sect. 4.

2 Related Works

The Internet of Things (IoT) is a novel paradigm that interconnects various physical devices where it enables connection between vehicles, buildings, and other items. Internet of Vehicles (IoV) is used to make an interconnection between these items, as well as vehicles and environments for data transfer between the networks. Internet of Everything (IoE) is an enhanced version of IoT and IoV [8]. With increasing demand for IoE, it changes conventional vehicular ad hoc networks (VANETs) to flying ad hoc network (FANET) paradigm which enables new levels of applications. New operating ML algorithms have been applied to enable the execution of more dynamic solutions [9]. In this manner, IoV devices integrate intelligent technologies such as deep learning, cognitive learning, and swarm computing by using network communications [4]. As part of IoV, IoFV devices also adapt intelligent technologies that IoV devices use.

Increasing developments in smart city and IoE paradigms have been made by academic researchers and scientists interested in studying the behaviors of these fields. In order to do deep research on these areas, researchers collect data and process them with data mining and ML techniques for creating accurate frameworks or models to design applications for these paradigms. Collection of data occurs from sensors and cameras embedded in IoE devices [3]. In their research [3], authors discussed different vehicular applications that use vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I). Additionally, security and privacy challenges in communications are also discussed. They argued that in order to create a public open smart city and applications which leverage on it, it is required to develop better infrastructure for security and privacy mechanisms.

Motlagh et al. [6] did an extensive and comprehensive research on UAVs, their challenges, and related issues in terms of both physical architectural structure and security and privacy degradations. Their research addressed also the regulations and standardization efforts for security challenges as well as public safety concerns. A detailed overview on IoFV devices is presented, and data collection is studied. Different communication technologies, especially new paradigms known as flying ad hoc networks (FANETs) and data routing algorithms known as VANET, for UAVs are presented [6].

Another research [4] discusses the technologies for IoV devices and introduces a network framework for different applications, which are based on IoV Technologies. In addition, they suggest feature aspects of IoV where known as IoFV. The researchers have been studied to combine multidisciplinary fields in order to improve and find more accurate, efficient, and effective technological solutions. One of the popular and preferred study field is machine learning techniques on smart environment solutions. In research [10], the authors tries to detect vehicles in images and offline videos. They developed two machine learning algorithms, support vector machine (SVM) and decision tree (DT), for detection and tracking tasks by deploying a dataset from Udacity. The target of their research was to design and develop a system which was able to detect and track the vehicles as well as pedestrians considering images and offline videos.

Similar studies have been done in [11, 12], where two methods of vehicle detection systems were proposed. These methods are known as sliding window and local features methods. In the former one, input images with a number of windows of different sizes are scanned and analyzed to detect the target, whereas the latter one usually finds features of objects and tries to categorize these features into different classes with different classification models.

As stated earlier, advancement aspects of IoFV devices or technology have been deployed in literature and market recently. Therefore, there have been significant studies in the literature providing survey studies for drones and addressing technological improvements, challenges, and issues especially in security and privacy, communication architecture, and machine learning algorithm-based applications.

Considering the attempted studies in IoT, IoV, and IoFV, researchers have reviewed drone technologies use cases, physical issues, collection of data, and open issues and challenges in detail through different studies [6]. Similarly, another study discussed drone-based applications especially forestry in [13]. Authors in [14] provided a research on physical structure and mechanism of drones accordingly. Moreover, another research is provided in [15], which discussed a detailed survey for drones, their applications, challenges like security and privacy, and also current limitations. Similar to [15], authors of other two studies [16, 17], presented and provided very detailed survey study for drone characteristics, their applications, their communication technologies, as well as the integration of drones with other vehicles. Also, they mentioned existing security challenges and possible solutions for them.

Last but not the least, a review study is presented in [18], regarding drone-based medical applications. Also, possible limitations and challenges which appeared in this area are also discussed.

Although IoE and IoFV have many implementations in different applications, they consist of various issues and challenges including big data, security and privacy, mobility, and network connectivity [4, 5, 8]. The data transmission of IoFVs is performed over public networks; however, because of their nature, network topologies (ad hoc networks are preferred) change often [19]. Also, because of their limited power, computation and storage characteristics create the following challenges.

(a) Network connectivity: IoFV devices among themselves are usually communicated with wireless networks. Therefore, it is required to improve broadcasting, reduced latency, and transmission overhead while roaming from one cell to another. Additionally, star, mesh topologies should be supported. Within this context, it is crucial to keep all the nodes connected. Therefore, mobility is also a challenge for the researchers and scientists [5, 8].
(b) Big data: Due to the large number of connected devices, and vehicles, a large amount of data is processed. In these circumstances, an effective and efficient platform should be generated between mobile cloud and IoFV structure. Additionally, advance scalable ML algorithms are desired for processing the big data [8]. In these circumstances. Reliability of the devices become important in order to deal with correct data information.
(c) Security and privacy: Since IoFV involves with many different technologies, services, users, and standards, data security is required. At the moment, their network structure depends on open public network. Hence, common existing security attacks, intrusions, and privacy leakages are majority of security and privacy challenges [1, 19].
(d) Standardization: In general, there is no common standardization in terms of communications between the vehicles, as well as the algorithms and platforms existing for utilization of intelligent system used in drones. Efficient ML algorithms should be suggested for routing schemes, low computation cost, and big data processing [8].

3 Suggested Framework

In this chapter, some applications as well as some tools to create a model will be studied. In this section, suggested framework will be discussed and analyzed in detail. As stated in [6], IoFV's applications are categorized into two as civilian and military. The former one can be used in different purposes from rescue operations to disaster events, such as fire or earthquake monitoring. Also, transportation of medical supplies, traffic surveillance, and farming are popular usage areas of this field [6].

Discussing the expected wide usage of flying vehicles (FV), it is difficult to introduce all possible scenarios and use cases. Therefore, in this section, some possible applications and use cases will be suggested, and expected challenges will be analyzed in details.

3.1 Severe Environmental Cases

Various natural or man-made disasters such as earthquakes, floods, and nuclear power plant explosion cost significant assets or infrastructure damage and, more importantly, living lives [1]. IoE devices especially IoFVs can help save lives and provide accurate information for those who are in these effected disaster areas. In this manner, a variety of tracking devices can be used or carried by rescue teams, firefighters, police, or social community helpers [1, 2].

In case of any natural disaster, well-equipped IoFV devices may fly over that region for assessing the damage and measure temperature, wind speed, or pollution levels.

3.2 Accidents and Emergency Cases

Flying over a target area, UAVs may connect to each other to facilitate the coordination and area surveillance. A real-time processing of the collected data is required in order to identify the most impacted areas and to assess whether there are any beings that need help. In case there are any, UAVs can deliver beverages, food, and medicament to the persons in urgent need until the arrival of rescue teams.

3.3 Real-Time Traffic Management

Real-time traffic management technologies to enhance vehicular, pedestrian, and passenger safety are of great interest for researchers and developers in order to avoid severe, fatal situations as well as real-time road traffic information. The drones can be used as sensors where they collect the data about road traffic conditions and in case of any accident situations. In these kinds of situations, drones can capture the image of the accident and use different ML algorithms to analyze and decide or predict how critical the situation could be and make calls to hospitals, police, and family members.

3.4 Crowded Events Surveillance

In the last couple of decades, suicide bombers and terrorist attacks have increased during large, important festivities and events such as Olympic games, concerts, political demonstrations, Christmas celebrations, etc. During these kinds of events, a huge number of security personnel or agents take part in order to monitor critical public places like undergrounds, bus stops, as well as entrances of the stadiums. However, intruders usually have a chance to divert security personnel within the crowd and reach their destinations. Even sometimes, although these people are detected, until the security reach their location, they can be diminished. If IoFV devices which are equipped with image processing algorithms are preferred, photos or videos of any suspicious person could be detected and tracked by security from a centralized location.

3.5 Deployment Aspects

In IoFV deployments, two main methodologies are used for the placement: controlled and random deployments. In random method, drones are deployed over the desired region in a random manner that does not follow a certain arrangement. Unlike random deployment, the controlled approach follows a deterministic arrangement where the drones are deployed in a line or a cluster of drones. Controlled deployment is essential for applications that require a certain arrangement of drones. For instance, tracking and localization of vehicles passing through a highway may require a controlled line topology. Controlled deployment can be further categorized based on the role of the drone. First, in wireless networks, drones can be used as relay nodes that connect data sources with destinations. This type of drone deployment can be represented as base stations or access points that help in increasing network reliability. Drones can be employed as relays in various networking technologies such as cellular and next-generation 5G/6G networks in order to restore the destroyed communication link. Moreover, drones can be deployed as data collectors in various scenarios such as providing access to harsh environments or tracking objects in rescue applications.

4 Conclusions and Future Works

When IoT became a novel paradigm as part of the Internet, IoV, IoE, and IoFV have become indispensable platforms to interconnect vehicles, humans, and other smart environments. They have attracted lots of attention of both researchers and industrial applications. Especially, integration of intelligent systems for more reliable, secure, and efficient IoFV systems have emerged due to the use of mobile communications, cloud computing, and big data usage. In this paper, existing suggested IoFV solutions in the literature are critically studied. Also, existing suggested ML algorithms are analyzed and studied. This paper proposes different machine learning applications and framework for drones as well as limitations and challenges, regarding the recent developments of IoV with artificial intelligence. Furthermore, a new ML algorithm, its issues, and challenges on security and privacy will be designed and evaluated in future works.

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Trends, Issues, and Challenges in the Domain of IoT-Based Vehicular Cloud Network

Arslan Musaddiq, Rashid Ali, Rojeena Bajracharya, Yazdan Ahmad Qadri, Fadi Al-Turjman, and Sung Won Kim

1 Introduction

Due to the new era of the Internet of Things (IoT), the concept of the vehicular ad hoc network (VANET) is evolving. VANET turns vehicles into wireless routers or access points to provide connectivity to other vehicles. The vehicular nodes are equipped with sensors that have computational, storage, and networking capabilities. The vehicular network could be either inter-vehicle network, intra-vehicle network, or vehicular mobile internet. The exchange information via vehicle-to-vehicle (V2V) or vehicles-to-infrastructure (V2I) is helpful in assisting safe navigation, traffic management, or early warning system. Hence, the vehicular network is a large-scale distributed system for information exchange between vehicles, roads, humans, and the Internet [1, 2].

The vehicles are equipped with numerous sensors, actuators, and communication devices. Thus, modern vehicles are capable of sensing the environment, processing the sensed data, and transmitting the information forming an efficient

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_4

vehicular network. The information is exchanged with the help of various different protocols such as Hypertext Transfer Protocol (HTTP), Transmission Control Protocol/Internet Protocol (TCP/IP), and Wireless Application Protocol (WAP). Due to the availability of communication infrastructure, many advance services and applications have been developed for vehicle safety, vehicular communication, and vehicle entertainment. With such a large scale and complex heterogeneous vehicular network, various challenges arise. One such challenge is to handle complex, IoT-based vehicular data using cloud computing. Similarly, addressing the interoperability of systems to exchange the information and use the information that has been exchanged is a challenging task [3, 4].

The automotive industry is focusing on utilizing the IPv6 to connect the IoT-based vehicles to any cloud platform. Similarly, addressing communication issues among heterogeneous devices is another challenging area. The intelligent transport system consists of three-layered architecture, which includes a client layer, a connection layer, and the cloud layer. The client layer provides information using sensors inside and outside of vehicles, e.g., speed, position, collision detection, forward and side obstacle, pollution information, tire pressure, oil pressure, and proximity. The connection layer supports the communication model and transmits the information to the cloud layer, which provides computational power, storage, and analysis of the data [3]. The vehicular cloud consists of stationary and mobile computing data centers or onboard computational devices. Standardization by cloud developers and vehicle manufacturers is required to allow the various heterogeneous operating systems [5], application programming interface, and radio-based devices to work together. As a result, it could lead to an efficient vehicular network without any additional cost.

With the advancement in the IoT-based vehicular network, it has attracted many researchers for the development of road safety, comfort, and entertainment applications for the drivers. Cloud computing services, on the other hand, also gained popularity due to its ability to provide real-time computing, processing, and data storage. Numerous researchers have proposed cloud computing models for the implementation of an intelligent transport system (ITS) such as vehicular data cloud services in the IoT environment [6].

The connected vehicles are moving toward integration with smart cities. The US Department of Transportation (USDOT) and the Intelligent Transportation Systems Joint Program Office (ITS JPO) are focusing on interoperability to allow devices, vehicles, and systems to work together simultaneously [7]. The vehicular cloud allows vehicles to share a different type of information such as road conditions, weather updates, or traffic jams. The purpose of sharing this information is to cope with accidents and collisions. IoT-based vehicular cloud network is helpful for transportation safety by ensuring different vehicles to communicate without any delay and hurdle. It brings further opportunities for vehicles to provide improved performance and mobility support. Communication for the vehicular network is a broad term, which could mean the communication at the devices level, operating system level, or cloud level. IoT-based vehicular cloud network's objective is to provide several computational challenges by using real-time software services and platforms. In order to provide these services seamlessly, the integrated vehicular cloud networks can play an essential role for the reliable, efficient, and synchronized network [8].

IoT-based vehicular cloud network is becoming more aware of their surroundings and environments. The connected vehicles containing numerous IoT devices, computational and storage facilities, are an important component of ITS. Traditional communication approaches are not meant to handle the complex vehicular network for reliable and efficient communication. Machine learning is one of the major branches of artificial intelligence that can build an intelligent system that can learn, operate, and analyze a large amount of data by finding patterns and underlying structures. In this way, it can bring self-learning, self-adaptive, and autonomous decisions-making capabilities in the network. This chapter brings more attention to this emerging research area to make vehicular networks more informed and data driven.

Similarly, blockchain has proved to be an effective decentralized technology for storage and security management. In this chapter, we discussed how blockchain technology can be implemented in vehicular networking to establish the authenticity of the generated information. Hence, the importance of IoT-based vehicular cloud networks, currents trends, and issues and challenges motivated us to write this book chapter.

2 Vehicular Cloud

The vehicular network is a particular case of mobile ad hoc network (MANET). The only difference is the moving pattern. In the case of the vehicular network, the vehicles follow a particular moving pattern or fixed path, unlike mobile ad hoc networks (MANETs) in which nodes move randomly. Establishing efficient communication between vehicles is the ultimate objective in VANET. The communications could be done either via V2I, in which vehicles communicate via roadside units (RSUs), or V2V eliminating the need for the third party or RSUs. Lastly, they could also communicate via a cellular network. The vehicular communications require various services, which include emergency management, roadway maintenance, processing, storage, and computation. In order to acquire these services, cloud computing could be adopted instead of investing in the infrastructure [8].

Cloud computing is a paradigm, which provides virtualized computing resources as a service via the Internet. The concept of cloud computing is used for webmail, storage, and web hosting services, which require the minimum management effort and service provider interaction. In terms of the vehicular network, the onboard computing resource of vehicles is integrated with the cloud. Vehicular cloud is different from the traditional cloud in terms of its characteristics, mobility, and agility. There are two types of vehicular clouds: (1) infrastructure-based vehicular cloud (IVC) and (2) autonomous vehicular cloud (AVC). IVC is similar to a traditional cloud platform in which vehicles access the services from roadside

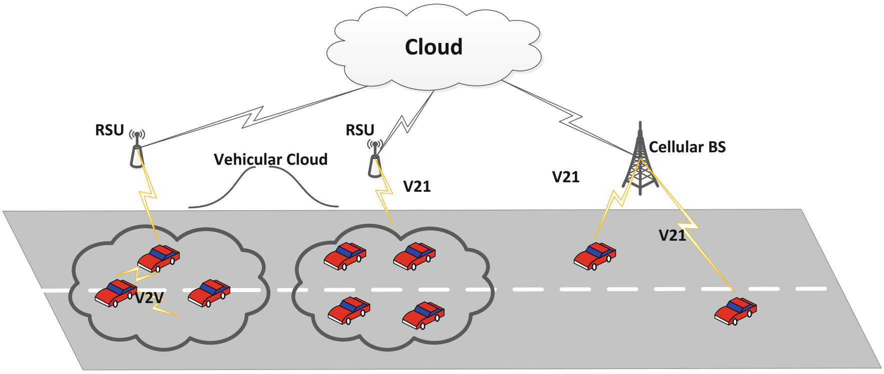

Fig. 1 Vehicular cloud network

infrastructure via network communication, e.g., global positioning system (GPS) or Google Maps. On the other hand, AVC slightly differs in terms of the way services are provided. The vehicles themselves can be organized to form an autonomous vehicular cloud in case of emergencies where roadside infrastructure is damaged due to earthquakes or hurricanes [9].

The vehicular cloud is formed by interconnecting vehicles and RSU resources, as shown in Fig. 1. The aim is to produce advanced vehicular services and resources which an individual vehicle cannot make. The services in the vehicular cloud are also slightly different from the ones in the conventional cloud. These services include storage as a service (STaaS), network as a service (NaaS), and cooperation as a service (CaaS). Compared to the traditional cloud, the vehicular cloud has several distinguishing features such as mobility, autonomy, heterogeneity, and agility. The services that vehicular cloud offers are nontrivial and complement to the traditional cloud network [8].

Cloud computing and vehicular IoT network are also attractive due to their economical advantages. Since it frees the vehicular manufacturers to invest in the IoTcomputational resources, it also shifts the need to provide technical equipment, optimization of hardware and software, energy efficiency, and performance flexibility to the service providers. Similarly, the vehicles can communicate in more distributed and dynamic manners. Cloud also acts as an intermediate layer between the IoT-based vehicles, hiding all the necessary functionality and complexity [10].

3 IoT-Based Vehicular Cloud Computing and Application Scenarios

The vehicular cloud computing consists of three layers of communication scenarios, i.e., (1) an onboard layer, (2) communication layer, and (3) cloud computing layer. In the onboard layer, the vehicle senses the environment and shares the sensed data

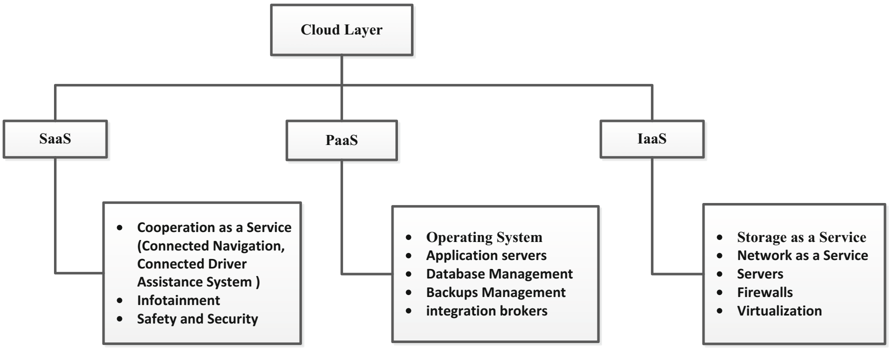

Fig. 2 Services at vehicular cloud layer

with neighboring vehicles. The communication layer provides connectivity between vehicles and the vehicular cloud via either V2V or V2I. The cloud computing layer is further divided into the permanent cloud and temporary cloud.

The vehicular cloud, similar to the traditional cloud, provides three types of services, i.e., (1) infrastructure as a service (IaaS), (2) software as a service (SaaS), and (3) platform as a service (PaaS). The computational and storage facility is provided by the IaaS. The complete taxonomy of vehicular network cloud service models is shown in Fig. 2. The vehicles consist of a number of sensors that sense the data to store in the storage facility. The vehicles can use their computational capability to access the stored data [3]. In the case of PaaS, it provides development tools hosted in the cloud. Similarly, SaaS offers various primary services that include (1) NaaS, (2) STaaS, and (3) CaaS [8].

- *Network as a service (NaaS)*: The main idea is to provide an Internet capability to those vehicles which do not have Internet access while moving. The vehicle can rent the essential Internet service from the other vehicles. The vehicle interested in providing Internet access can advertise it among all the vehicles in the vicinity and can act as an access point. The basic idea is to utilize the underutilized Internet connection resources to access vehicular network applications.
- *Storage as a service (STaaS)*: Similar to NaaS, some vehicles have extra storage capabilities that can be shared among other vehicles. The storage can be rented to the interesting vehicles in the same way as NaaS. One of the main issues is the mobility of the vehicles, and thus the storage for the backup purpose cannot be used for an extended period of time. To overcome this problem, a technique of replication-based storage is proposed in which multiple copies of files are stored in multiple storages. As a result, it increases the availability and reliability of data. Hence, if vehicles leave the place, the copied version of the file can be accessed.
- *Cooperation as a service (CaaS)*: In the case of CaaS, the vehicles can cooperate among themselves to share information, e.g., traffic jam warning, accident information, road conditions, and parking availability. Consequently, a number

of these services can be provided without the need for additional infrastructure. A vehicle can obtain or provide certain services to form a CaaS with simple publish/subscribe mechanism.

Based on the implementation services, various outcome application scenarios are provided by the vehicular cloud network.

- *Data storage application*: The vehicles could form a cloud network to share the abundant and underutilized computational resources with vast storage capacity. Consider a parking space where hundreds of cars are parked for several hours a day, e.g., airport, company, or university. The storage resources of these vehicles can be exploited for better use. In this scenario, the entire parking space could be used as a data center. Similarly, a local cloud could be formed instantly in high traffic jam scenario to search for an alternative route. The data sensed by vehicles are most relevant to the vehicular environment. Therefore, the sensed data could be stored in the vehicles, which could be accessed instantaneously and autonomously by other vehicles in the vicinity. Thus, it reduces the time and computational capability to search and download the relevant information from the Internet [11].
- *Traffic management application*: Vehicular cloud also provides new opportunities to offer better traffic management. In this case, the real-time information related to traffic congestion, road conditions, and accidents can be shared among vehicles. The vehicles can use shared information to solve the congestion autonomously. Another interesting scenario is the traffic signal management in which vehicular clouds could be helpful to automate the street and traffic lights [12].
- *Surveillance application*: The vehicles could participate in the surveillance of roads and surroundings. Sensors on vehicles, specifically video camera, could be used to assist in road and surroundings surveillance. The vehicles could report suspicious activity via the cloud to the concerned organization. The surveillance could be on demand or real time [13].
- *Infotainment application*: A variety of infotainment applications are suitable to be used as SaaS. A user can subscribe to a number of applications such as multimedia streaming, voice-over IP, online gaming, local information like weather, and information about gas stations or restaurants.

The sheer number of vehicles on the road and their dynamically changing position and density make IoT-based vehicular cloud networks challenging to implement. The lack of proper infrastructure makes it challenging to implement the aforementioned applications. Similarly, valid authentication and authorization mechanism impacts data communication security. Additionally, the lack of proper global standards, protocols, and benchmarks arises an interoperability issue. The issues and challenges are explained in detail in Sect. 4.

4 Challenges and Currents Issues in IoT-Based Vehicular Cloud Network

Integrating IoT-based vehicles and cloud computing contains several challenges. In this section, we are discussing the challenges and issues faced by a complex IoT-based vehicular cloud network.

4.1 Application Programming Interfaces (APIs)

The vehicles must have the capability to transfer application components from one cloud service to another cloud. The application programming interface (API) of different cloud services are not standardized, and different cloud platforms use different API. The API describes how to connect, configure, and interact with the vehicular cloud. It also includes the method of how to save and retrieve the date from a cloud. Moving from one cloud service to another typically involves a change in the interface, which in turn brings a great interoperability challenge. The user interface might not be identical for two different cloud services. However, they may offer similar functionality to reduce the overall cost. The vehicle's applications produce a large amount of sensor data collected from the environment or from neighboring vehicles. Thus, the vehicle cloud system provides a wide variety of services. Thereby, managing this diverse system and components to ensure they work together successfully is of paramount importance [14].

Various automobile manufacturers and government organizations are venturing into the development of the vehicular network. Similarly, significant projects are initiated at the industrial level, e.g., Daimler-Chrysler, Toyota, and BMW, for smart vehicular communications [15]. Some of these prominent projects include DEMO 2000 by the Japan Automobile Research Institute (JSK), CarTALK2000 [16], California Partners for Advanced Transit and Highways (California PATH) [17], Chauffeur in EU [18], CAR 2 CAR Communication Consortium (C2CCC) [19], FleetNet, and Advanced Driver Assistance Systems in Europe (ADA SE2) [20]. Vehicle manufacturers require cloud services to manage connected vehicles network infrastructure. Several cloud service providers manage data centers and infrastructure to maintain and host the cloud services, e.g., Amazon Web Service (AWS) connected vehicles [21], Microsoft Connected Vehicle Platform [22], Google Cloud Platform [23], IBM Watson [24], Salesforce, and Oracle Cloud. Ford Motor Company announced to provide their customers with a transportation mobility cloud. The system would comprise cellular vehicle-to-everything technology as the backbone for this platform, allowing the vehicle to communicate with other vehicles or infrastructure. Ford is using Microsoft Azure Cloud Service to update the car's infotainment system, e.g., Ford Service Delivery Network is a cloud-based system to update vehicle navigation and infotainment system. Similar to Ford, Toyota Motor Corporation and Mercedes-Benz are also utilizing Microsoft Azure to manage the applications and services for connected vehicles. The Honda Motor Company and BMW are leveraging IBM cloud to provide connected car platform. Volkswagen Group opts to use an open-source cloud computing platform named OpenStack to manage the connected vehicular cloud. The Hyundai Motor Company, on the other hand, is working with Cisco to develop interconnected car services. Thus, portability challenges grow in the complex interconnected environment.

4.2 Security and Privacy

Moving critical IoT applications in vehicles such as real-time telematics tracking, vehicle location tracking, and mobile devices and vehicle integration require strong cybersecurity. Some malware can disable a critical system in the vehicles. The attack patterns could be firmware update manipulation, remote car execution, cross-site scripting, or manipulation of critical communication channels. Data from different sources require integration and optimization for smooth operation. The cloud system is formatted differently and cannot share exchanged data and applications. Different programming languages (Java, PHP) incur another problem. The authentication mechanisms have to be agreed on clouds to enable accessing resources from other platforms [25].

4.3 Performance and Reliability

The IoT-based vehicular cloud network consists of several levels, such as communication, computational, and storage. Meeting the performance and reliability requirements for each level is a challenging task. Particularly, in the case of mobility, data and services require a quick real-time response. Real-time applications particularly require efficient and reliable support. Similarly, the management and organization of storage by different cloud platforms are different. The functional interface specified by the different cloud platforms to create, delete, update, and retrieve must be interoperable. Application-level communication and remotely accessing these applications across the vehicular cloud must have a standardized mechanism [6].

At high speed, the vehicle's communication is often unreliable. Moreover, when the transmission data size is large, the cloud capabilities can help overcome some of the problems by off-loading the heavy tasks and reducing the computational burden. However, in the case of large-scale dense networks, the resources at the cloud layer can also be insufficient, for example, storage capacity and computational capability. One of the main challenges is to handle latency and connectivity issues in a distributed large-scale IoT-based vehicular network [26].

4.4 Big Data

IoT-based vehicular network is expected to generate a massive amount of data. Due to the recent growth and development in IoT application for a vehicular network, it is predicted that there will be 200 sensors per vehicle on future vehicles in 2020. In a dense vehicular network, clouds will be unable to perform complex analysis on big data. Particularly, the high-speed mobility of vehicles containing numerous sensors calls for scalable computing resources. No proper solution exists to manage the big data based on semantic features in the cloud [27].

4.5 Heterogeneity and Interoperability

IoT-based vehicular cloud network is widely heterogeneous in nature, i.e., operating systems, platforms, radio-based application interfaces, and services. Interoperability issues in cloud computing arise when different cloud service providers exchange data and applications between each other. The problem is nonnegligible and includes the following: the programming languages are not compatible, virtualization implementations are different, or the APIs are incompatible. There must be a capability to retrieve vehicle data from the source cloud to the target cloud service [14].

4.6 Cloud-Layered Architecture and Service Models Issues and Challenges

Cloud services are particularly grouped into three main categories: (a) SaaS, (b) PaaS, and (c) IaaS. SaaS allows vehicles to access the various applications within the cloud infrastructure. Companies provide several SaaS applications such as traffic management, autonomous driving, road safety, and urban surveillance. SaaS is the main component of IoT-based vehicular cloud networks. At SaaS level, the issues arise among applications inside a single cloud when applications exchange information and trigger operations across different SaaS environments or during the migration of a cloud application from one cloud provider to another cloud SaaS system. Similarly, connecting multiple cloud environments using a software program to integrate data and application in a unified manner incurs another challenge [28].

The major vehicular companies work toward smart cars, and, as a result, cloud computing is growing exponentially. SaaS may include applications accessible over a network such as the Internet, e.g., voice and video communications and gaming. Different service providers offer different interfaces to access their services. Thus, moving from one SaaS application to another application of similar functionalities typical incurs a change in interface. Therefore, the vehicular cloud would need to employ a middleware or common standard to integrate different APIs. For example, service-oriented architecture (SOA) offers common interfaces that aim to link the various functional units in an application system.

The IBM SmartCloud and Microsoft Connected Vehicles Platform are significant examples of the SaaS model. The SaaS platform for vehicles aims to provide advanced navigation, predictive maintenance, improved in-car productivity, and autonomous driving capabilities. Microsoft Cortana is one of the SaaS services. Similarly, the IaaS cloud service mainly provides storage, networking infrastructure (including firewalls and security), and data centers. With the IaaS, vehicles can run an operating system and various software [29].

- *Access mechanism*: Cloud service providers need to allocate different services to vehicles with different requirements. Defining the method of how service in the cloud is accessed by the vehicles is necessary for the cloud management framework, e.g., Microsoft Azure Active Directory Access Control Service (ACS).
- *Virtual machine*: Virtual machines deliver the services as a complete software stack. The features and functionality provided by a considerable number of other cloud management frameworks must be able to move to different cloud platforms.
- *Storage*: Management and organization of storage by different cloud platforms are different. The functional interface specified by the different cloud platforms to create, delete, update, and retrieve must be interoperable.

PaaS as a service model provides the computing platforms, e.g., operating system, programming language execution environment, database, or web server. For application migration purposes, the service provider must certify that the application environment, e.g., database server or web server supported by the cloud service provider, is compatible with the vehicle on-premises application environment.

Similarly, the application environment is based on open technologies to increase the number of viable alternative cloud service providers that can facilitate migration if a change in provider is warranted. PaaS mostly depends on the development frameworks (e.g., PHP). The respective development community can better support the integration among different PaaS clouds.

Cloud network in the context of the vehicular communication has some similar requirements as traditional cloud, e.g., cloud authentication, cloud authorization, the security features, programming interface, applications, deployment, and monitoring. Furthermore, it can be built by using open protocols, open APIs, semantic repositories, domain-specific languages, standards, and layers of abstraction. Data integration can reduce the complexity of data storage and structure. In the case of the large data set, cloud methodologies such as collecting and maintaining large data sets for storing and reusing the data are available [13]. At the cloud layer, one of the main issues in big data analysis is that different systems have formatted data differently and cannot exchange information [30, 31]. The vehicular network data transmission, processing, and information gathering produce new challenges to be addressed in a multi-cloud environment. There are many aspects that cloud service providers need to include to guarantee the trust and efficient service for the portability, semantic interoperability, reliability, availability, and security [32].

To develop a practical and efficient IoT-based vehicular cloud network, many additional research challenges need to be addressed, for example, incompatible virtualization implementation and semantics. During the exchange of data and applications between virtual machines (VMware, Xen, and KVM), the cloud providers also use different modeling notations for showing the same feature. The problem is in linking the data as there are missing parts to interconnect computing clouds. It also must use HTTP and HTTPS to ensure security to allow applications to communicate with each other. Similarly, the content management and archiving system are required since vehicular systems may produce multimedia data.

5 Machine Learning for IoT-Based Vehicular Cloud Network

For IoT-based vehicular cloud networking issues, it is necessary to move from traditional approaches of network design to a more intelligent data-driven learning-based approach. To build an intelligent vehicular network to operate in a large-scale dense environment with high-speed mobility, a machine learning framework represents an efficient tool. Machine learning has found many successful applications, such as robotics, language, and image processing. To analyze data and recognize patterns in a vehicular big data environment, machine learning can be useful in a wide range of applications and efficient routing, e.g., traffic flow prediction, vehicle path prediction, data storage, and traffic congestion control. It could make the system more efficient, informed, and data driven for self-driving and location-based services. In this section, we are discussing a machine learning-based framework to address intelligent decision-making in IoT-based vehicular cloud networks.

Machine learning methods can widely be used for traffic load prediction using historical data from onboard sensors, radars, cameras, GPS, or social media. The authors in [33] utilize a deep learning algorithm to predict the traffic model. Deep learning is a multilayered architecture to extract a number of features from a set of data. The idea is to learn the generic traffic flow features and learn the pattern greedily. The autoencoder is used to learn the features of traffic flow, and it takes spatial and temporal correlations in the modeling to provide better predictions. Similarly, a machine learning-assisted route selection (MARS) system [34] is proposed to assist vehicle routing. The RSU units utilize machine learning mechanisms to learn the traffic pattern and assist the vehicles in choosing a suitable routing path. According to the authors in [35], a probabilistic graphical model, Poisson regression trees (PRTs), is for LTE connectivity prediction and vehicular traffic prediction. LTE connectivity prediction is used to measure the performance of the communications system, and vehicular traffic prediction enhances the IoT-based vehicular network performance.

Vehicle trajectory prediction to avoid collisions and accidents plays an essential role in vehicular networking. The probabilistic trajectory prediction mechanism

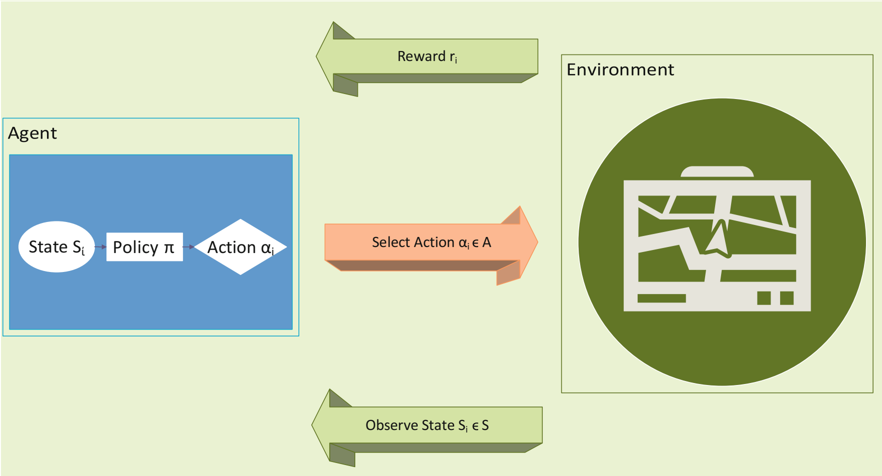

Fig. 3 Reinforcement learning in IoT-based vehicular cloud network

based on Gaussian mixture models is studied in [36]. The trajectories are learned based on the previously observed trajectories, and then map the historical data to future actions. With deep learning, the detailed traffic pattern, road structures, and congestion can also be learned using historical data. A deep neural network and recurrent neural network can be used for more accurate prediction results.

One of the most significant approaches for efficient IoT-based vehicular network communication is reinforcement learning. In reinforcement learning for the vehicular routing, a vehicle is a learner and a decision-maker about the routing path (Fig. 3). There exist several factors that influence the decision of selecting a particular path in a specific environment. The vehicle strives to achieve the shortest or less congested path; thus, it iteratively learns the actions to pursue its goal, adapting to various network conditions. The vehicles take some actions in the current environment or state. This action can have either a positive or negative influence on the system. The vehicular node receives some reward or feedback to evaluate the effect of the action. The target of the vehicle is to find the optimal policy to optimize the reward. Given a certain state, the optimal reward values are discovered by pursuing an epsilon-greedy strategy, which is a multiarmed bandit (MAB) technique. The MAB is an RL decision-making probability solving technique to trade off exploration and exploitation. Exploitation means to choose the best decision given current information, and exploration is to gather more information. In reinforcement learning, there are α possible actions an IoT-based vehicular node can take. With each action, the node receives a reward r, and the ultimate goal is to find the optimal reward in a sequence of trails. Observing the number states–action–reward (s, a, r) triplets, a vehicular node can create an optimal policy π.

The IoT-based vehicular cloud network is heterogeneous due to the different performance goals and resource utilization. Reinforcement learning can play an important role to make vehicular communication cooperate using the SDN controller. The method based on a Nash bargaining solution where each agent tries to achieve near-optimal performance can help to maximize the cumulative network reward. The deep reinforcement learning algorithm can also be utilized to check the path availability in a high-speed real-time environment. Queue learning-based ad hoc On-Demand Distance Vector Routing (AODV) algorithm for vehicular network routing can use dynamic link-state information and change in routing patterns.

6 Blockchain for IoT-Based Vehicular Cloud Network

The vehicular ad hoc networks (VANETs) are highly dynamic, and their network conditions change within a small interval of time. A distributed VANET has nodes in the form of vehicles that join and leave the network after small intervals. This presents a unique set of challenges when disseminating information in such network conditions [37].

Blockchain provides an eloquent solution for data exchange in decentralized peer-to-peer networks when security and privacy are taken into consideration. A blockchain can be implemented in a VANET to establish the authenticity of the generated information. Blockchain for IoT-based vehicular cloud network is shown in Fig. 4. Vehicles form the nodes or the building blocks of VANETs, and all the nodes have access to the information stored in the blockchain. Therefore, the provenance of the information should be established. In the proposed blockchain, the events messages are analogous to the transactions of cryptocurrency blockchains. The trustworthiness of these messages is established as they are stored in the public blockchain. The use of a public blockchain enhances node trust and data integrity.

The scalability of the VANET is enhanced by implementing a geography-based blockchain. This geographically divided blockchain provides relevant traffic information in a specific geographical location. In the proposed system, a country is considered as a geographical unit, and each country has a distinct blockchain. Additionally, the scalability is greatly influenced by the "proof of work." Consensus mechanisms are selected based on the application. The selection of a suitable consensus algorithm affects the latency of the system. The scalability and consensus of the proposed system are based on "Proof of Location" (PoL). It is essentially a location certificate authenticated when a node is connected to RSU. All the nodes in the network that has high computational capability and trust participate in the mining process. To confirm if a message is true, 15 confirmations are required from the miners. The proposed system incorporates edge computing in the VANET in an attempt to reduce the latency by off-loading the complex computational tasks to the edge node.

Two types of messages are generated by the nodes, i.e., beacon and safety event messages. The beacon messages are periodically generated and broadcasted. The

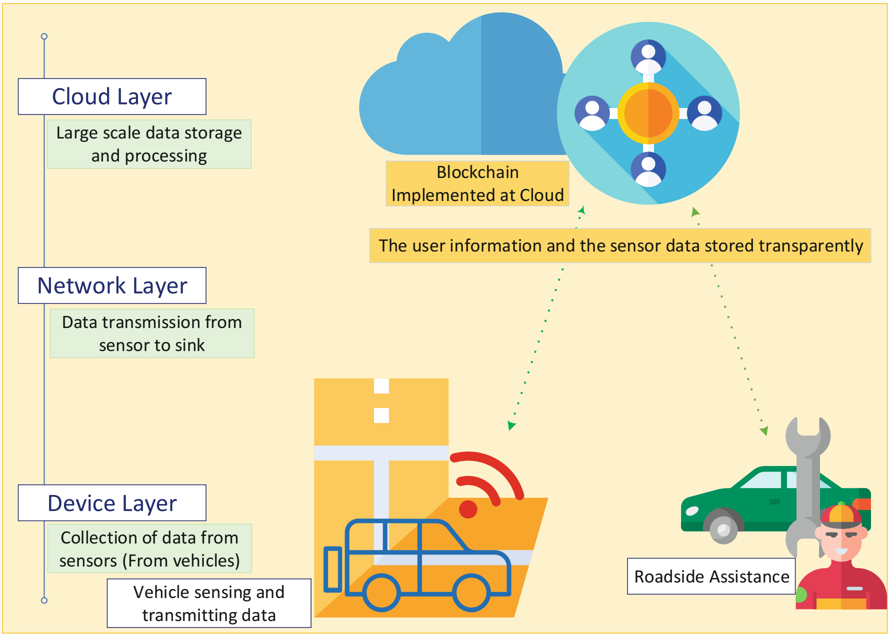

Fig. 4 Blockchain for IoT-based vehicular cloud network

beacon messages update the neighboring nodes about the general road and traffic status. The safety event messages are generated only when anomalies are found, i.e., accidents or traffic jams. Each anomaly is categorized with level 1 being the most critical while level 3 as least critical. All the vehicles send the periodic beacon messages from a specific location. The location of the nodes is established by the location certificate that acts as a PoL. In each geographically independent blockchain, the miners mine the new blocks based on the messages generated by the nodes. After the blocks are confirmed, the newly minted blocks are added to the national blockchain. The hashes of each block are chained sequentially to build a blockchain containing the traffic and road information. The data being shared publicly while upholding the security and privacy of data and nodes, respectively.

7 Conclusion

The modern vehicles are equipped with a number of sensors and actuators. These IoT-based vehicles contain efficient communication devices and embedded hardware. The IoT-based vehicles and its integration with cloud networks can significantly improve the transportation system. In this chapter, we provide a detailed analysis of all the challenges an IoT-based vehicular cloud network faces.

In a vehicular network, different operating systems and radio-based devices are required to exchange data among different vehicles. We provide the characteristics of vehicular network and cloud computing and how it could increase the transportation system capabilities. We first explain the complex and heterogeneous nature of the vehicular network and the fundamental challenge, trends, and issues such as application programming interfaces (APIs), security and privacy, performance and reliability, big data, heterogeneity and interoperability, and challenges related to cloud-layered architecture and service models. In order for the vehicular cloud to interoperate seamlessly, cloud service providers, the automotive industry, as well as local and federal governing bodies must agree on rules, regulations, and standardizations. We also point out that the main technical problems such as incompatible programming languages (Java or PHP), incompatible virtualization implementations (VMware, Xen, and KVM), and different modeling notations for the same features incur the interoperability issues. This chapter further provided how vehicular networks can combine various technologies and techniques such as machine learning and blockchain to provide self-learning, self-configuration, and efficient security mechanism. Machine learning can build a data-driven, more informed, and self-learning capable intelligent vehicular network. Similarly, a blockchain can be implemented in a vehicular network to establish the authenticity of the generated information.

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Detection and Identification of Vehicles from High-Resolution Aerial Images Using Deep Learning Approaches with the Tuned Parameters

Muhammad Zeeshan Khan, Saleet Ul Hassan, Hafiz Umer Draz, Muhammad Usman Ghani Khan, and Razi Iqbal

1 Introduction

Intelligent transportation system (ITS) is an advanced information and telecommunication system for the people on roads and vehicles. It is an integrated application of advanced technologies such as electronics, computers, communications, and advanced sensors. Travelers are provided with important information while improving the safety and efficiency of the transportation system using these applications. ITS is also helpful to solve the social problems caused by roads. In the area of ITS and smart city, extraction of automatic vehicle information became the dominant part for the past few years. This vehicle information includes vehicle detection, vehicle license plate detection and recognition, vehicle color recognition, vehicle type recognition (car, van, truck), etc. Researchers have also been working on the efficient and secure information transfer generated by the ITS [1, 2]. Vehicle information is very useful in the fields of video surveillance and applications of smart city for the sake of the security and safety of people. The ITS is very beneficial for existing transportation system as it can be used for reducing the pollution and making the traffic safe. These domains include intelligent vehicular system, intelligent highways, and autonomous intelligent driver system. The research on the automatic vehicle detection and classification by using unmanned aerial vehicles (UAVs) has a huge impact on the development of the autonomous and the intelligent transport system. The applications of surveillance using UAVs has a very vast range in daily life such as automatic toll tax charging in the highways, statistics about traffic flow, and autonomous parking system. In the past, one of the major methods

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_5

for the vehicle classification is to lay down the sensors under the roads; after specific time intervals, data from the sensors were collected, which were later used for classification purpose. But after the advancement in the computer vision algorithms, the accuracy related to the detection and classification tasks has been increased to a great extent. Due to these reasons, computer vision and latest machine learning techniques have also been utilized in the area of ITS.

Unmanned aerial vehicles (UAVs) have gained a lot of popularity in almost every field of life. The applications of the UAVs include the surveillance of border area between the countries, monitoring of the fire detection, surveillance of the prohibited areas, vigilance of forest for natural and manmade disaster, and inspection of traffic and the infrastructure. UAVs are basically based on the sensors, built-in processors, and the intelligence which help them to make the autonomous decisions. Basically, the UAVs are the integration of the altitude, position, and the velocity control parameters in order to achieve the fully autonomy. UAVs have also a huge impact on the image processing and the computer vision fields. It can be used as a surveillance tool which can automatically detect any suspicious and abnormal activity from protest, procession, concerts, and any other public place. The advantages of utilizing the UAVs includes the low cost; portability; compactness; environmental friendliness; fast, easy, and on-demand acquisition of the images; as well as the videos. In traffic management system, one of the major works is the car detection and the classification. Surveillance using UAVs has many implications like estimation of vehicles in the particular area, parking management system, traffic signal controlling system, etc. The accuracies of the classification and the detection of specific objects from the videos and the images gained tremendous boom after the deep learning [3].

In this paper, we have proposed the vehicle classification system by applying the deep learning techniques. The dataset is generated with the help of UAVs. The dataset contains the images with the two different heights, set by us. The first one is from the aerial view. This dataset is used to detect the car wherever it is present on the particular frame of the video. In the second type of the dataset, we have generated the dataset by flying the UAVs at the fixed length of 10–12 ft. Our proposed algorithm is based on the Fast R-CNN approach. We have detected and classified the different types of Pakistani-made cars. The proposed algorithm is trained on the six different classes which are Honda City, Mehran, Corolla, Cultus, Wagon R, and Vitz. The proposed system will be able to detect and recognize the vehicles in real time. Moreover, the proposed system has also the practical implications of generating the statistical report. These reports depict how many vehicles along with its types were entered into the particular area, where the UAVs are moved for surveillance. All these statistical analyses are generated on the offline videos. Once the video is recorded for the particular time stamp, then it is passed to the developed system, which will generate the statistical report. The system diagram is shown in Fig. 1.

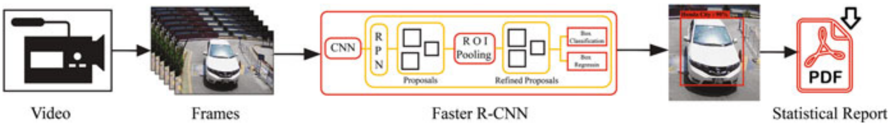

Fig. 1 System diagram

This chapter makes the following contributions into the research community:

1. We have used the state-of-the-art computer vision and machine learning techniques for vehicle detection and classification.
2. Fast R-CNN which is latest in deep learning have been utilized in proposed solution.
3. Generation and the annotation of the dataset related to the Pakistan-made vehicles with the help of the UAVs.

2 Literature Survey

From the past few decades, various methods have been purposed for vehicle-type classification. They have been successfully applied on the smart cities as well as the highly secured areas like military zones, etc. Currently, most of the existing approaches in the literature are based on the acoustics signal [4], radar signal [5], ultrasonic signal [6], infrared thermal signal [7], magnet signal [8], 3D LiDar signal, and [9] image and video signal. During the recent few years, vehicle classification and detection are mainly based on the machine vision approaches. These approaches used the traditional image processing techniques for this purpose such as scale-invariant feature transform (SIFT), speeded-up robust features (SURF), and histogram of oriented gradients (HOG). These features are then combined with support vector machine for classification purpose. Sarfraz et al. [10] extract the shape characteristics of the vehicle's frontal area. They named these characteristics as local energy-based shape histogram (LESH). They claimed that their features are invariant to color, shape, and illumination factors. These characteristics are further passed to the Bayes prior model for classification purpose. But the drawback of this methodology is that it only works well on the frontal images of the vehicle.

This problem has been solved by Ramnath et al. [11] by classifying the car into model and its name by taking consideration the different views of the vehicle. They extract the 3D curves of the vehicle's images based on the silhouette-based visual hulls. These 3D curves are matched with 2D image, based on the 3D view alignment technique for the classification purpose. Their proposed work did not perform well on the constrains like light and illumination factors and also needs large number of calculations. Chang et al. [12] proposed a real-time vision-based vehicle detection and classification system. They have utilized the AdaBoost of different strong classifiers, instead of using the single classifier for vehicle detection and classification system. The main drawback of this approach is that it requires the huge time for computation on a traditional computer vision approach. Alonso et al. [13] proposed the multidimensional classification method for the detection of the vehicles on the roads. Kazemi et al. [14] utilized the three different algorithms for feature extraction. These algorithms include Fourier transform, wavelet transform, and curvelet transform. They have used the K-mean clustering algorithm for classification of five different types of vehicles. The curvelet features have achieved the best result on the K-mean classifier. Chen et al. [15] proposed an algorithm for vehicle detection, tracking, and classification system from the input stream coming from the closed-circuit television (CCTV). The vehicle has been detected using the Kalman filter. Then they extract the features from the vehicle silhouette and histogram-oriented gradient (HOG) features. These features are then trained on the support vector machine (SVM) for classification purpose.

Wen et al. [16] used the Haar-like feature pool on the grayscale image to detect the vehicle appearance and then apply the AdaBoost to enhance the performance of the algorithm. Arrspide et al. [17] analyzed the different algorithms for vehicle verification and found on the base of the experiments that the classifier based on the Gabor and HOG achieved the best results as compared to principle component analysis on vehicle classification. Mishra et al. [18] detected the vehicle by extracting Haar, scale-invariant features transform (SIFT) features and then designing a multiple kernel classifier using k nearest neighbor to classify the vehicle into the four categories. Tourani et al. [19] combined different image processing techniques which include object detection, Kalman filter, frame detection, and frame differentiation for classification of vehicle detection. The above described approaches have utilized the traditional computer vision and machine learning approaches. Although these approaches achieved good accuracy, they have some limitations. First, extracted handcrafted features are limited, so they are unable to extract the rich information from the image. Second, they require lot of computation and only performs good for the specific scene and background environments. Currently, the major focus of the researchers for the vision-related task is on deep learning. The main reason behind the boom of deep learning is due to high achievable accuracy on the vision-related task [20]. Moreover, the availability of the large dataset and the computation power is also the major factor. Zhang et al. [21] proposed an algorithm for vehicle classification system based on the convolution neural network. Their proposed architecture is based on the two folds. The first fold used the pretrained model which confirms the presence and the absence of the car. The second fold is used for the classification of the car. They have used large-scale car dataset and achieved 79% accuracy on the validation of data. The main drawback of this approach is that it does not perform well on the detection of the vehicle. Dong et al. [22] proposed the semi-supervised convolution neural network architecture for vehicle classification system. They have utilized the Laplacian filters to get the filters of the network for the large amount of the unlabeled data. They have utilized the BIT-Vehicle dataset which contains the images for the frontal images of the vehicle.

Sheng et al. [23] apply the different neural network architectures for the vehicle detection and classification purpose. They have achieved the best accuracy of 86.78% on the ResNet-101 architecture. He et al. [24] proposed a convolution neural network for vehicle detection and classification. They claimed that they achieved good results onto the convolution features as compared to the handcrafted features. Wang et al. [25] proposed an algorithm for vehicle detection and classification based on 2D deep belief network. The input to their proposed model is the second-order plane of the image. They have retained the discriminative information to increase the accuracy of the vehicle detection. Yi et al. [26] used the pretrained AlexNet architecture for detecting whether the particular patch of the image contains the vehicle or not by using the wide area motion imagery analysis. Li et al. [9] presented the 3D range scan data into 2D data map points. These 2D data points are further passed to the 2D convolution neural network for the classification of the vehicle and predicting the bounding box simultaneously. They claimed that they achieved the state-of-the-art results on the KITTI dataset. Recently, the research has also been taken on the detection of the vehicles from the images taken from the drone cameras. Ammour et al. [27] have utilized the images using the UAVs to detect and count the number of cars in a particular image. They have utilized the auxiliary classifier with the linear support vector machine to classify the regions where the car is present. Radovic et al. [28] detect the vehicles from the UAV's images using the YOLO object detection framework. Recently, object detection and classification based on the convolution neural network have achieved state-of-the-art results [29].

In 2013, Sermanet et al. [30] first used the convolution neural network for object detection, classification, and localization. They claimed to achieve the very competitive results on the classification and detection task. Up till now, several techniques for object detection based on the convolution neural network have been utilized. These techniques include R-CNN [31], Fast R-CNN [32], YOLO [33], SSD [34, 35], and R-FCN [36].

From all the above described literature, we have concluded that the work on vehicle detection and classification on the UAVs images is very limited. Most of the work done, on the vehicle detection and classification using the UAVs images till now, utilized the traditional approaches and failed to achieve state-of-the-art results. In this paper, we have utilized the latest deep learning technique for object detection and classification. In our proposed algorithm, we have utilized the Fast R-CNN technique for the detection and the classification of different types of vehicles on which our proposed architecture is trained. The proposed methodology is capable of dealing the above described limitations like color, angle, illumination, etc. and achieved the state-of-the-art results on the validation of data.

3 Methodology

3.1 Proposed System

The input to our proposed system is in the form of the video. The video is passed to the proposed model frame by frame. The proposed architecture predicts the bounding box having the specific object and also classifies the detected object. On the basis of the detected objects, the proposed system is also able to generate the statistical report. The statistical report depicts how many cars of the specific category entered into the specific area under consideration.

3.2 Pre-Processing

Training data collected from the video streams for vehicle detection and classification demands different preprocessing steps. These steps include to remove the redundant frames from the training data. Here, redundant and unnecessary frames refer to those training data frames which contain half and not clear objects. Moreover, the videos collected from the camera stream placed on the roads have a possibility that frames of the video are usually bad in quality. There are several reasons behind the bad-quality images like foggy weather, rain, lighting conditions, and improper configuration of the hardware instruments. The poor-quality images are a real challenge in the color recognition techniques. To overcome these illuminations and lightening problem, we have applied color contrast method [37] and haze method [38] as a preprocessing technique. We have utilized the deep learning-based Fast R-CNN algorithm for vehicle detection and classification. The network is based on the three different parts. The first one is the convolution neural network which is also termed as backbone architecture, the second one is the region proposal network (RPN), and the last one is the classification network for the detected object. The architecture of the network has been shown in Fig. 2.

3.3 Region Proposal Network

Region proposal network is basically proposed regions where the probability of having the specific objects are very high. Region proposal network used the convolution parameters extracted from the backbone convolution neural network architecture. The features extracted from the region proposal network are then passed to the classification layers to get the prediction about the regions of the objects as well as the classification of the detected objects. The input to the region proposal network is the features map of the image extracted after the convolution layers, and as a result, it returns the number of rectangles containing the objects

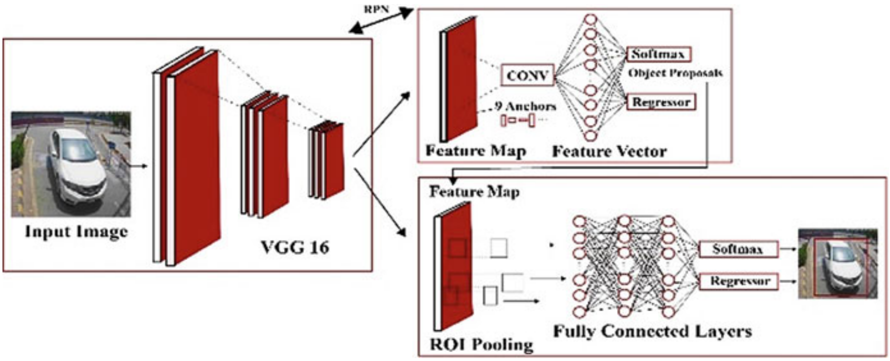

Fig. 2 Proposed convolution neural network

based on the highest probability. Region proposal networks work on the features map extracted from backbone convolution neural network architecture. It makes it faster as compared to the R-CNN [31] and Fast R-CNN [32]. Both R-CNN and Fast R-CNN work on the selective search for region proposal. In R-CNN first they extract the 2000 regions from the image using the selective search and then pass it to the CNN for classification. But the drawback of this methodology is that it cannot be implemented real time because it takes about 47 s for each test image. Moreover, it takes a lot of time to train the proposed network because it has to classify 2000 regions per image. However, In Faster R-CNN instead of feeding 2000 regions, an image itself is directly passed to the CNN. Then they extract the features map and identify the regions from the features map. These regions are passed to the ROI pooling and Softmax layer for classification of the detected objects. But the drawback of this methodology is that the region proposal slows down the algorithm in terms of speed significantly. Both of the above described techniques used the selective search for region proposal. The selective search is slow and time-consuming in terms of speed and affect the network performance. In Fast R-CNN, you have not to apply the selective search algorithm to find the regions. Fast R-CNN have region proposal network which predicts the regions of the object, based on the learning of the data. So, instead of applying selective search on the feature map, a separate network is developed termed as region proposal network to predict the regions of the objects. In order to generate the regions, architecture slides the small network on the features map extracted from the last convolution layer of the convolution neural network architecture. The region proposal network takes the input of $n \times n$ spatial window on the convolution feature map. Then after that these features are passed to the two fully connected layers, termed as the regression layer and the classification layer of the predicted boxes. For each sliding window, the algorithm predicts the multiple region proposals. The maximum number of proposals for each sliding window predicted by the algorithm is denoted by k. So, the regression layer of the region proposal network has the Nk outputs of the bounding boxes, and class layer has the $2NK$ output scores against each box.

Here N represents the number of classes presented in our training dataset. The score predicts whether the object presents into the particular bounding box or not. The predicted proposal is generated with the help of these anchors. Anchors are basically the center of the sliding window and directly linked with the aspect ratio and the scale. By default, the anchor uses the three scale and three aspect ratios yielding as the nine anchors for each point. The used region proposal network is invariant in terms of translation. The invariant translation behavior has been shown both in terms of the anchors and the proposals that had been produced with the help of these anchors. If function will able to translate the object into the image, the same function will also be able to predict the location of the proposal.

The proposed algorithm is built onto the pyramids of the anchors, which is cost effective in terms of speed and memory. The method classifies the anchors, and the bounding box regresses based on the reference anchors of different scale and aspect ratio. Figure 3 shows the anchors drawn on the vehicle containing image. For the training purpose of the region proposal network, we assign the binary class label to each anchor that predicts whether it contains object or not. The algorithm selected two kinds of anchors and assigns positive label to it. The algorithm selects two kind of anchors and assign labels to them. First one are those whose intersection over union score is highest, and the second one are those whose IOU score is greater than 0.7 with respect to ground truth.

The intersection over union has been calculated by comparing proposed anchor scores with the ground truth anchor score by using Eq. (1).

$$\mathrm{iou} = \frac{\text{Overlapped area of compare boxes}}{\text{Union area of compare boxes}} \tag{1}$$

The negative value is assigning to those anchors who has the intersection over union less than the 0.3 with respect to the ground truth boxes. Anchors that do

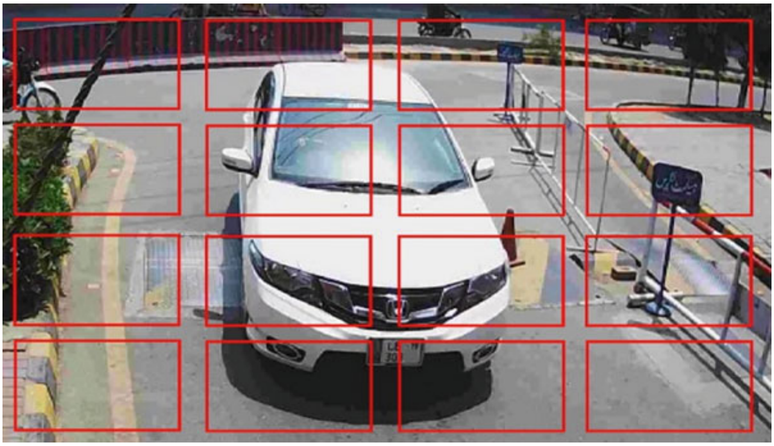

Fig. 3 Anchors drawn on image

not fall in both categories which means they are either negative or positive have been discarded and do not contribute toward the training of the object detection in the region proposal network. The loss of the region proposal network has been calculated using Eq. (2).

$$\text{Loss}\,(x_i, y_i) = \frac{1}{M_{\text{class}}} \sum_i N_{\text{class}}\left(x_i, x_i{}^*\right) + \lambda \frac{1}{M_{\text{reg}}} \sum_i x_i^* N_{\text{reg}}\left(y_i, y_i^*\right) \qquad (2)$$

Here, i represents the index of the proposed anchors, whereas x_i depicts the predicted probability for the specific anchor containing the object. The x_i^* represents the ground truth label for the predicted anchor; the ground truth probability is 1 if the predicted probability is positive and 0 if the predicted probability is negative. The predicted bounding box by the region proposal network is represented by the y_i, whereas the y_i^* is the ground truth bounding box which is associated with the positive anchors. N_{class} shows the classification loss which is calculated based on the presence and the absence of the object, whereas the N_{reg} measures the regression loss which is only activated when the anchors value is positive ($p = 1$) and disabled when the anchors value is negative ($p = 0$). The two terms M_{class} and M_{reg} are used to normalization and also weighted by the balancing parameter lambda. In our case, M_{class} is normalized with the help of the mini batch of 256, whereas the M_{reg} is normalized with the help of the 2400 anchor positions.

These terminologies are equally weighted by the balancing parameter of lambda. We have set the value of lambda to 10, which weighs equally for both M_{class} and M_{reg}.

4 Vehicle Classification

For a backbone architecture, we have utilized the VGG-16. There are total 16 layers in this architecture including convolution, max pooling, and fully connected layers. The input to our proposed architecture is in the form of 224 × 224 × 3 RGB image. In the first convolution layer, 64 filters have been applied with the kernel size of 3 × 3 having stride of 1. After that the second layer is the max pooling layer. The max pooling has been applied onto the output of the first convolution layer with the same kernel size, and the number of filters have been applied on the first convolution layer. After that there is third and fourth layer of the architecture. The third layer is convolution, and the fourth layer is the max pooling layer. In the third and the fourth layer, 128 filters have been applied with the kernel size of 3 × 3. The fourth layer is also the max pooling layer having the stride of 2. This max pooling layer is the same as the previous max pooling layer except the 128 filters due to which the output of this layer is reduced to 56 × 56 × 128. The fifth and the sixth layer are also the convolution and max pooling layer. In both layers, we have applied 256 filters with the stride of 3 × 3. In the fifth layer, we have set the stride of 1, whereas in the sixth layer which is the max pooling layer, stride of 2 has been applied onto the 256 features map.

After that, from the seventh to twelfth layer, there are two sets of three convolution layers which are followed by the max pooling layer. All convolution layers present from 7 to 12 contains the feature map of 512 having the kernel size of 3×3 with the stride of 1. The output size which we obtained from the last layer has been reduced to $7 \times 7 \times 512$. The 13 fully connected layer flattened the output of the 12-convolution layer by applying the 1×1 convolution. After that we get the 25,088 features. After that we have three fully connected layers. The first 2 fully connected layer outputs the 4096 features, whereas the last convolution layer maps to the 6 neurons which is equal to the number of our defined classes. After the fully connected layer, we have the output layer, which converts these feature values into the probabilistic scores against each class. For an output layer, we have utilized the Softmax classification function to get the probabilities against defined classes using Eq. (3).

$$P_j = \frac{\exp{(y)}^j}{\sum_{i=1}^{n} \exp{(y)}^i} \tag{3}$$

Here P_j represents the predicted probability of the class, and $\exp y_j$ represents the score after taking the exponent of the input of the specific class which is divided with the sum of exponential of all the classes scores.

5 Dataset

One of the major concerns in deep learning is the preparation of the accurate and precise data into the proper format according to the specific problem. Data collection and preprocessing are a key factor in deep learning-based research work. In deep learning-based research work, most of the researchers do experiments on the datasets present over the Internet according to their needs. In our proposed work, the data for vehicle detection and classification over the Internet does not fulfill our requirements. So, in order to train our model, we collect and prepare data for vehicle detection and classification ourselves.

To minimize the human efforts, UAVs (unmanned aerial vehicles) are used for the data collection purposes. Through this smarter data collection vehicle, the risk of human life and human involvement can be totally minimized. Sometimes humans have to go to the field and collect the data themselves. Now humans no longer need to go out and capture the videos. We have a drone flying on the main entrance gate of an educational institute to capture the videos at the height of 12 ft. It records the videos from the aerial view, as we know it is a challenging task to identify the vehicles from the aerial view, so we also solved this problem by training our model on the aerial view images. We have recorded multiple videos from the livestreaming camera of 1 week and then converted it into frames at 10 frames per

Fig. 4 Some frames from our generated dataset

second and skipped the unnecessary frames. After cleaning the data, selected frames are carefully annotated. We have also prepared the dataset of the cropped images for simple classification purpose. We have categorized these frames into six different classes which includes Honda City, Mehran, Corolla, Cultus, Wagon R, and Vitz. Each class contains 500 annotated frames. We will make this data online, and it will be helpful for the research community for training purposes. Some frames of our dataset have been shown in Fig. 4.

6 Training Parameters and Implementation Details

Both region proposal network and convolution neural network have gone through the training phase. The weights of these architectures have been optimized using the backpropagation and stochastic gradient descent. Image sampling strategy has been applied to train the network on both detection and classification of the object. The data is passed to the network in the form of batches. In case of region proposal network, the mini batch is arising from the single image containing the negative and positive anchors. It is possible to find the loss function based on all the anchors proposed by the algorithm for the single image. But it is more biased toward the negative anchors as it is more in quantity than of the positive anchors. So to overcome this problem, randomly selected 256 anchors have been used to compute the loss function of the mini batch. These anchors have the equal ratio of the positive and the negative anchors. Initially, the weights of all the layers have been initialized using the zero mean Gaussian distribution with the standard deviation of 0.01. To calculate the loss of our proposed algorithm, we have used the function of mean square error (MSE). MSE is to be defined as the indication of how much near a regression line is a set of points. It does this by taking the distances from the points to regression line and then squaring them.

These distances are said to be errors. To eliminate any negative signs, squaring is necessary to be taken. If the mean square error is smaller, then you have to find the best fit line. Sometimes it is impossible to find the best fit line, but it totally depends on the type of data you have trained. The value of the MSE is always nonzero, and the values closer to zero are better and show that the training is going in the right direction. The algorithm is trained on the momentum of 0.9 and the weight decay of 0.005. We have set the 200,000 number of epochs for the training of the algorithm by applying the early stop function on it. Too much training of the dataset will lead to over-fitting, whereas the little training of the dataset will result to the underfitting of the model. In both of the cases, we have a poor result on the test data. The possible solution of this problem is to train the network till that point where the performance starts to decrease on the validation data. So the possible, effective, and simple method to train the deep neural network is by utilizing the early stop function. Usually, when we train a large neural network, there is a point when the model will stop learning and generalizing. The model starts to memorize the noise from the training dataset. This will cause over-fitting, and as a result, the generalization error will increase, and the model make less useful predictions on the unseen data. So, to avoid all these illumination and problems, we have utilized the early stop function. This early stop function enables the algorithm to stop the training where we get the minimum loss value on the validation data. To calculate the MSE, Eq. (4) is to be used.

$$\mathrm{MSE} = \frac{1}{n}\sum_{j=1}^{N}\left(\hat{L_j} - L_j\right)^2 \tag{4}$$

In Eq. (4), n represents the number of classes, N represents number of samples, $\hat{L_j}$ represents the presicted loss of the model while L_j represents the actual loss. Initially the learning rate was set to 10^{-1}, and it was eventually decreased with the 10^{-1}, a factor, if the loss value and validation accuracy do not improve much. The proposed architecture is built on Python using the TensorFlow deep learning framework. The model is trained using the NVIDIA 1080 Ti GPU. The system took approximately about 5–6 h for the complete training of the system.

7 Experiments and Results

We have split the generated data into the train and test data. For the training purpose of the proposed architecture, we have made a distribution of 80% of training data and 20% of the test data. As we have set the maximum 200,000 epochs, the model is trained till the convergence of the loss value on the validation data using the early stop function. Training and validation accuracy on the validation data on different

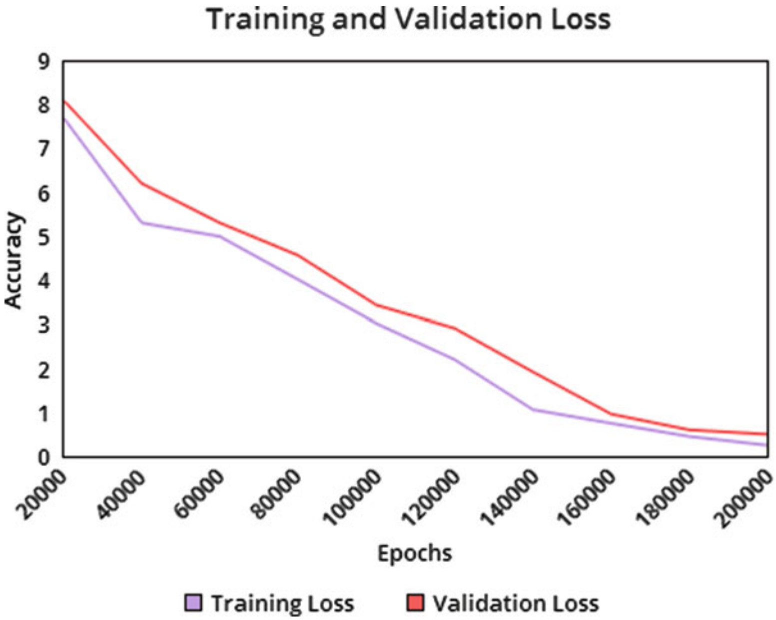

Fig. 5 Training and validation accuracy on object detection

epochs have been shown in Fig. 5. From Figs. 5 and 6, it is clearly observed that in the initial's epochs, the learning of the model is slow in terms of accuracy and loss value. But with the passage of time, the accuracy is gradually improved and the loss value is decreased. The loss value on the validation data has been shown in Fig. 6. To evaluate our proposed model and generated dataset, we have also generated the results on the inception v3 module, which is pretraineded on the ImageNet dataset. We have utilized the same dataset to train this model, which we used in our proposed architecture. To classify the image based on predefined classes of our dataset, we have to first crop the vehicle from the frames on the training data, and then separate the vehicles as defined in our methodology. We separate the vehicles into the six categories as defined in our proposed dataset. The reason why we do the separate data preprocessing on the generated dataset in due to the requirements of the architecture.

In Fast R-CNN, we have to make sure that we have the targeted objects as well as backgrounds on the training frame.

To classify the vehicle, we have to pass the detected object to the architecture. So, the detected object which is vehicle in our case is passed to the architecture. We have utilized the pretrained YOLO [33] for vehicle detection. We have utilized the inception v3 module to classify the detected vehicle. The reason of utilizing the inception v3 module is that it is the automatic selection of kernel size. In deep learning the algorithm automatically selects the best features related to the problem, but we have to specify the kernel size for the specific layer.

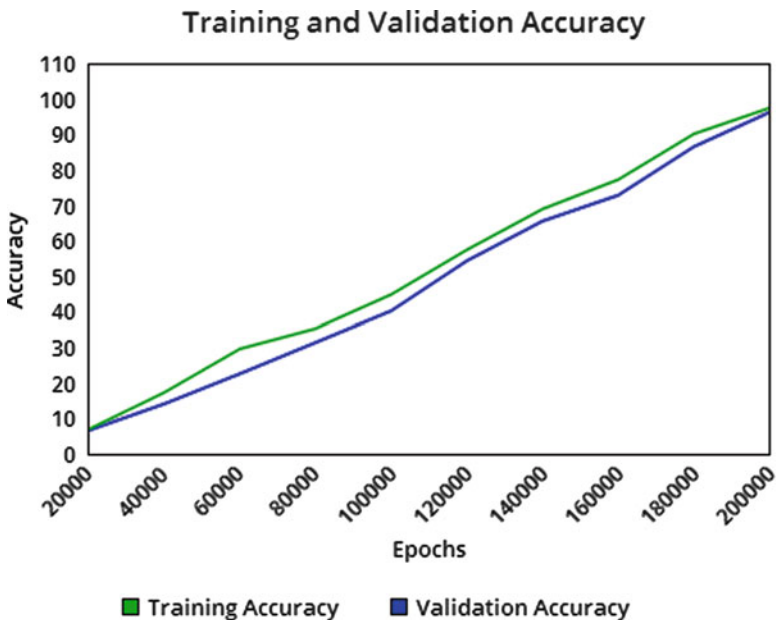

Fig. 6 Training and validation loss on object detection

So, to automate the kernel size, we have utilized the inception module. The inception module performs all types of convolution at the same time and then concatenate these features and pass to the next module.

Global information is extracted using the large kernel size, and local information is extracted using the small kernel size. The inception module is fine-tuned on our dataset. The inception v3 module is initially trained on the ImageNet which contains 1000 classes.

After the inception layers, we have built the linear model containing the three fully connected layers. The inception modules output the 2048 transfer values. In the first fully connected layer, 2048 neurons are mapped to 1024 features. In the second fully connected layer, 1024 features are mapped to 512 features. In the last convolution layer, 512 feature are mapped to the 6 neurons which is equal to the number of classes. At last, the output layer gives the probability against each class. The inception module is trained till the 2000th epochs, in which we achieved the 87.9% accuracy on the validation data for classification. The training and validation accuracy of the inception v3 module have been shown in Fig. 7. But the detection accuracy is comparatively very low. The reason of this low accuracy is that we have used the pretrained model of the YOLO for the vehicle detection purpose for this experiment. We have also evaluated the proposed architecture onto the Vehicle Make and Model Recognition dataset (VMMRdb). The comparison between the accuracies of different experiments has been shown in Table 1. From Table 1, it is

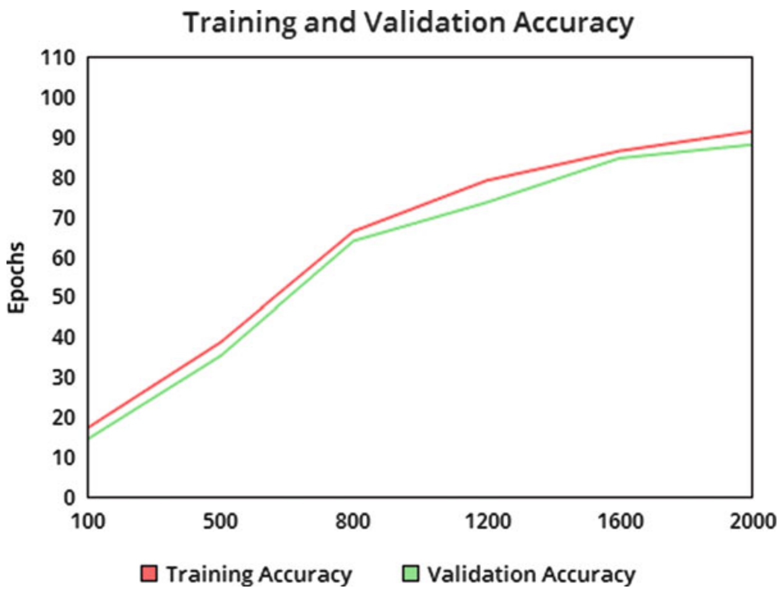

Fig. 7 Training and validation accuracy on inception

Table 1 Results of different experiments

Methodology	Dataset	Accuracy (%)
Proposed (faster CNN)	Self-generated	96.2
Inception	Self-generated	87.9
Proposed (faster CNN)	VMMRdb	93.6

clearly depicted that our proposed methodology on generated dataset achieved good results as compared to other techniques on which the experiments have been done.

The reason is that we have generated the dataset by taking considerations of all kinds of illumination factors and effects and tuned the architecture parameters according to it. VMMRdb contains 291,752 images of 9170 classes of different cars of a model from 1960 to 2016. We took the images of Honda Civic of a model from 2009 to 2016. So, we have 8 different categories; each category contains 200 images. After taking the images from this database, we have annotated the data for training purpose. The architecture also outperforms on this dataset, but it does not achieve as much accuracy as we achieved on our generated dataset. The reason of this is that our dataset is generated into the controlled environment. The comparison between the accuracies of our generated data on proposed architecture and VMMRdb data has been shown in Table 1. So, from the above experiments, we have conclude that our proposed model and dataset are efficient – in terms of accuracy related to the vehicle classification problem. We have also performed the experiments on different methodologies referred by some latest papers. We have utilized our generated dataset to evaluate these architectures. In the first technique of Table 2, CNN-based YOLO architecture have been utilized for car detection and classification. But the drawback of this methodology is that it does perform well when we have a small object on the input frame of the video. Since in our case we have a video obtained from the UAVs, there is a possibility that the object present in the video is in a smaller size. So, that's why this algorithm fails to achieve as much accuracy as we achieved in our proposed algorithm. In the second methodology, CNN features are trained on the support vector machine for detection and classification of the vehicle. The reason why this methodology has not achieved the good accuracy is that SVM does not perform well in case of the detection purpose. SVM usually performs well when we have the classification-related task and the data is linearly separated. In the third methodology which is referred in Table 2, deep convolution neural network has been utilized for the classification of the detected vehicle. But the drawback of the methodology is that they first detect the object using the traditional image processing techniques and then pass these objects to the convolution neural network for the classification of these detected objects.

In our utilized algorithm, the regions for the detected objects and the classification of these objects are both done with the help of the convolution neural network; that's why we achieved the good accuracy as compared to the discuss techniques in Table 2.

Some predictions which our model made have been shown in Figs. 8 and 9, respectively.

Table 2 Results on different methodologies

Paper	Methodology	Dataset	Results (%)
Ammour et al. [27]	CNN-based model (YOLO)	Self-generated	91.8
Radovic et al. [28]	CNN features along with SVM	Self-generated	84.6
Qu et al. [39]	DCNN	Self-generated dataset	88.2

Fig. 8 Prediction on frame for detection and classification

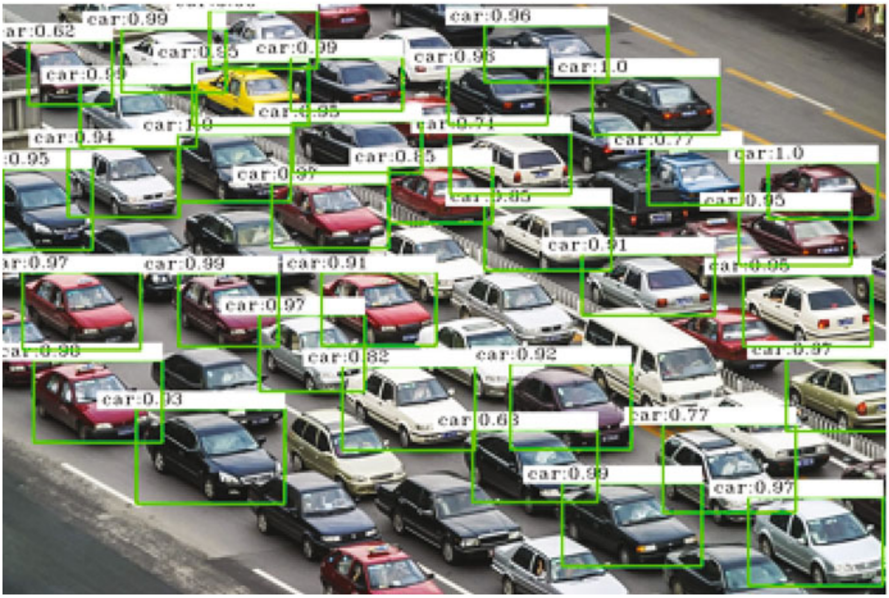

Fig. 9 Prediction on frame for vehicle detection

8 Conclusion

The purpose of this work is to classify the vehicles based on their makers and models. Latest techniques of deep learning have been utilized to achieve state-of-the-art results. The proposed methodology classifies six different cars based on their appearances; firstly region proposal network predicts the regions with the highest probability of occurrence of vehicle and then it is classified by fully connected layers. We have trained our model on self-generated dataset using the UAVs and achieved 95.3% accuracy on validation data. Future work includes vehicle color classification and number plate detection and recognition and the analysis of the crowd behavior using the UAVs.

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An Efficient Palm-Dorsa-Based Approach for Vein Image Enhancement and Feature Extraction in Cloud Computing Environment

Kamta Nath Mishra

1 Introduction

Nowadays, security has become a primary concern for the public. So, the biometric system is increasingly gaining interest because of the technology based on the uniqueness of an individual's physical or behavioral characteristics. Vein biometric is emerging from other modalities due to its strength and advantages. Consumer devices including smart phones show increased interest in the biometric system. One of the important things to consider in designing a biometric system for consumer electronic handheld devices is speed [1]. Biometric technology uses complex and computation-intensive image processing algorithms that require them to be implemented on powerful computers for acceptable processing time. However, handheld devices are usually constrained in resources and performance [2].

The fingerprint is the most widely used biometric technology and is widely known for its small device size. But at inferior environments such as construction sites, certain fingerprints can be worn out making the fingerprint biometric lack the usability in such a place. Iris biometric has a low error rate, but the use of light into the user's eyes makes some users feel psychologically uncomfortable. Hand geometry has a high false acceptance rate although it has excellent performance in terms of usability [3]. The advantages of vein biometric are difficult to forge, user-friendliness, and uniqueness [4].

The sensors or readers are being used by researchers to acquire the vein images. Then authentication is processed using the software on the computer or embedded system. However, a software implementation of vein biometric cannot achieve high computation performance that is needed for real-time applications. Hardware

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_6

can provide solutions for higher performance. However, the hardware design of the biometric system in hardware is challenging. Although few vein biometric hardware designs has been proposed, there is still room for improvement especially in performance [5].

The fingerprint is a well-known biometric and is widely used because of the small device size. However, fingerprint biometric is less functional for workplaces such as construction sites due to the fact that certain fingerprints can be worn out. Hand geometry has excellent performance in usability, but unfortunately, it also has a high false acceptance rate. Iris is good because it has low error rates, but some users might feel psychologically uncomfortable with light into their eyes. Furthermore, iris recognition requires an accurate eye position, causing the user to experience difficulty in providing this requirement every time, whereas the vein can overcome all these weaknesses because the vein will not wear out or change due to environment factors, is contactless, is hygienic, and is extremely difficult to forge [6].

The infrared (IR) ray captured by the camera not only contains a vein pattern but also a reflection of the surrounding shades such as the bones, muscles, and tissues. These reflections from the surrounding will worsen the vein image quality. The distribution of the vein image grayscales is also very small. All these factors make it difficult to extract the vein features properly. For this reason, the author is motivated to develop an algorithm to enhance and extract the vein feature from the palm-dorsa region [7].

While biometrics as a technology has been around for decades, improvement for customer usability in terms of speed of recognition is a major need. Ensuring biometric performance or customer experience is one way to develop biometric technology in line with market demand. In addition to concerns about privacy and security, researchers also need to focus on maximizing user-friendliness and a more efficient and faster verification process. Nowadays, many researchers have developed many algorithms to enhance and extract veins for biometrics. However, most researchers only focus on the use of software such as MATLAB/Python/C language, with the algorithms not optimized for hardware design. Researchers do not take into consideration the hardware resources or processing time constraints while developing vein enhancement and feature extraction algorithm. Designing of the algorithm in hardware is challenging due to hardware resource constraints and the complexity of hardware. When developing the algorithm, the processes in the algorithm are considered; whether they can be processed in parallel on hardware due to parallelism capability in hardware is the key advantage to improve the performance of the algorithm. With the hardware design, a faster verification process can be achieved [8, 9].

In this research work, the palm-dorsa vein enhancement and feature extraction algorithm are developed using MATLAB. Then the hardware design of the algorithm is proposed and developed using Verilog hardware language description. The hardware designs are developed individually for each technique. Then using ModelSim-Altera, the designed hardware is simulated to verify the functionality. After that, each hardware designs are integrated to produce hardware design for

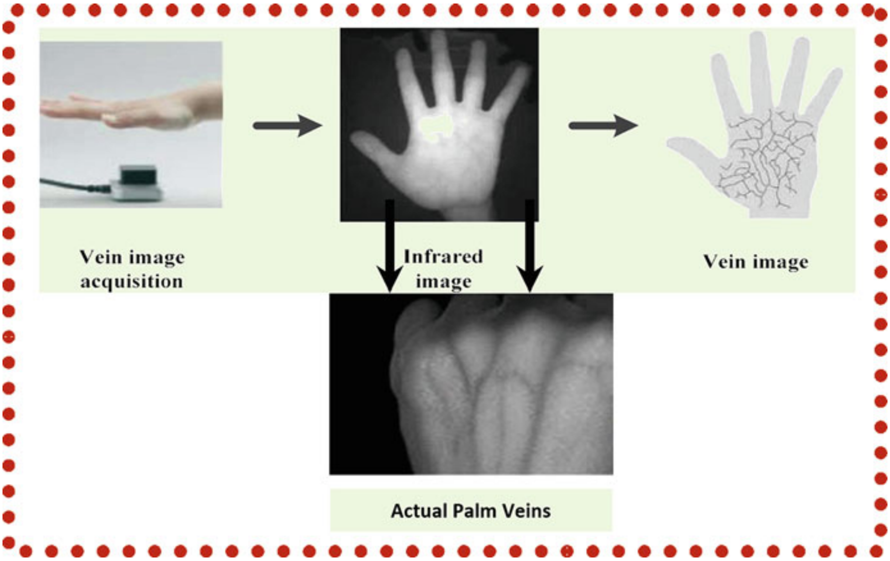

Fig. 1 Vein image example (palm vein recognition)

the palm-dorsa vein enhancement and feature extraction algorithm. Functional verification is simulated to check the integration function. The proposed hardware design performance analyses are evaluated to assess the characteristics of the proposed hardware design. The palm-dorsa vein based image recognition as an example is given in Fig. 1.

The unmanned aerial vehicles (UAVs) are basically used for collecting fewer distances and stumpy altitude information in wireless and remotely controlled environment. The UAVs can also serve as electronic jamming instrument in cloud and Internet of Things (IoT)-based distributed network systems where authentication is based on multi-biometrics. These UAVs can be used for sensors and artificial intelligence (AI) based remotely on allocated biochemical weapon detection where specific biometric codes are required for physical access of these highly sensitive areas. The UAVs fly at high speed in open areas and fly at slow speed in densely populated areas in order to avoid hitting steady objects including buildings, towers, etc. The other applications of UAVs are in the areas of natural disasters and communication relay. The technologies like AI, machine learning, and concepts of deep learning are the driving forces which are driving the drone evolution into an era where drones and UAVs are remotely accessed using vein-based biometric systems and are integrated with IoT and cloud computing systems for performing day-to-day activities of sending and receiving packets of different types of things like pizza, letters, etc. [10, 11].

The deep learning concept is bringing more potential to solve day-to-day problems in practical application scenarios. Certain research areas like big data, genetic algorithms, Internet of unmanned aerial vehicles, mHealth monitoring using

UAVs, and blockchain computing are more powerful and have captured almost all of the recent technologies. The deployment of wireless networks (network structure), allotment of node sharing points, path planning of data movement, and data collection in cloud- and IoT-based environment are the major parameters to be addressed in designing of drone/UAVs architecture. In the twenty-first century, the UAVs are being considered as one of the best remote sensing techniques used to gather sensitive data spread over a large area in a wireless environment. The UAVs are now frequently being used as AI-enabled sensing tools for proactively preventing/solving many issues and helping in the decision-making processes in information technology and other industry sectors [12].

The UAVs can be considered as highly reliable technological platforms used for efficient and cost-effective data analysis/event monitoring in real-time environment. In the case of UAVs monitoring and control, the Internet of Things (IoT) will send data-to-data processing systems which are being used by cloud computing system to monitor and execute processing requirements. In the case of fog computing, the IoT gateway will link the divergent objects of fog to the Internet. It can operate as a cooperative interface for different networks and supports divergent communication protocols in cloud- and IoT-based computing environment. The researchers have worked hard in developing UAVs and multi-UAV systems. The beauty of UAV lies in the truth that the UAV can be automatically integrated with an industrial control system through an IoT gateway platform to provide the assigned monitoring and controlling tasks where videos/images obtained through UAV in real-time environment are thoroughly and instantaneously computed and analyzed in the cloud. The visual administration of remotely located objects including gas pipeline monitoring, high-tension electric wire monitoring, border monitoring, etc. by drones and cloud services is integrated with control loop of IoT control system in real-time environment [13].

Most recently, the flying sensor systems have been used by researchers to provide critical administrations and services in certain regions like fiasco territory. A global positioning system (GPS) or a worldwide situating framework can give close and precise information related to certain areas if an immediate viewable pathway like satellite-linked communication system is available. Further, the GPS beneficiaries may face blackout situations in certain regions where satellite signals are delayed by impediments, e.g., the normal mists in the sky and specific jammed structures in certain high-security zones. This may bring momentous corruption in crisply developed UAV-/drone-based remote detecting/flying applications. Further, the cloud- and IoT-based control system of UAVs/drones may be hacked by hackers. Hence, there is a serious need of developing a foolproof cloud- and IoT-based UAV control system which is possible using vein biometrics because it is almost impossible to fabricate vein biometrics in any environment [14]. In this chapter, the author has presented a palm-dorsa-based vein image enhancement feature extraction technique which is useful for providing access and control rights to the authorities or machines responsible for issuing control signals to the UAVs from remote locations in cloud- and IoT-based wireless environment.

2 Literature Review

In the section, the theories and research works related to vein image enhancement and feature extraction in cloud- and IoT-based environments are reviewed in detail. First, the vein biometric theoretical background, the example applications in industry, and the vein image capture method are reviewed. Then, the related works on vein image enhancement and feature extraction algorithm and their work results are discussed in detail.

The vein-based biometrics use the vein patterns available in the human body as identification tool for authentication and access control purposes. Different parts of the human body such as the hands, palms, fingers, and wrists can be used for this technology. Vein biometrics uses infrared (IR) light generated from light-emitting diodes (LED) to penetrate the human skin. Due to the difference in the absorption of blood vessels and other tissues, the reflected or transmitted IR light is captured by a sensor. The red blood cells present in the blood vessels absorb the IR light and form as a darker image than the surrounding structure where the surrounding appears to be a brighter image as shown in Fig. 2 [15].

In the palm-dorsa vein biometric, the IR light from LED penetrates the skin, absorbed by red blood cell in the blood vessels, and reflected to be captured by the sensor. The part where the IR light is absorbed or where the veins are appears dark as shown in Fig. 2. After capturing the vein image, it is processed by image processing techniques to extract the vein pattern. Various feature information of

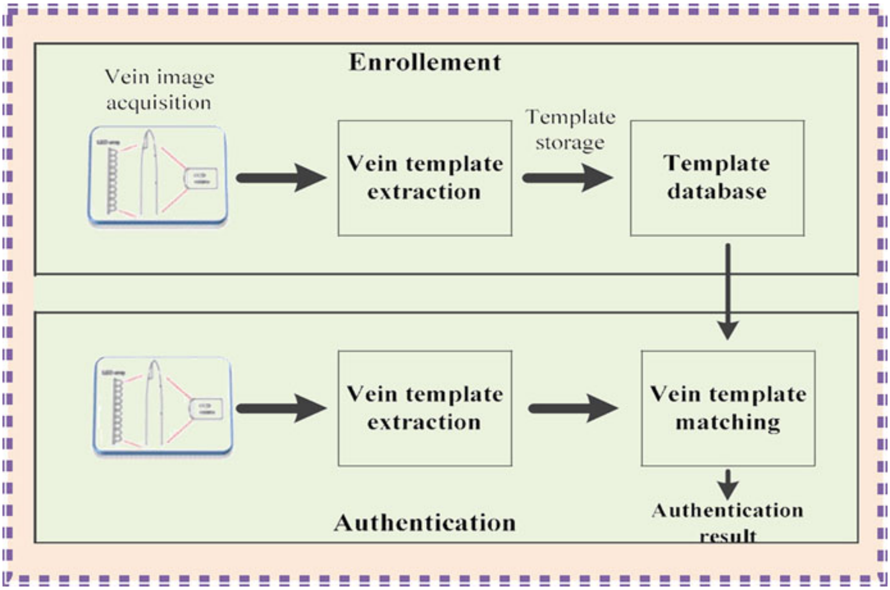

Fig. 2 Palm-dorsa vein image processing example using authentication technologies

Table 1 Comparing the modalities of biometrics in cloud computing environment

Biometric modality	Exactness	Price	Size of template	Long-term firmness	Safety level
Facial	Low	High	Large	Low	Low
Iris image	High	High	Small	Medium	Medium
Fingerprint	Medium	Low	Small	Low	Low
Finger vein	High	Medium	Medium	High	High
Voice signals	Low	Medium	Small	Low	Low
Lip motion	Medium	Medium	Small	Medium	High

the vein pattern such as branching points, thickness, and so forth are extracted and stored as a template. The extracted vein pattern information is then stored as a template in the database for authentication purposes. The comparison of biometric modalities in cloud-based environment is presented in Table 1 [16, 17].

At present two types of infrared (IR) imaging technologies are being used to get the vein patterns from the human body for the purpose of biometric identifications. Both of these mentioned imaging technologies are far infrared (FIR) and near infrared (NIR). The authors [1, 18] have invented FIR and NIR imaging technologies for biometric purposes. The FIR imaging technology is superior for capturing large-size vein patterns on palm dorsa, but it faces difficulty in capturing vein patterns of the palm and wrist. Further, the FIR technology does not provide steady image quality because it is sensitive to the human body. Furthermore, the FIR images have a low level of dissimilarity which makes it difficult to separate the vein images from the background. The FIR image of palm dorsa has thermograph-based information, but the veins are not as visible as the NIR image [2, 3]. The NIR imaging technology is superior for capturing vein patterns on the palm dorsa, palm, and wrist, but it has a defect that hairlike structure can also be seen on the surface of the skin. The NIR imaging technology is more tolerant of changes in ambient conditions [4, 19]. The NIR image for palm dorsa has no thermograph-based unnecessary information, and the veins are very clearly visible and are trouble-free to detect [5]. Hence, the NIR is frequently used to capture the vein pattern because the NIR imaging technologies provide far better quality vein images than the FIR. Figure 3 is showing the light reflection method which uses reflected infrared lights to capture the vein patterns. In this method, the infrared LED is placed next to the sensor, while the hand or finger is kept in front of the sensor. This method is generally used to capture the veins of the palms, palm dorsa, or wrists of the human body.

Therefore, the light reflection method is the finest method to capture the veins in these parts. The foremost benefit of this light reflection method is for final product design because infrared red LED and sensors can be packaged together to bring compactness in the product. On the contrary, the reflection effect of all parts of the human body such as the skin and thin penetration of infrared light under the skin make the contrast low [2, 20]. Figure 4 is describing the light transmission method. The finger is placed between the infrared LED and sensor. The infrared light that

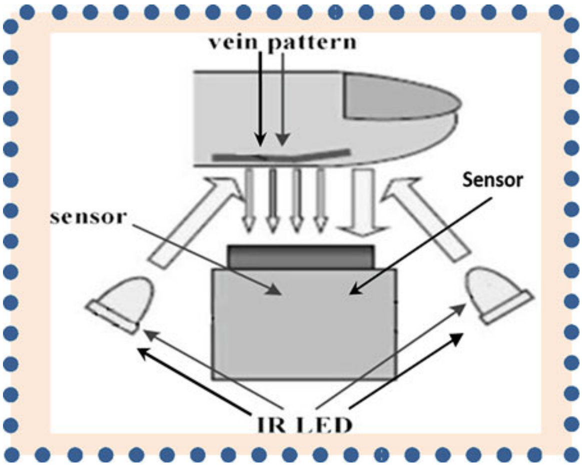

Fig. 3 Light reflection method

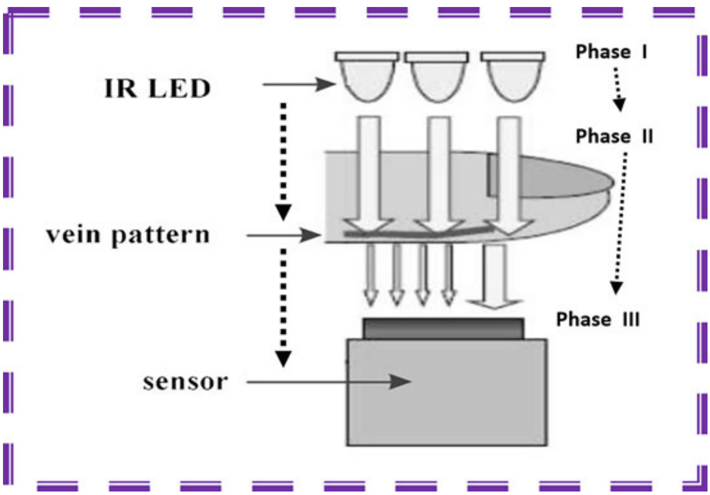

Fig. 4 Light transmission method

passes through the finger will be captured by the sensor at the other end, since this method requires infrared light to pass through the human body. Therefore, only parts of the body with an appropriate thickness such as a finger can be used to capture vein pattern. This method produces high-contrast vein image than light reflection method, but the weakness is that the final product will be larger, especially using palm or palm dorsa as biometric modal [2, 20, 21].

Hashimoto et al. [2] introduced a side lighting method that puts the IR LED on both sides of the finger as shown in Fig. 4. In this method, the infrared lights from both sides pass through the fingers, scatter in the fingers, and then pass on the other side of the finger before being captured by the sensor. This particular method produces very high-contrast vein image patterns, but it has a difficulty that the final obtained product using this method will be a little bigger than the light reflection method and lesser than the light transmission method.

3 Hardware Design Performance Evaluation

Once the proposed hardware design of the vein image enhancement and feature extraction algorithm has completed, the performance of the proposed hardware design is evaluated. The proposed algorithm is simulated with the vein sample images using MATLAB and Python. The results from MATLAB and Python are used as a reference for the performance evaluation of the proposed hardware design. The proposed hardware designs are simulated using the hardware design language simulator ModelSim-Altera with the vein sample images. The results from ModelSim-Altera are compared to the results from MATLAB and Python for the performance evaluation of the proposed hardware design of the algorithm. First, hardware design performance is individually evaluated for the resample, segmentation, median filter, and thinning techniques. Then hardware design performance is evaluated for the top vein which is the integration of all the techniques to function as the proposed algorithm [21, 22].

3.1 The Algorithm

As veins exist beneath the human skin, vein images are acquired by an IR transillumination method. However, due to light scattering and characteristics of human skin absorption, the vein image captured qualities are not always good. The vein image comprises of noises, poor illumination, and shading artifacts. Therefore, it is very difficult to distinguish between vein and non-vein. Simple technique cannot distinguish whether it is a vein or not. Hence, vein image enhancement is essential for vein feature extraction. Thus, an algorithm has been developed to enhance the vein image and finally can extract the feature of the vein pattern in the palm-dorsa hand [23, 24].

The flowchart of the proposed palm-dorsa vein image enhancement and feature extraction algorithm is shown in Fig. 5. The detailed explanations are discussed in the sections afterward. The proposed algorithm has been implemented using MATLAB and Python for the purpose of authenticity verification in cloud-based environments.

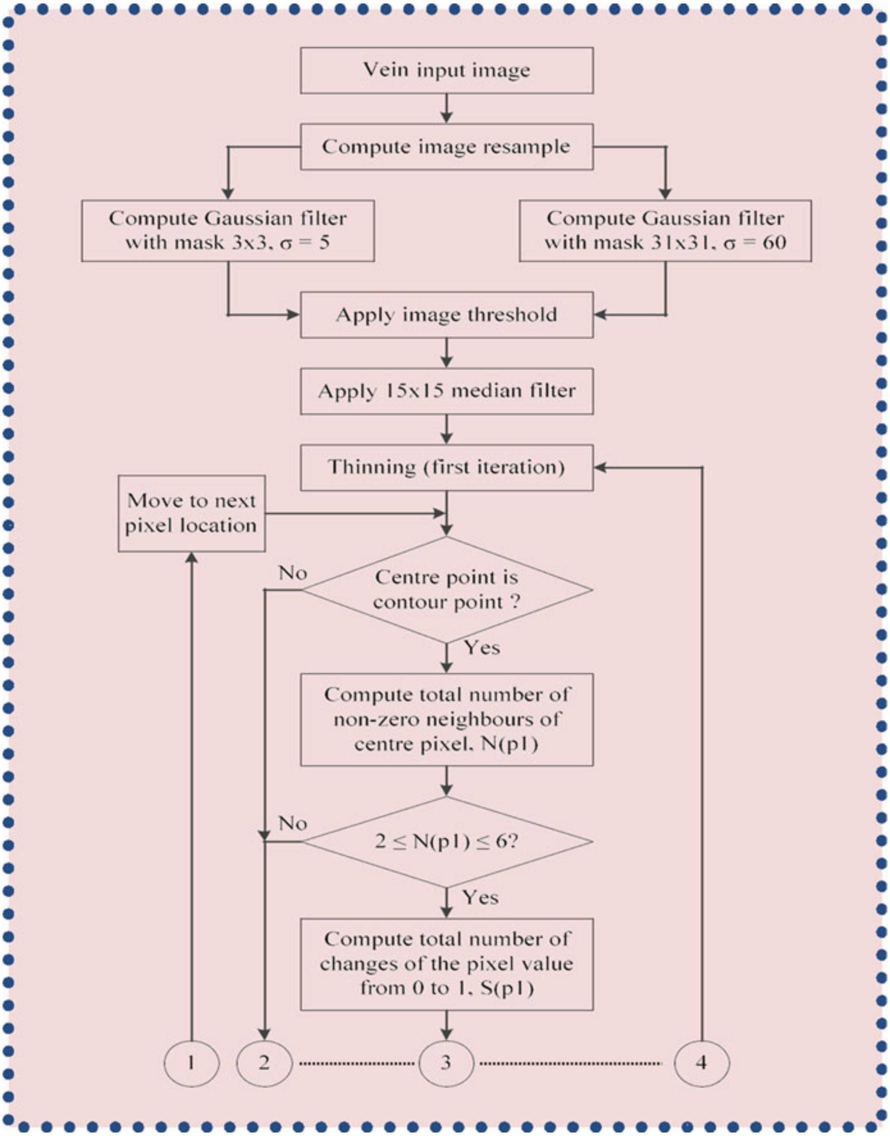

Fig. 5 Flowchart of the algorithm

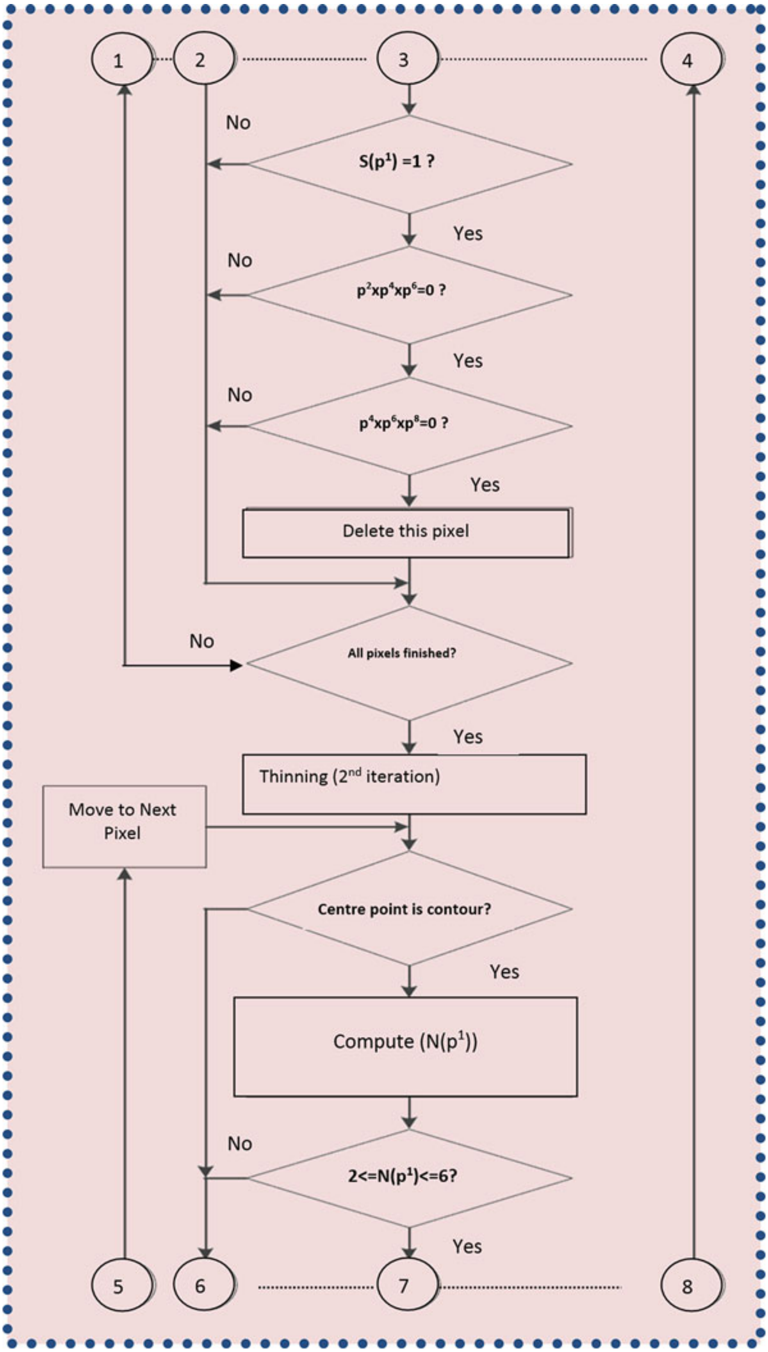

Fig. 5 (continued)

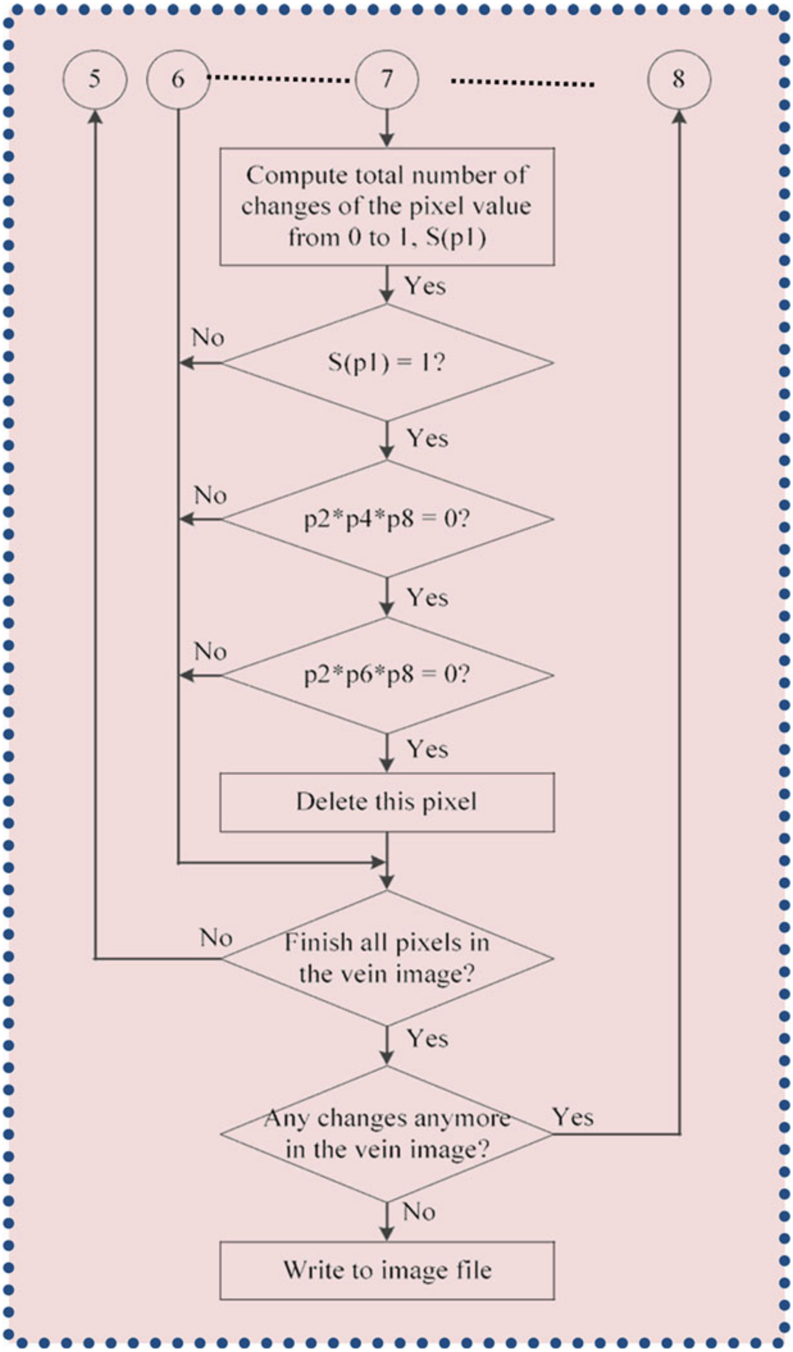

Fig. 5 (continued)

3.2 *The Input Vein Images*

The obtained palm-dorsa vein images have been used in this research work. Originally the vein image captured by a webcam produced a 640 × 480 pixel RGB image in JPEG format. Then, the vein images have been cropped to 384 × 288 pixels by cutting the unnecessary part from the original image. The GIMP software [25, 26] has been used to convert this image to a 384 × 288 pixel size with 8 bits grayscale image.

3.2.1 The Resample

Due to the noises from reflected IR caused by other substances, the captured vein images comprised noise. Typically, a Gaussian filter is used to remove the noise. However, Gaussian filter using a lot of multiplication and addition operations primarily involves the bigger mask filter size. The multiplication and addition operations increased drastically when the mask filter size increases. This requires large hardware resources to implement the Gaussian filter in hardware. The multi-resolution technique is known to have the ability to remove noise in the image [24, 25]. In the multi-resolution technique, the vein image is resized to the size of the quarters from the original image, then resize to the original size, before finally resizing to one-third the original image size. However, an experiment that has been carried out shows that resamples or down-samples, the vein image alone can also significantly remove the noise in the image.

To remove the noise in the input vein image, the image resample technique has been used in the proposed algorithm compared to Gaussian filter and multi-resolution techniques. Resample has been selected instead of the Gaussian filter because resample uses fewer hardware resources than the Gaussian filter that uses a lot of multiplication and addition operations. Furthermore, it also significantly reduces the number of pixels in the image, resulting in less processing time, reducing the cost of computation and fewer data storage needed for hardware requirements. In resample, the vein image has been down-sampled to half the size of the original vein image of 288 × 384 pixels to 144 × 192 pixels. Under-resampling will not remove the noise effectively, while over-resampling will remove the vital information in the vein image.

The vein image size after resampling is 192 × 144 pixels. After resampling, the number of pixels in the image is 27,648 pixels compared to 110,592 pixels in the original input image, which is about 75% reduction of the original image. This reduction of pixels not only reduces hardware storage requirements but also reduces computation in the next process. In the next process of segmentation, median filter, and thinning, instead of having to calculate 110,592 pixels, only 27,648 pixels need to be calculated. Computation reduction leads to a reduction in processing time. For resample, bi-cubic interpolation is used. Bi-cubic interpolation is the optimal

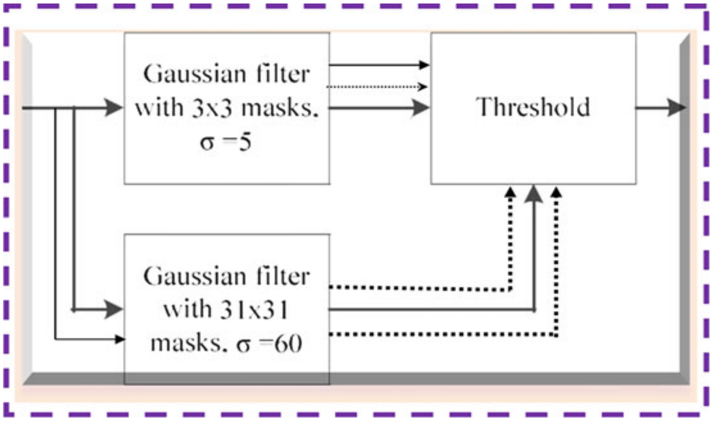

Fig. 6 The block diagram of vein image segmentation steps

technique to use for the image resampling. An experimental investigation will be described and discussed in the experimentation section of this paper.

3.2.2 Vein Image Segmentation

The block diagram of the image segmentation is shown in Fig. 6. It consists of a difference of Gaussians (DoG) and threshold operation to distinguish the vein pattern from the background. DoG is an effective technique for noisy image segmentation by performing two different values of standard deviations of the same image with different blurring radius, then subtracting them to produce a result (Kang et al., 2014). DoG consists of two Gaussian filter functions that subtract the blurred image with another blurred image on the same image. The two Gaussian filter functions must have different standard deviations to get two different blurred images to improve the visibility of edges in an image. In the proposed algorithm, the first Gaussian filter has 3×3 masks and a standard deviation of 5, while the second Gaussian filter has 31×31 masks and a standard deviation of 60. Experiments and analysis were conducted to determine the best filter mask sizes and standard deviations for both Gaussian filters. Figure 7 shows the distribution for the first Gaussian filter, while Fig. 8 shows the distribution for the second Gaussian filter.

Usually, the Gaussian filter outputs are subtracted before applied with the threshold technique. However, by using a certain threshold technique, the subtraction can be removed. Instead of subtracting and then comparing the value for threshold, only a threshold is used. The Gaussian filter outputs from DoG are applied with the threshold technique. In threshold, the grayscale vein image will be converted to a binary vein image. The two outputs from both Gaussian filters are compared. If the output value from first Gaussian filter is less or equal than second Gaussian

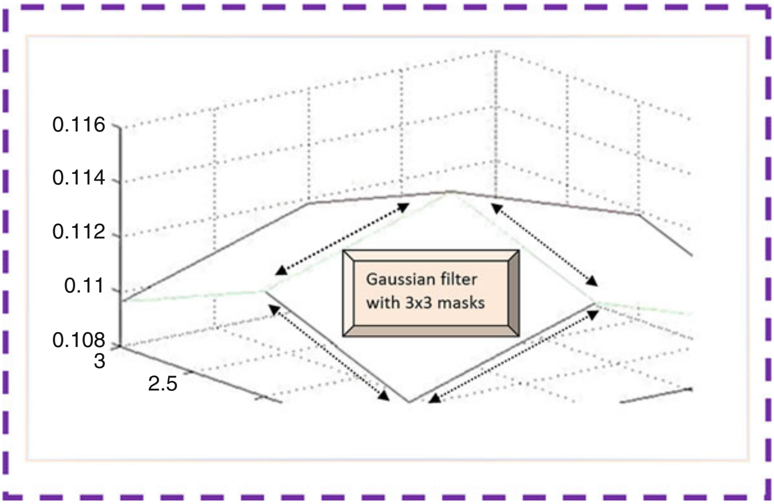

Fig. 7 Distribution of first Gaussian filter function with 3 × 3 masks and standard deviation of 5

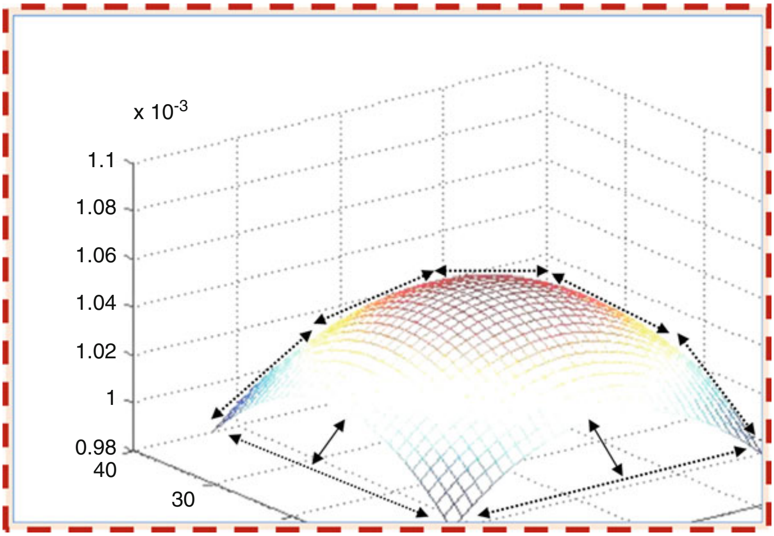

Fig. 8 Distribution of second Gaussian filter function with 31 × 31 masks the standard deviation of 60

filter, the threshold output will be a binary "1," while if the output value from first Gaussian filter is greater than second Gaussian filter, the threshold output will be a binary "0." The desired vein line will be represented by binary "1" or white color, and the background will be represented with binary "0" or black.

3.3 The Median Filter Implementation on Vein Images

The resulting vein image from the previous image segmentation process has noise where the edges are not smooth and burrs. It is important to remove noise and improve the resulting vein image to the next processing of thinning. To remove this noise, a median filter is applied to reduce speckle noise, and it preserves the edges making it an advantage where edge blurring is not needed [26]. In this algorithm, a 15 × 15 median filter is used. Experiments on different median filter sizes were conducted to determine the optimum size.

3.4 Thinning of Vein Images

The next process in the algorithm is to thin the vein image. Thinning will reduce the thick vein line to the thickness of a single pixel. For this algorithm, the thinning technique of Zhang et al. [27] has been used. The technique is fast and involves simple calculations. It repeatedly deletes pixels within the object to shrink it to a single pixel. Therefore, this particular technique is selected to minimize the hardware complexity of the system. This thinning technique consists of two iterations that check the conditions set to determine if the pixels should be deleted or not.

In order to perform thinning, the desired vein image line is set to "1," and the background is "0." A 3 × 3 mask size has been used in this technique as shown in Table 2. The 3 × 3 mask has p^1, p^2, p^3, ... p^9 points with p^1 at the center point. Before applying the condition check to the center point, determine whether it is a contour point. Contour point is a pixel with value 1 and having at least one neighbor with value 0. In the first iteration, the p^1 pixel is marked and deleted if it meets all of the following four conditions:

$$2.0 \leq N\left(p^1\right) \leq 6.0 \tag{1}$$

$$S\left(p^1\right) = 1.0 \tag{2}$$

$$p^2 \times p^4 \times p^6 = 0.0 \tag{3}$$

$$p^4 \times p^6 \times p^8 = 0.0 \tag{4}$$

Table 2 The pixel values of the vein line after having single-value thickness

p^9	p^2	p^3
p^6	p^1	p^4
p^7	p^6	p^5

Here, $N(p^1)$ is representing the total number of nonzero neighbors of p^1, and $S(p^1)$ is representing the total number of changes of the point value from 0.0 to 1.0 in the order of $p^1, p^2, p^3, \ldots\ p^9$. Here, pixel "$p^1$" is deleted if and only if it meets all the conditions. In other cases, the pixel "p^1" is not deleted.

In the second iteration, the "p^1" pixel is marked and deleted if it satisfies all of the following four conditions:

$$2.0 \leq N\left(p^1\right) \leq 6.0 \tag{5}$$

$$S\left(p^1\right) = 1.0 \tag{6}$$

$$p^2 \times p^4 \times p^8 = 0.0 \tag{7}$$

$$p^2 \times p^6 \times p^8 = 0.0 \tag{8}$$

The p^1 pixel is not deleted if it does not meet all the conditions. The conditions (3) and (4) are representing the differences between the first and second iterations of proposed cloud-based biometric identification and authentication system. Here, both of the iterations are used to the vein images repetitively until no change situation in the vein image is obtained. This conditional thinning algorithm is fast enough, and it needs a simple calculation which makes it most suitable to be used in the hardware design of cloud-based biometric authentication and access system.

3.5 Output Vein Images

After the thinning process, the vein image has been saved in the "TIF" image format. The "TIF" image format has been used because it preserves the binary value of the vein image.

3.6 Hardware Design of Vein Image Enhancement and Feature Extraction Algorithm

In this section, works related to the hardware design of the vein image enhancement and feature extraction algorithm are reviewed in detail. Then, the theories and related works associated with the hardware design of the proposed vein enhancement and feature extraction algorithm are discussed in detail.

The authors [26, 27] implemented finger vein biometric feature extraction and matching system using an embedded system on the Altera field-programmable

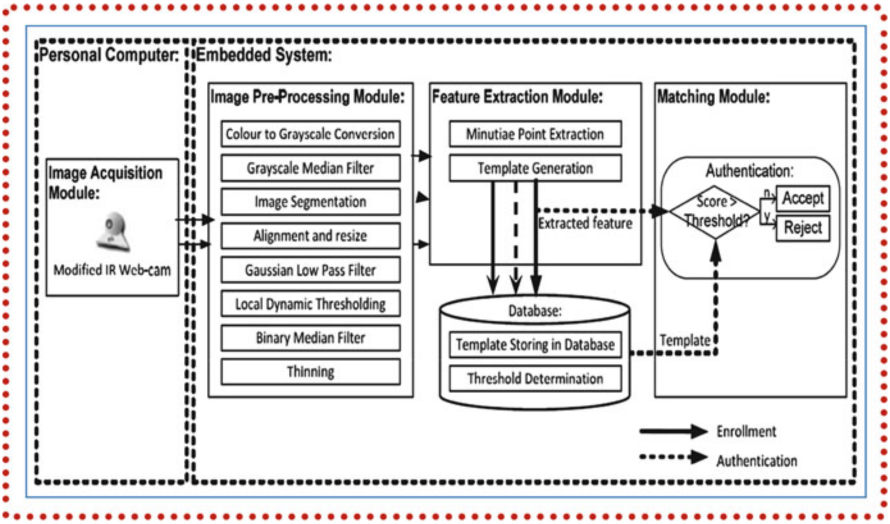

Fig. 9 Embedded system architecture of the finger vein biometric system used for authentication in cloud-based systems

gate array (FPGA) with Nios-II Linux Real-Time Operating System (RTOS) as shown in Fig. 9. The proposed cloud-based biometric authentication system consists of image acquisition, image preprocessing, feature extraction, and matching. The image preprocessing consists of color to grayscale conversion to convert images obtained to grayscale values. Then the grayscale median filter was used to smooth the noisy background from image acquisition. For image region of interest (ROI) segmentation, Canny edge detection technique was used. Then image alignment and resize were applied to get the region of interest. After that, a Gaussian low-pass filter was used to remove high-frequency noise in the image. After that, the local dynamic threshold was applied to segment the image into a vein and non-vein region. The binary median filter was applied to remove unwanted noise from the threshold technique.

Finally, the thinning technique from Zhang et al. [27] was used to extract the vein region to a single line vein. However, the disadvantage of the proposed biometric system is that it is implemented using an embedded system that does not provide the hardware parallel processing capability for use. Furthermore, intensive calculations in the median filter, Canny edge, and thinning are time-consuming in addition to being implemented in an embedded system with limited capabilities as opposed to hardware.

The researchers implemented a finger vein biometric system on chip (SoC) on Altera Nios2 FPGA development board with the Nios-II-Linux RTOS. They improved performance by proposing a hardware–software co-design approach which implements hardware for image preprocessing and image buffer management, while the feature extraction and matching are implemented in software on

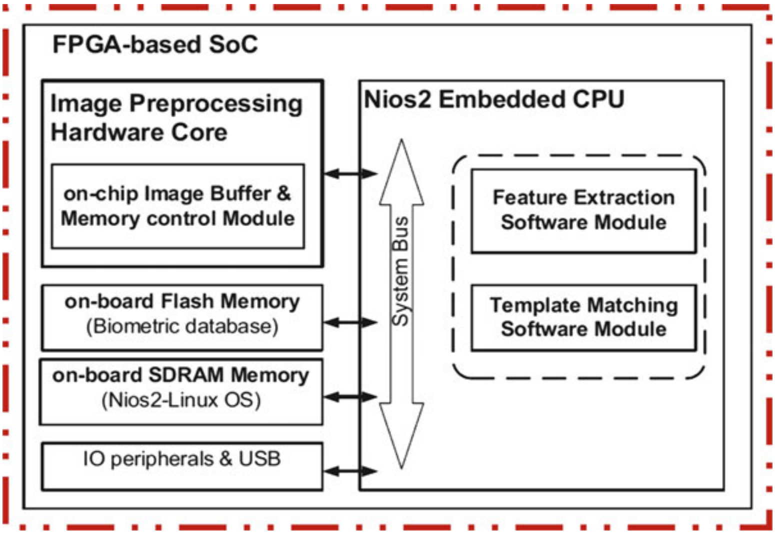

Fig. 10 SoC architecture of the finger vein biometric system to be used for authentication in cloud-based systems for accessing services [28, 31–33]

Nios-II as shown in Fig. 10. Figure 11 shows the image preprocessing techniques consisting of a grayscale median filter, ROI, alignment and resize, Gaussian low-pass filter, threshold, binary median filter, thinning and image buffer control, and address generation implemented in hardware accelerator engine (HW Core) [28–30].

Sun et al. [31] proposed a finger vein biometric system using digital signal processor-based implementation. In the system, it was divided into two main modules, image processing module and control module. The image processing module's function is to read the image input, image preprocessing, feature extraction, and matching, while the control module function is to set the parameters of the equipment and manage the communication control function. The algorithm consists of Sobel edge detection to obtain the ROI. Then, noise reduction was applied to reduce noise in the image and smooth out the image. High-pass filter was applied to sharpen the image. Maximum curvature technique was used for image segmentation. After segmentation, the median filter was applied to reduce impulse noise, and finally thinning was used to obtain a single-line vein pattern.

4 Conclusions and Future Work

This research work presents the vein image enhancement and feature extraction algorithm in a detailed way. The novel hardware design architecture of the vein image enhancement and feature extraction algorithm has also been proposed in this paper to further improve the performance of the algorithm by utilizing the

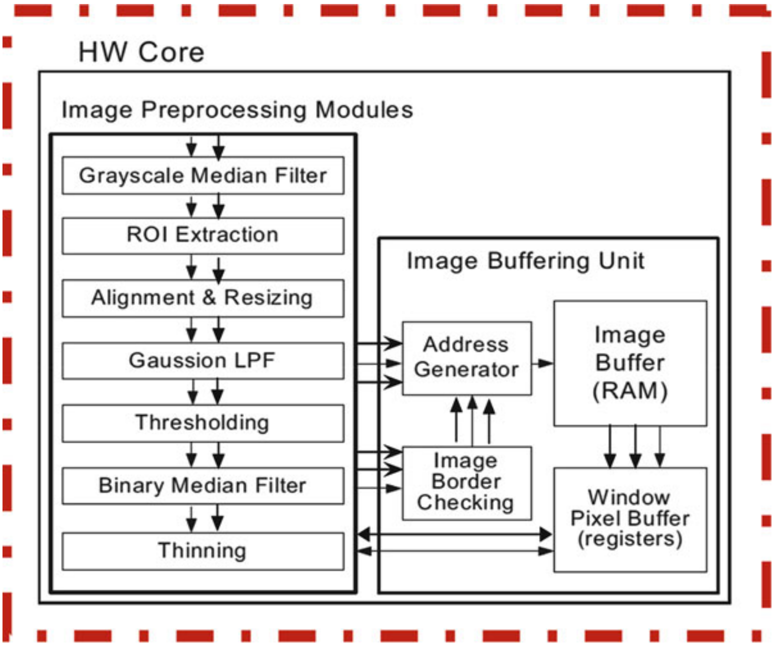

Fig. 11 Vein image preprocessing techniques implemented in hardware [28, 34, 35]

parallelism capability in hardware [36, 37]. As a result, the proposed hardware design performs significantly faster than any other related works. This paper also describes the performance evaluation of the proposed hardware design of the vein image enhancement and feature extraction.

In this research work, hardware design architecture of resampling is proposed. The proposed hardware design is an efficient architecture that enables pipelining computation with less hardware resource that excludes redundant calculation, reduces computation complexity, and improves the throughput. For the interpolation process, instead of using multipliers, shifters are used to reduce hardware usage. Shift registers are used as an intermediate buffer between horizontal and vertical interpolation so that memory buffer or FIFO (*First In, First Out*) is not required. The hardware design architecture also features padding capability by reading the same address of memory as before for the padding pixel. Here, novel hardware design architecture of one-dimensional Gaussian technique that operates concurrently for first Gaussian filter and second Gaussian filter is proposed [38, 39].

The hardware design architecture also features padding capability that comprises of a coherent control unit that allowed the padding operation during data access. Novel hardware design architecture of median filter is proposed. The improved moving windows technique is proposed to accommodate a larger median filter size which involves a lot of calculations due to filter size. In the improved moving windows, instead of calculating all the pixels in the window, only certain pixels are calculated. The presented palm-dorsa-based vein image enhancement feature extraction technique is useful for providing access and control rights to the authorities or machines responsible for issuing control signals to the UAVs from remote locations in cloud- and IoT-based wireless environment.

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Leveraging Unmanned Aerial Vehicles in Mining Industry: Research Opportunities and Challenges

Alok Ranjan, H. B. Sahu, Prasant Misra, and Bighnaraj Panigrahi

1 Introduction

Mining industry plays a crucial role in the economic growth of the country. There are two predominant methods of mining, viz. opencast and underground. Additionally, a few variations of opencast mining are also practiced, viz. strip mining, hydraulic mining, placer mining, etc. In order to meet the increased demand of minerals, there is greater stress on opencast mining compared to underground mining where the production is limited. Moreover, with increased mechanization, it has become possible to mine the minerals/coal occurring at greater depths from the surface. As a result, the opencast mines are getting bigger and deeper. In fact, opencast mining contributes to 93.31% of India's total coal production [1]. Almost all of the iron ore, manganese, limestone, dolomite, and bauxite are produced only by opencast mining.

In this competitive market scenario, Coal India Limited (CIL, India) and other mine industries have started several technology advancements in their different opencast mines. The objective of such automation in the mine is to enhance the safety of miners and improved productivity per shift of operation under the theme of so-called Intelligent Mining. These initiatives involve the remote operation of mine equipment, mine wide communication using fiber optic cable, strata monitoring with new technology such as time domain refractometer (TDR), etc. [2]. However, mining operations being dynamic in nature, efficient communication system still remains a problem, particularly after a disaster. The provision of a robust and

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_7

reliable communication system in deep opencast mines will not only enhance the production, but also will improve the safety goals.

This technology revolution has opened the scope for a new class of emerging technology, particularly the unmanned aerial vehicles (UAVs) also known as drones or unmanned aerial systems (UAS). Due to the ease of deployment, high maneuverability and hovering ability, reduced maintenance cost and low acquisition, UAVs are becoming practical choices for several commercial and civil applications. Natural disasters, large sports events, emergency communication, agriculture monitoring, search and rescue (SAR), constructions, etc. are few of the application areas where UAVs have been researched extensively [3–5].

Though advancement in communication and mine automation in underground mines are actively researched [6–8], very few findings about reliable wireless communication and mine wide coverage infrastructures in opencast mines have been reported in the literature. It is still a challenge and open research area to the wireless designer community in order to propose a reliable communication framework providing communication support at pit bottom and different benches. Slope failures in opencast mines are a cause of concern. Sometimes men and equipment get buried under the material due to slope failure. Providing a timely rescue operation in such a scenario is of paramount importance. Timely exchange of data (in the form of voice or video data) from the mobile terminal carried out by the rescue team members at different benches to the command center and vice versa is significant. However, the lack of communication infrastructure support affects the rescue and speedy operation. Recent studies have advocated the use of UAVs in mission critical applications such as natural disasters and on-demand temporary communication coverage. However, positioning of UAVs, energy consumption, and communication among UAVs are some challenges for such technology adoption. Recent studies address positioning and energy efficient communication using UAVs in a mission critical application [9, 10].

Motivated by such a challenging problem, safety improvement in mines, and the promising features offered by UAVs, this chapter first presents an outline of the potential application of UAVs in mines followed by basic networking architecture and channel characteristics of opencast mines. A UAV assisted novel wireless communication framework to support rescue operation in deep open pit mines is then formulated and presented in the following section followed by the performance evaluation of the proposed framework. In addition, different design considerations for UAVs in mines have also been discussed considering different features of the mining operation.

The rest of the chapter is organized as follows. In Sect. 2, we discuss the background of different UAV platforms used extensively in recent time and potential application in the context of mining industry. It is then followed by basic networking architecture and channel characteristics of UAV based communication. A detailed discussion on the design consideration of UAV based networking and communication is presented in Sect. 3. We then present our novel emergency communication framework named *SkyHelp* for emergency wireless communication in an event of

Table 1 Used abbreviations and definitions

Abbreviation	Definition
AB	Aerial base station
BS	Base station
CIL	Coal India Limited
CNPC	Control and non-payload communications
CS	Command station
DSM	Digital surface model
FSPL	Free space path loss
GNSS	Global navigation satellite system
ISM	Industrial, scientific and medical
LiDAR	Light detection and ranging
LOS	Line of sight
LAP	Low altitude platform
NLOS	No line of sight
PER	Packet error rate
QoS	Quality of service
QoE	Quality of experience
RPAS	Remotely piloted aircraft systems
SAR	Search and rescue
SFM	Structure from motion
TDR	Time domain refractometer
UAV	Unmanned aerial vehicle
UAS	Unmanned aerial system

mine disaster in Sect. 4. Detailed performance analysis of the proposed framework is discussed in Sect. 5. We then conclude our findings reported in this work in Sect. 6. Table 1 details the acronyms used in this chapter.

2 Background

UAV platforms can be classified mainly into two categories: fixed wing and rotary wing. Fixed-wing UAVs can fly at higher altitudes with high endurance support. This further makes it a suitable choice for applications which have wide spread area and can be remotely located. These have high energy capacity compared to rotary wing UAVs. Hence, such platforms can support events which require long flight time. Unlike the fixed-wing platform, rotary wing platforms seem to be more popular in applications such as natural disasters and temporary events [3, 4]. Due to different advantages over fixed-wing platforms, viz. size, hovering capacity, low altitude flight, and cost makes rotary wing platform a suitable candidate to support different on-demand temporary wireless communication services in post-disaster scenarios [11].

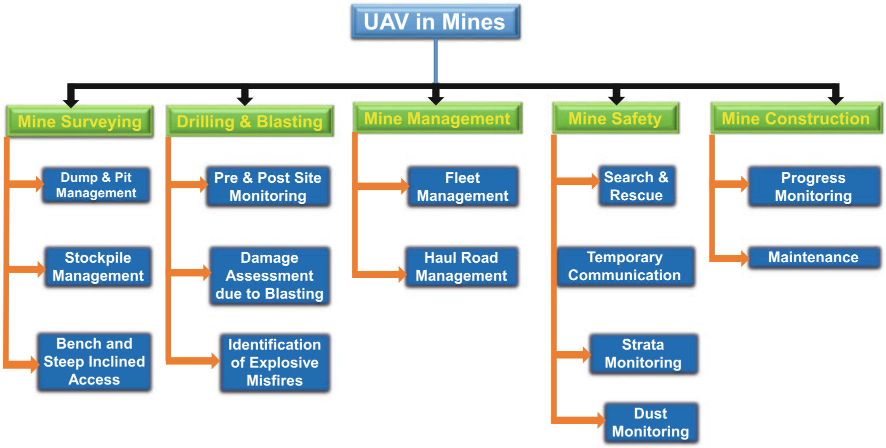


Fig. 1 UAV based application in open pit mines

2.1 Potential Application of UAV in Mines

Some of the potential application areas of UAV based communication and monitoring in opencast mines are presented in this section. Different UAV based applications in mines have been classified, and it has been presented in Fig. 1.

2.1.1 Mine Surveying

Typically, in open pit mines, the topographical survey is not performed on a regular basis because of expensive measurements, unavailability of proper equipment and skilled professionals. Moreover, the survey based on satellite-based data is affected by different climate factors such as clouds, raindrops, and sometimes the sand color. Hence, to get meaningful data of the interested region within the desired time slot is a challenge [12]. To solve this problem, recently UAVs are used for mine surveying of the interested regions.

A Germany based company named AIBOTIX carried out a topographical survey of Argyle gold mine located in West of Australia using a rotary wing based UAV. The UAV had a camera and a total of 8 flights were performed to measure 1 km^2 of mine area. Each flight duration lasts 10–15 min. Later the same company performed an aerial survey of Milas quartz mine of area 0.29 km^2 using two UAVs. The measurement data was then used to make a high-resolution digital surface model (DSM). This DSM could be further utilized in the interpretation of any changes in the topographical structure of the mine over time [13]. Similarly, a USA based company, Prioria in Gainesville, Florida dealing in military UAVs at large scale carried out an aerial survey to study the topographical conditions and also performed an analysis of volumetric calculation, a complex task of stockpile management [14].

To understand the potential of UAV based surveying and volume computation in opencast mine, a comparative study on UAV based volumetric computation and global navigation satellite system (GNSS) is carried out by Raeva et al. [15]. They first performed the surveying task using the GNSS and later used a fixed-wing UAV platform named eBee from senseFly for stockpile mapping of an open quarry located in the Bulgarian capital Sofia. An accuracy difference of only 1.1% between the UAV based computation and GNSS based measurement was observed in the volumetric computation of stockpile. From the findings, it is understood that UAV is a promising platform which could be used in opencast mine for such surveying task offering a rapid mapping over the conventional method.

A discussion on the advantages of UAV based volumetric computation over traditional measurement methods viz. terrestrial light detection and ranging (LiDAR) and GNSS is also reported in the literature [16]. A total of 13 objects were surveyed using UAV, out of which only 6 findings had a relative error of 5%. Whereas due to the poorly constructed 3D model, 7 objects were reported with a relative error of 15%. It was suggested that the accuracy is directly proportional to the 3D model constructed from UAV data. Nonetheless, the system provided a cost effective and time efficient mapping compared to the traditional approaches. Few more recent studies related to surveying and mapping of mining area using UAVs can also be seen in the literature [17–19]. Though few recent works have been reported by the research community, UAVs in such application category is still in a progression phase and need the careful realization of such tool for efficient utilization and coordination with daily mine activities.

2.1.2 Drilling and Blasting

Mining operation is highly mobile, and the topology changes are frequent. Once the extraction of minerals is finished at some level, then further advancement of mine areas for future extractions are required. To this, drilling and blasting operations are the routine operations of a mine. In addition, the drilling operation is also performed to serve several other objectives such as strata management and joints. Blasting operation in mine causes for severe ground vibration and also results in fly rock propagation causing environmental damages such as crack propagation in nearby surroundings and houses and sometimes also caused injuries to the mine personnel [20]. Therefore, mine safety regularities have fixed the minimum distance to be followed by mine personnel from the blasting site to perform a blasting operation. 3D modeling approach may be useful to analyze the behavior of rocks and strata in both pre and post analysis of blasting operation.

UAV based 3D modeling resulted from the post DSM could be further used to have a relevant analysis of effects of blasting in nearby surroundings by comparing both pre and post topographical changes due to blasting [12]. An example of such an application is shown in Fig. 2. Moreover, a DSM could also be useful in regular monitoring of mine sites. Hence, it will help in taking preventive measures to achieve different safety goals.

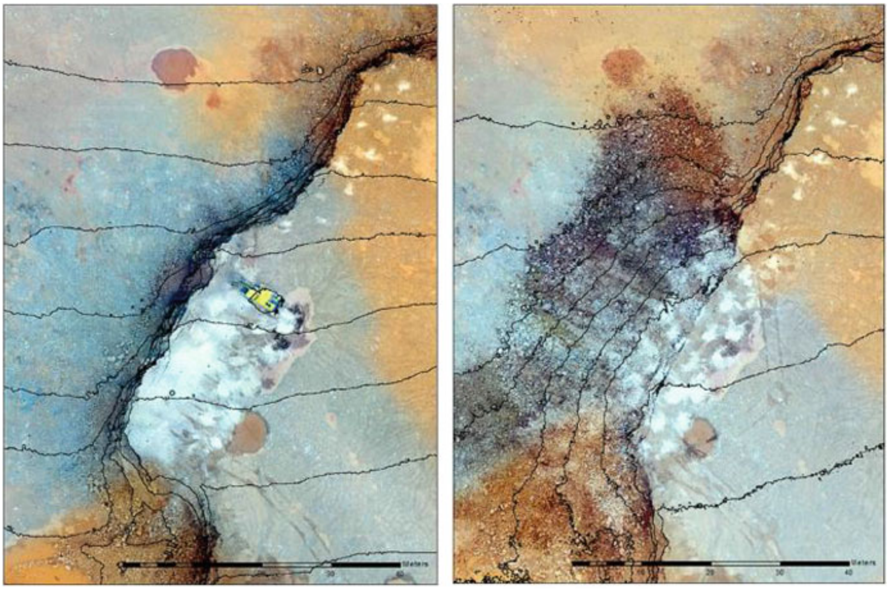

(a) (b)

Fig. 2 Contours created using a UAV in open pit mine for analysis [12]. (**a**) before blasting. (**b**) after blasting

A recent study by Bamford et al. [21] also supports the candidature of UAVs in mine application. They used UAV in post-blast fragmentation analysis. The main idea to use a UAV was to avoid the manual data collection which is costly and time consuming. Further, a laboratory set up was carried out to study the rock fragmentation analysis using UAV. In addition, a comparative analysis of UAV based results with manual pile fragmentation was also performed. It was concluded that UAV takes less time over conventional method and has high accuracy. However, the work was limited to the laboratory environment.

2.1.3 Mine Management

In a mine, several mine equipment and fleet of mine trucks are used. Since the mining activity is highly mobile, mine trucks and equipment are distributed serving different purposes such as dumping of overburden from one place to other, transportation of extracted minerals, and water sprinkling in mine roadways to suppress the excess of dust concentration, etc. Regular monitoring of positioning of mine trucks and equipment is crucial for efficient utilization of infrastructure, hence will help in improved mine productivity per shift of operation. Moreover, as the operation advances from one level to other the communication coverage to the new site is typically not available, and it may take several days to have a fully functional two-way communication support. In such cases, to track the mine equipment and trucks is a challenge.

To this challenge, UAV could be utilized on demand based tracking of mine equipment and trucks. Such tracking support is highly reliable, real-time, and may cover a wide area of the mine site. In addition to this, in case of a vehicle collision at some level or in mine roadways, UAV is useful to serve as a reporting agent of the accident location as UAVs are capable of providing aerial images, support rapid deployment, high speed, and greater communication capabilities to the base station or command center.

2.1.4 Mine Safety

Mine sites are highly exposed to safety problems. Regular and real-time monitoring of strata behavior and dump yard is hard to perform, and the current measurement techniques are either manual or periodic, hence vulnerable to safety risks and lives of miners. Such measurement techniques may not accurately help in analyzing the strata behavior and may cause for sudden collapses of slopes or benches, or even a complete failure of dump yard which result in fatal injuries, loss of lives and infrastructure losses. In addition to safety vulnerability, spontaneous heating of coal is another concern for the mines [22, 23]. The sudden change in the temperature beyond the threshold point may lead to a mine fire. To avoid such unforeseen circumstances at the workplace in open pit mine, UAV based monitoring is recently performed in United Kingdom (UK) by Hexagon. A thermal camera mounted on the UAV is used to detect the heat arising from the area of interest such as running belt conveyor. Moreover, a scope for the infrared based thermal camera is also studied to further monitor the self-ignition of coal at stockpiles and in different working levels [24]. Francioni et al. [25] also carried out research on the use of UAV based slope monitoring with the integration of remote sensing technique in mining environment.

Salvini et al. [26] carried out a study on the geological investigation of a closed marble mine in Italy using remotely piloted aircraft systems (RPAS). The main idea behind using RAPS was to avoid the unfavorable conditions of surveying risks due to different geomorphic properties of mine. A detailed characterization of rock behavior is further analyzed based on the 3D model, and different recommendations are provided to address the safety hazards due to strata or bench failures. When a disaster takes place in a mine, it may affect a large working area and may also affect the communication infrastructure. Considering such a scenario and dysfunctional of communication and monitoring devices, UAVs could be useful in the establishment of temporary communication support. Moreover, UAV could be utilized as a message ferrying agent to gather data from one device to other which are out of communication range from each other during any accident or mine disaster.

Another potential application of UAV in open pit mine is dust concentration monitoring in mine roadways. It is observed that the high concentration of dust in mine roadways have caused poor visibility. This poor visibility further may lead to mine vehicle collisions and sometimes resulted in fatal injuries to the miners or loss of lives [27, 28]. In the present time, dust monitoring is done manually in most of the open pit mines and is time taking. Moreover, to monitor the dust concentration to different working levels is a very much complex task and needs more mine personnel. A UAV based dust monitoring in mine roadways may help to map the complete mine in a timely manner. Hence, quick response to dust suppression might be achieved.

2.1.5 Mine Construction

In general, a mine is spread over several kilometers, and mining operation keeps on advancing further to those planned areas. Initially, mine managements start their exploration activities with the basic infrastructure required to carry out mining activity. However, with time new construction plans and further advancement of mine face will take place. Since the mine is wide spread and dynamic, a reference geometry of the entire mine plan would be significantly useful to the mine management for future construction plans. Such an example of maintaining a reference point for the mine management is recently performed.

A fixed-wing based UAV was used to perform a topographical survey of a deep open pit mine in Scotland with an objective of efficient mine management. The UAV platform named eBee from senseFly, a Swiss company was used for this purpose. The UAV covered an area of 0.51 km^2 and captured 127 photos for the management purposes from an elevation of 300 m. The captured images were then used to develop a DSM and orthoimages for the studied mine. The developed DSM is now being used for short term mine management and mine planning targeting different environmental management tasks and construction planning [29]. In another effort led by the largest gold mine company (BARRICK) in the world, a DSM for the Pueblo Viejo mine in the Dominican Republic using the 3D modeling with an objective of mine constructions and planning is developed. The collected data could be further utilized as reference data for future mine management [30].

Nicoll et al. [31] also used UAV based aerial photogrammetry to avoid the safety risks involved in the geotechnical studies. The collected data were further used to study the crack propagation around the perimeter of the cave subsidence for better management and construction of haul road. A UAV based hyperspectral monitoring of acid mine drainage was performed by Jackish et al. [32] in the Sokolov lignite district of the Czech Republic. They concluded that it is feasible to use UAVs for mine monitoring application which may reduce the complexity of ground based sampling and additional costs to perform such study. Jakob et al. [33] also supported the feasibility of UAVs in mines. They further proposed a processing tool box for frame-based hyperspectral imaging which can be used in precise corrections of hyperspectral based imaging for geological mapping especially in rough terrains such as mining sites.

Rauhala et al. [34] performed a UAV based surveillance of a mine tailings impoundment in Sub-Arctic Conditions covering an area of 0.5 km^2 of Laiva Mine in Finland. The main objective of this project was to measure the potential subsidence of mine tailings. Structure from motion (SFM) photogrammetry was used to generate the topographical structure of mine tailings so that structural deformation could be tracked and reported in a timely manner. The findings suggested that UAV could be utilized for the management of mine tailings for tracking surface displacement and maintenance with an accuracy of decimeter range. Few early findings on the use of UAVs in mine management and constructions are also discussed in recent work [35].

Tables 2 and 3 list features of few UAV platforms recently used in mining applications [13–15, 17, 18, 36]. A summary of a few recent studies based on UAVs in mines is presented in Table 4.

2.2 Basic Networking Architecture and Channel Characteristics

Reliable networking and communication protocols remained significant concerns for the mobile networking researchers. In this context, 5G enabled networking and communication need several research efforts in designing robust data communication protocols, new architecture design considering UAVs in 5G era, adaptive routing, cross-layer protocol designs, and multimedia delivery [37, 38]. Since, UAV

Table 2 Fixed-wing UAVs used for study in open pit mines

Features	UAV platform			
	eBee	UX5	Maveric	F550
Weight (kg)	0.69	2.20	1.16	3.87
Wing span (cm)	96	100	74.9	54.8
Battery (mAh)	2150	8000	NA	5500
Camera (mega pixel)	16	10	NA	Gopro
Maximum flight time (min)	50	45	45–60	20
Speed (km/h)	40–90	80	34–101	61.2
Wireless link range (km)	3	5	7.6	3

Table 3 Rotary wing UAVs used for study in open pit mines

Features	UAV platform		
	Phantom2	eXom	Inspri1
Weight (kg)	1.24	1.80	2.94
Wing span (cm)	35	56	55.9
Battery (mAh)	5200	8500	4500
Camera (mega pixel)	14	18.2	12
Maximum flight time (min)	25	22	18
Speed (km/h)	54	28–43	79
Wireless link range (km)	0.3	2	2

Table 4 Recent studies on UAV based application in mines

Application	UAV platform	Altitude (m)	References
Mine tailings monitoring	Fixed wing	300 and 150	[34]
Surface extent variations and volume prediction	Fixed and rotary wings	110.43 and 187.45	[17]
Quarry monitoring	Rotary wing	50	[18]
Subsidence inventory	Rotary wing	100	[19]
Geological investigation of rock slope	Rotary wing	93.9 and 60.7	[26]
Acid mine drainage	Fixed and rotary wings	50 and 120	[32]
Mine mapping based on hyperspectral imaging	Fixed and rotary wings	50 and 118	[33]
Geological condition monitoring	NA	NA	[31]
Blast fragmentation	Rotary wing	NA	[21]
3D mapping of open pit and archeological excavation	Fixed and rotary wings	NA	[36]

assisted emergency wireless communication coverage is also mobile in nature, contributions in developing new routing protocols and networking architecture will further advance the future research direction. However, depending on the deployment environment the channel characteristics may change [39–41]. In this section, the basic networking architecture for UAV based communication and monitoring in open pit mines followed by different channel characteristics for UAV deployments have been presented. Figure 3 depicts the generic architecture of UAV network in mines for different applications perspectives and consists two links viz. control and non-payload communications (CNPC) link and data link.

2.2.1 Control and Non-payload Communications

To ensure the safe operation of all UAVs, CNPC links are considered to be very significant. These links should be highly reliable, capable of providing secure two-way communications and delay bounded services to support mission critical data exchange among UAVs, as well as command stations (CS) at the ground to UAVs, e.g., mobile terminals mounted on vehicles on the ground. In a broader sense, CNPC link information exchange is categorized into three main categories [42–44]:

- Control from CS to UAVs;
- Status of the aircraft information from UAV to CS at ground;
- Information exchange among UAVs

Considering the case of autonomous flight of UAVs in case of any emergency, e.g., unusual behavior of UAV due to any malicious practice or malfunction, the CNPC links are required for the explicit intervention of a human. Due to the

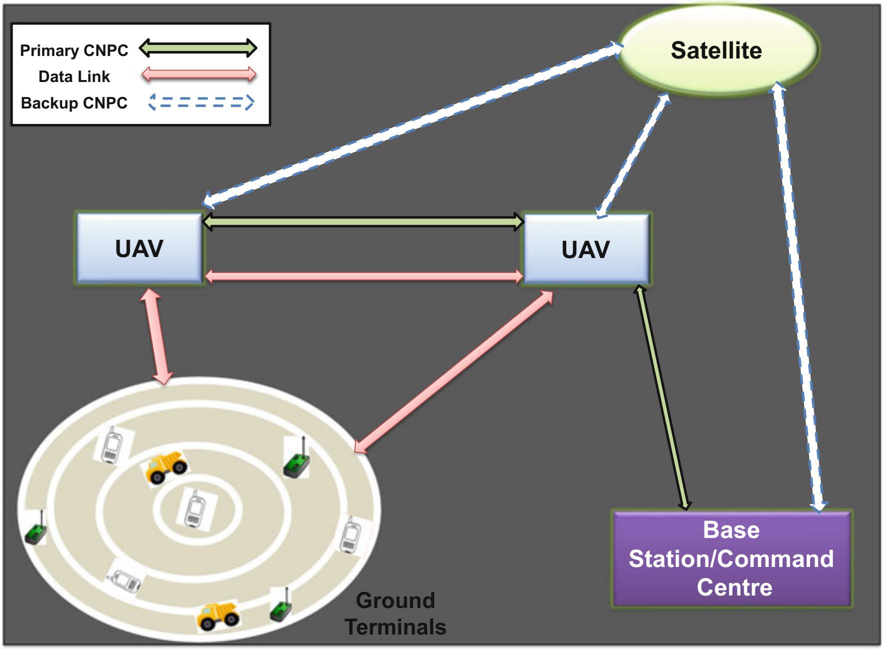


Fig. 3 Basic networking architecture for UAVs in mines

different critical functions and tasks assigned to UAVs, it is suggested that CNPC links, in general, should operate in the protected spectrum bands. In the present scenario, two such bands have been allocated known as L-band, and C-band operates in the range of (960–977 MHz) and (5030–5091 MHz), respectively [45]. However, researchers have also explored other bands such as industrial, scientific and medical (ISM) to explore the capabilities of UAV based communication and networking.

Though direct CNPC links between CS and UAVs are preferred and act as primary links due to delay bound services, secondary CNPC links could be established via satellite act as backup links. This will further enhance the reliability of the network. It is to be noted here that an effective security mechanism for CNPC links is required to protect the UAVs from unauthorized users or individuals which may control the UAVs flight causing ghost behavior and functionalities. To this security mechanism, emerging physical layer powerful authentication techniques could be applied to CNPC links in UAV based wireless communication.

2.2.2 Data Link

The data links aim to support mission-specific communication need. This may further include different communication devices depending on the application requirement such as mobile terminals, terrestrial base stations (BSs), gateway nodes, wireless sensor nodes, etc. Considering the on-demand UAV aided temporary wireless communication and monitoring in deep opencast mines, the data links maintained by the UAV should support the following modes of communication:

- Communication between mobile units to the UAV in case of BS is malfunctioned or dysfunctional and offloading of data to the BS;
- UAV to gateway nodes and UAV to BS; and
- UAV–UAV communication.

Depending upon the application requirement, the capacity of such links may vary from few Kbps to Gbps.

2.2.3 UAV-Ground Communication Channel

In comparison to piloted aircraft where the wireless channels of air-ground communication are well understood and researched, experimental measurements and extensive simulation studies of UAV-ground wireless communications are still ongoing and is an area of interests to the wireless communication community. The propagation environment of UAV based wireless communication is quite complex as compared to the piloted aircraft which are having high rise antenna towers mounted in open space usually [42]. However, in case of UAV based wireless communication channel for the air-ground communication link, it may or may not have a clear line of sight to BS/command center or gateway devices in case of data collections [46].

In general, it is expected that for air-ground communication channels there should have a line of sight (LOS) links. However, in certain situations viz. terrains, high rise dense buildings, or due to man-made structures such as subway, links might be obstructed and caused for no line of sight links (NLOS) [47, 48]. In fact, recent studies have detailed that for low altitude platforms (LAP) for wireless and broadband communication services, an air-ground channel suffers from different multipath components due to scattering, reflection, diffraction by hilly terrain or buildings in both urban and near urban environment, and foliage distributions, etc., [49, 50].

The channel characteristics of open pit mines are not the same as of normal propagation environment such as free space, urban and suburban environment, etc. For example, an open pit mine has slopes and benches enriched with minerals causing for high reflective surfaces, hence work as attenuators for radio propagation. Moreover, the change in the topology of mine benches further makes reliable communication coverage a complex task. For UAV based wireless communication and broadband services, researchers have studied and implemented different channel models of which widely used channel models for different use cases are free space when there is a dominance of LOS probability, a two-ray model for over sea surface and agriculture monitoring, and stochastic Rician fading with deterministic LOS component [46, 50, 51]. Nevertheless, UAV to ground channel modeling in case of measurements performed in the mining environment is yet to be studied and needed in near time to provide UAV based communication and networking services in both routine and emergency scenarios.

2.2.4 UAV–UAV Communication Channel

In case of UAV–UAV communication channel the effect of the multipath component on the link is comparatively minimal than that of air-ground communication channels, hence results in better link quality. However, a UAV–UAV link may suffer from high Doppler frequencies due to the relative velocity of UAVs for wireless communication or data exchange [11, 52]. More systematic measurements in this regard would be helpful to develop an understanding of such UAV–UAV communication link and their impacts on different prospects such as spectrum allocation, the capacity of the network, routing protocols and reliability considering unique propagation environment characteristics of open pit mines.

Though few works have been carried out to perform surveying, digital map generation, and pre and post analysis of blasting operation in mines; to the best of our knowledge, no such study is reported which detailed and discussed the UAV aided wireless communication network in the open pit mine environment. Therefore, it would be an interesting research problem to understand the signal propagation behavior in open pit mines considering different measurement scenarios and how the propagation characteristics are different than the propagation in a normal environment. In addition, proper systematic measurement and consideration will help to formulate different application requirement and novel communication and protocol design targeting such high-stress work environment.

3 Design Considerations

3.1 Optimized Path Planning

Considering the potential applications of UAVs in mines, path planning of UAV is a significant concern for the reliable design of UAV based networks in mines offering different services. Appropriate path planning may effectively reduce the communication distance between UAVs and sensor nodes. In addition, this could also be a case for the UAV–UAV communication link. This will further help to achieve the high-capacity performance of UAV based communication networks. However, optimization of UAV path considering different application scenario in mines is a complex problem. Such optimization of UAV path planning needs more systematic measurements, and modeling approach as the mine propagation environment is different than the normal terrestrial scenarios such as urban or suburban UAV aided networks [53].

The optimization problem of UAV path planning in mines further has two aspects. First, path determination and continuous tracking of the trajectory of UAVs in mines, which involves several variables that might affect the path planning of UAVs in mines viz. UAV speed, the spatial distribution of sensors (in case of data gathering), antenna orientation, and altitude, etc. Second, constraints which are practical in nature and need to be considered such as the reliable and robust link between UAV and node, flight time, collision avoidance, desired data rate support and network capacity, etc. [54]. However, modeling all practical constraints are difficult and also may vary for different propagation environment targeting different applications.

It is imperative that the path determination of a UAV in mines will also depend on the type of application. For example, in order to support a disaster scenario in a mine, it is evident that there should be more than one UAV deployment to provide communication coverage to the users at ground; whereas tracking of mine vehicles may need only one UAV for information exchange. In addition, data collection from sensors monitoring strata behavior/dump slope will require only one UAV for data dissemination, as such kind of data exchange follows delay-tolerant network application, hence can be periodically reported. However, considering the disaster scenario and rotary wing UAVs to be deployed and serving as an aerial base station (ABS), in such cases finding an optimal altitude of UAV for wireless communication support is another crucial problem. Notably, researchers have studied the optimal altitude of UAVs for the provision of wireless and broadband services targeting maximum coverage in an urban and suburban environment, but is yet to be ascertained for mining scenario [45, 55]. Hence, optimal altitude study and coverage analysis of UAVs in open pit mines are open research problems.

3.2 Energy Efficient Communication

Though UAVs have been exploited in different civil and military applications in the past, but the on board energy and flight time always remained a concern to researchers. In a broader sense, such energy constraint problem can be solved through two different approaches. First, on board energy management mechanisms for different communication supports. Second, replenishment of energy source with minimum compromise in communication links. Hence, it should not affect the quality of service (QoS) [56, 57].

In the context of application in mines, on-demand temporary wireless communication coverage is required during advancement of mine operation from one level to other, where no basic communication infrastructure is present. In such a scenario, considering more than one UAV serves the purpose of reliable wireless communication coverage than an adaptive energy replenishment scheduling mechanism exploiting inter UAV distance by increasing the transmission power can significantly help to achieve energy efficient deployment. In addition, the scheduling mechanism of energy source should be in such a manner that it should not affect the network.

One approach to this scheduling may be to identify the types of data traffic in a particular shift of mine operation. Hence, the time slot where the low data rate traffic is expected (for instance, fleet monitoring and reporting) could be used to implement the scheduling mechanism. Energy efficient communication support, on the other hand, aims to minimize energy consumption while communicating to sensor nodes/gateway devices or UAV–UAV communication. This can be addressed by different mechanisms, of which the significant ones include efficient routing, controlled mobility, and optimized access mechanisms.

4 UAV Aided Emergency Wireless Communication

In this section, the on-demand UAV assisted emergency communication framework to support rescue operation in deep open pit mines is discussed. It is then followed by proof of concept of the proposed emergency communication framework named SkyHelp for mine safety and rescue operations.

4.1 Proposed Framework

Due to the increased demand of raw materials, the mining operation is going deeper day by day. To this increasing deep operation, mine personnel is exposed to risks of accidents and injuries. Also, several mine equipment is widely spread involved in different kind of mine activities. It is evident from the past disasters in deep opencast mines that bench failure and dump failure caused for many fatal injuries and loss of lives [20]. Moreover, such disaster also leads to infrastructure losses to the mine management, which hampers the overall productivity of a mine. One of the most common reasons for communication failures in opencast mines is the destruction of infrastructure during a bench collapse. In fact, given the nature of deep mining via open pits, any strata failure at the top level has a ripple effect on the mine benches below it; which not only dysfunctionalizes the respective equipment but also causes serious injuries to the mine personnel. Figure 4 shows a case of bench/strata failure in open pit mine. Moreover, such consequences will lead to a complete communication blockage to the affected mine site. In such events, providing a timely rescue operation to the miners trapped beneath the ore body or rocks is of paramount importance for the mine management. In addition, such timely rescue will help to mitigate the effects of a disaster to the miners.

4.1.1 The Design of SkyHelp

In case of a disaster in any mines, the first priority is to rescue the miners to save theirs' lives and minimize the infrastructure losses. In this context, speedy

Fig. 4 Slope failure in Bingham Canyon mine [58]

rescue operation and emergency response are the most critical steps and should be conducted quickly and efficiently. The major problems to achieve these tasks are lack of communication infrastructure and situational awareness during a mine disaster due to remote and wide spread operation of mines. Hence, affecting the search and rescue (SAR) operation in mines. Therefore, in this work, an emergency response system named SkyHelp has been proposed. The idea behind the SkyHelp framework for emergency response in deep open pit mines, given the high dynamism of the operations environment, is to use an UAV as the immediate responder to resurrect the communication link between the mine personnel (trapped in the deep pit) and the remotely located base station (on the mine surface).

4.1.2 Wireless Channel Characteristics of Opencast Mines

The study of wireless channel characteristics in opencast mines is limited [59, 60] as opposed to underground mines [6, 61–63], and it is often seen similar to free space radio propagation. However, a recent work by Barbosa et al. [64] disapproves of this hypothesis and shows a compelling need for better wireless channel model for this application category. Based on the recent experimental findings carried out in deep open pit mines, a modified free space path loss model for the wireless communication channel is adopted in our work [59]. The modified model consists of two components.

- The *inverted pyramid* architecture (due to the unique topology from pit bottom to surface) for communication from the deep pit bottom to the mine surface and vice versa; and is affected by severe multipath (due to structural constraints) and signal attenuation (due to the material absorption).
- The straight line architecture for communication between the surface landing station and the base station.

The consolidated end-to-end path loss is given as follows:

$$\text{FSPL}_{\text{inverted}} = 25\log_{10}(d) + 25\log_{10}(f) + 32.44 \quad (1)$$

$$\text{FSPL}_{\text{surface}} = 23\log_{10}(d) + 23\log_{10}(f) + 32.44 \quad (2)$$

where: d = distance of the receiver from the transmitter in km, f = signal frequency in MHz. For this work, the path loss exponent of 2.5 and 2.3 are used for the inverted pyramid and straight line architectures, respectively; and is based on the results reported by De Almeida et al. [59].

4.2 SkyHelp Framework

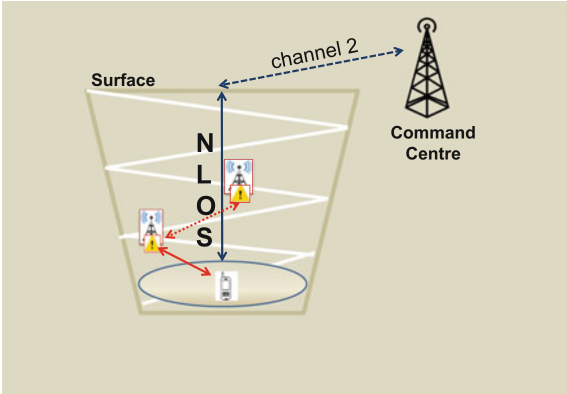
The proposed architecture is shown in Fig. 5, given that a mine disaster at any level may cause physical damage to the installed communication and monitoring infrastructures. Emergency communication framework may be classified into three categories.

- **Case 1**—No UAV: It may happen that due to the physical damage of the communication gateways, the only mode could be a direct communication link between the pit bottom and the BS, and vice versa; but with no line of sight (NLOS). This NLOS is mainly due to the topographical features of the open pit mines.
- **Case 2**—One UAV: Here, one UAV as the relay or forwarder node is introduced, which would hover at some specified distance from the pit bottom, with direct line of sight (LOS) between the user devices and the UAV. Hence, the communication link will be better than the former defined case.
- **Case 3**—Two UAVs: As the mine operation goes deeper, it may happen that one relay node may not provide good coverage between the pit bottom and the BS. In such a case, an additional UAV could be used to close the coverage gap.

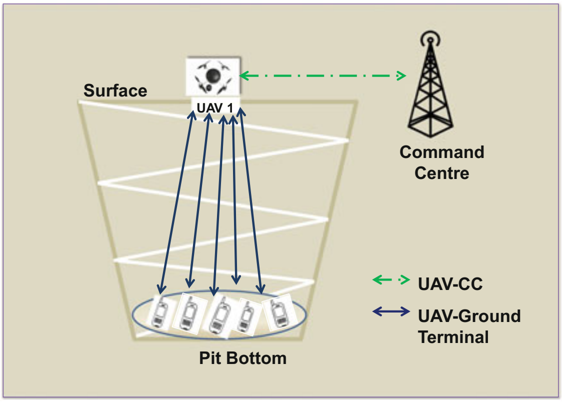
5 Performance Evaluation and Preliminary Analysis

In this section, performance evaluation and preliminary analysis of SkyHelp framework are presented. For the analysis, a detailed simulation study is performed.

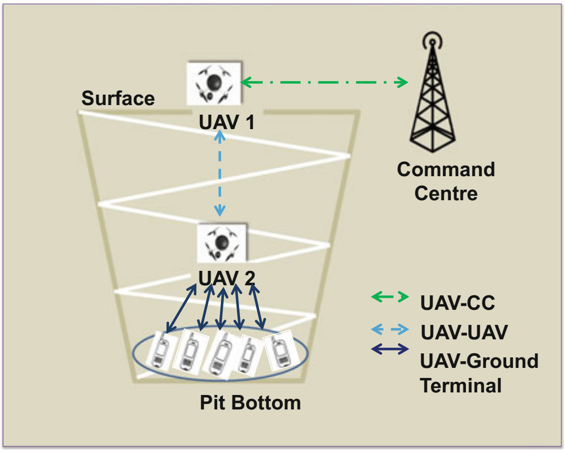
Fig. 5 Proposed emergency communication framework in deep open pit mines. (**a**) No UAV, during disaster. (**b**) Introducing one UAV post disaster. (**c**) After disaster, two UAVs for deeper pit coverage



(a)



(b)



(c)

MATLAB 2015b is used to build a simulation model for UAV based emergency communication. A signal frequency of 2.4 GHz is chosen for link characteristic analysis. Different pit depths, viz., 100–600 m are considered. The motivation behind considering greater pit depths is to illustrate the benefit of the proposed framework. Table 5 lists the simulation parameters used in this study.

Based on the channel characteristics, a user transmits 1000 bits to the receiver from its location. It may be noted here that for No UAV scenario, BS serves as a receiver. However, in case of one UAV, the user first transmits all data packets to the UAV working as relay and the UAV then transmits all data packet to BS. Same assumption is followed in case of two UAVs for deep open pit mines. Nevertheless, the total hops in the latter Case will be more compared to the former two Cases. For all the categories (described in the above subsection), the distance between the user to the BS/command center is 600 m. However, in the case of one UAV working as a relay or forwarder, the distance between the UAV and BS is 500 m whereas the distance between the user and UAV is 100 m from the pit bottom to UAV flying at the surface and it keeps on increasing till 600 m. In case of increased depth (for example, 200 m), two UAVs have been used for the analysis. The distance between the UAV hovering close to the user is fixed at 100 m, and the distance between the UAV-to-UAV is also 100 m. The same deployment setting is assumed for rest pit depths consideration. For the UAV flying near to the surface, the distance between the UAV and BS is 500 m which is same as of with one UAV consideration.

To validate the assumptions of guaranteed communication during a disaster in deep open pit mines following performance metrics are considered.

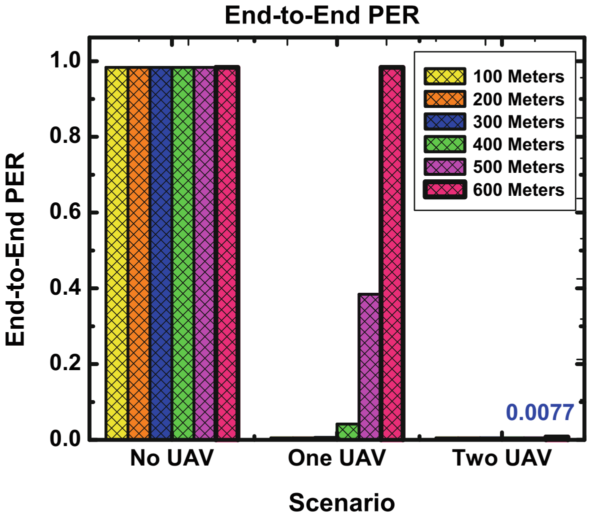
- End-to-End Packet Error Rate (PER): It is defined as the successful packet received at the BS from the receiver and vice versa.
- Successful End-to-End Per Packet Delay: It is the performance metric used to measure the total transmission delay of each packet which is successfully received at the BS and vice versa.
- Number of Retransmission: It is the measure to express the total number of attempts to transmit a packet to BS and vice versa based on the channel condition.
- Successful End-to-End Per Packet Energy Consumption: The total amount of energy consumed to transmit a successful packet to the BS and vice versa.

The plot for end-to-end PER is shown in Fig. 6. It is observed that when there is no UAV (case 1, 100 m pit depth), the end-to-end PER is 0.98; whereas introduction

Table 5 Simulation considerations

Simulation parameters	Values
Transmit power	20 dBm
Bandwidth	1.4 MHz
Signal frequency	2.4 GHz
No of bits	1000
Depth of pit bottom	100–600 m
Noise figure	−95 dB

Fig. 6 End-to-End PER



of one UAV in the emergency communication framework (case 2, 100 m pit depth), the end-to-end PER is significantly reduced and is recorded as 0.0051 only. This is because in the case of no UAV, the communication link is unreliable and packet drop is more due to the inferior signal reception at the receiver. However, introducing one UAV reduces the total distance between the transmitter (user node) to the receiver (UAV as a primary BS to the user).

This finding confirms the benefit of utilizing UAV during an emergency in mine accidents and ensures the reliable communication link between user and receiver. Encouraged from the initial results, further investigations were performed to understand the communication coverage with only one UAV. Therefore, different pit depths were considered, viz. 200 up to 600 m with a uniform depth gap of 100 m. The objective behind this assumption was to consider the practical mine depths which is typically followed for mineral exploration. It is analyzed that the end-to-end PER for greater depths, viz. 200 and 300 m were limited to 0.0051 only. However, the end-to-end PER slowly increases after 300 m pit depth and reached a maximum value of 0.98 which is same as of Case 1 (No UAV) where the user has to communicate directly to the BS. This suggests that one UAV can serve the purpose of providing wireless coverage in an event of emergency up to a depth of 500 m only. If the pit depth is more than 500 m (which is the case of several open pit mines in real-world) then another UAV could be used to fill the communication coverage gap. This can be seen in Fig. 6, where second UAV has an end-to-end PER of only 0.0077. In the event of an emergency, delay bounded communication is very crucial. A quick response is possible if the message is delivered in a timely manner. Considering the catastrophic event of slope failure in mine, successful end-to-end per packet delay for each case is also performed. The result for this parameter is shown in Fig. 7.

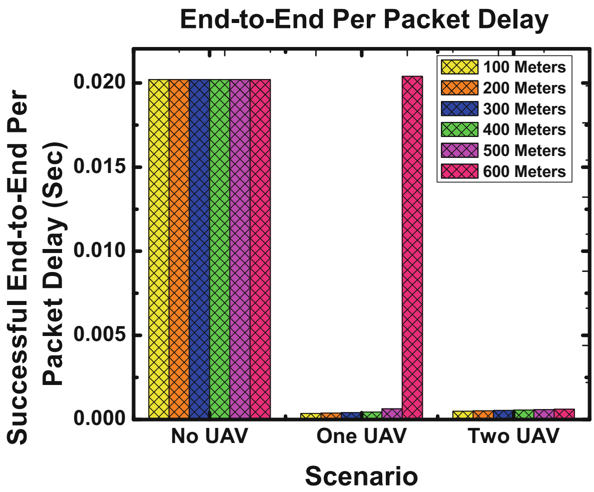


Fig. 7 End-to-End Per successful packet delay

From the plot, it is observed that No UAV case has the highest successful per packet end-to-end delay compared to one UAV and Two UAV cases for all pit depths. Though the hops in case 2 (one UAV) and case 3 (two UAVs) are more compared to case 1 (no UAV), the delay for each successful packet transmission is less. Hence, the proposed communication framework ensures the quality of experience (QoE) to the end users.

Considering the channel characteristics of open pit mine, it is learned from the path loss that the channel quality for case 1 (No UAV) is severely attenuated. Hence, such link will affect the communication between user to BS and vice versa. Therefore, an analysis of number of retransmission per hop and end-to-end number of retransmission for each use case is also performed. Plots for both assumptions are shown in Figs. 8 and 9 for number of retransmission per hop and end-to-end retransmission per packet respectively.

It was observed that for each single packet the total number of retransmission required in case of no UAV is 61; whereas it is reduced to only 1 after consideration of one UAV in the proposed framework. The same was noticed in the case of two UAVs. The end-to-end retransmission per packet for different pit depths can be seen in Fig. 9. It is observed from the plot that the number of retransmission is significantly reduced in the case of UAV based communication infrastructure. The rest of the observations were the same as of end-to-end PER and delay.

6 Conclusion

In this chapter, different potential application of UAVs in opencast mines is formulated and discussed in detail. Considering the future utilization of UAVs

Fig. 8 Number of retransmission per packet in each case

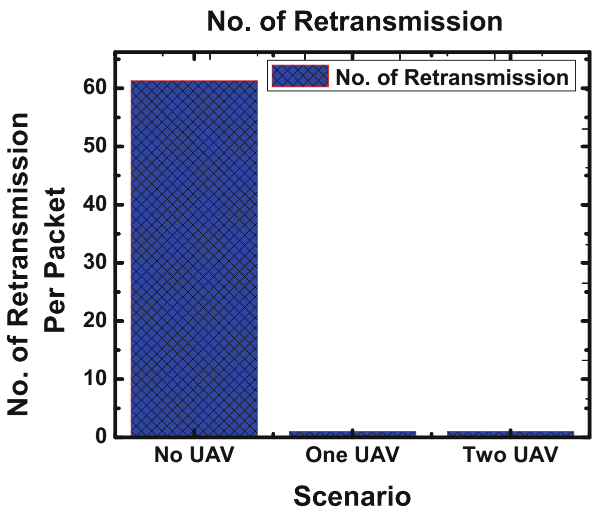
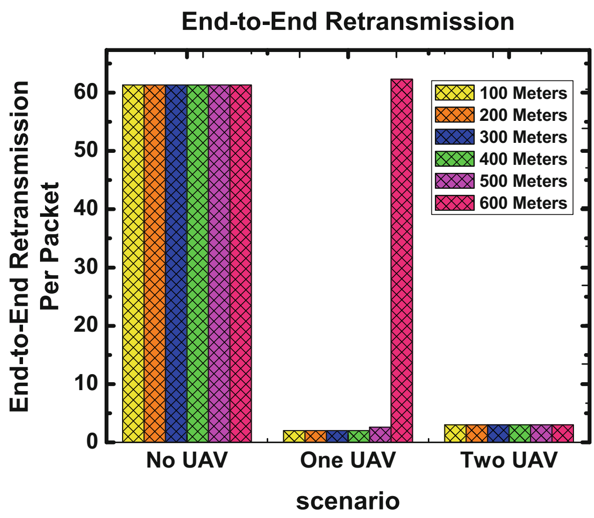


Fig. 9 End-to-End retransmission per packet



in both routine to an emergency scenario in mines, a basic communication, and networking architecture is also proposed. In addition, the scope for UAV based wireless emergency communication framework in deep opencast mines is proposed. As a proof of concept, detailed performance evaluation of the proposed novel communication framework named SkyHelp is carried out. Different performance metrics for this objective is considered such as end-to-end PER, end-to-end delay, and per packet retransmission. It is shown that UAV serves as a useful tool during an emergency scenario and fills the coverage gap when there is no communication infrastructure. From the detailed analysis, it is found that the proposed novel framework significantly improves the wireless communication services during an emergency. It is believed that the proposed framework could be very useful to provide a speedy rescue operation and may serve as a reporting agent in case of any mishaps. As a future work, we intend to perform real-time measurements and channel modeling for UAV based wireless communication and monitoring in operational open pit mines. We believe that the findings and challenges discussed in this chapter could be utilized in advancing the future research in this application category.

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UAV and Fog Computing for IoE-Based Systems: A Case Study on Environment Disasters Prediction and Recovery Plans

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1 Introduction

With the rapid increase of population in cities and the continuous movement of people from rural areas to the cities, the challenges for city's administrators who are striving to maintain or enhance the city's services and the citizens quality of life (QoL) [1] increase. This push the community to adopt and invest in new technologies to help city's administrators to not only control the city, but also to provide reliable, sustainable and high quality of services to the citizens. This results in adopting various types of embedded systems that rely on sensors, actuators, drones, machine learning technologies and different type of data processing mediums (e.g., fog and edge computing) to create intelligent and powerful internet systems, introducing the so- called internet of everything (IoE) [2, 3], hence bringing the concept the smart city (SC) as everything becomes connected and able to exchange data [1, 4]. IoE and SC technologies are rapidly becoming interested in utilising the advanced information and communication technologies (ICT), such as robotics and unmanned aerial vehicles (UAVs) [2] in order to provide convenient services. The goal of SC is to provide efficient infrastructures and services that satisfy citizens' needs, whilst reducing costs. The European Network of Living Labs and EPIC (i.e., European Platform for Intelligent Cities) defined the SC as "The use of discrete new technology applications such as RFID and Internet of Things through more holistic conception of intelligent, integrated working that is closely linked to the concept of living and user generated services" [1, 5].

ICT aims at developing efficient infrastructures that involve dynamic monitoring and adjustments to the infrastructures to handle sudden occasions, such

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_8

as environmental disasters and hazards. Environmental disasters are events that cannot be prevented [6]. The physical extent of the disaster makes it very hard and in some cases completely impossible for humans to react to it and face the problem [7]. In addition, after a disaster occurrence, it is usual that most of the communication infrastructures were collapsed due to the damage created by the disaster to the infrastructure [6], such as communication antennas, control stations, power resources, etc. Nevertheless, some systems such as natural disaster management systems can be used to forecast that neutral disaster is approaching. Hence, their effects can be mitigated by adopting proper early warning systems and post-disaster recovery plans, thus aiding the communication systems that are essential to support disaster management systems. Therefore, the ICT recent trend is about adopting the use of UAV and fog computing as a data processing medium for disasters management.

UAVs can be adopted for both pre and post disaster systems processes. The UAVs are able to aid the pre disaster processes by providing a real-time data from the sky about any environmental changes that could lead to a disaster or forecasting that a disaster is approaching [1, 8]. UAVs can fly over certain areas in a given time-period and with a given update-frequency to monitor and assist in disaster prediction and taking actions when it occurs [5, 9]. Also, in post disaster situations, UAVs can assist rescue teams to find vulnerable people or maintain connectivity with vulnerable people and direct them to safe areas and evacuation routes based on the information gathered when disaster is progressing.

Fog computing also can be adopted for both pre and post disaster system processes. Fog computing is used to gather and process data gathered from wireless sensors network (WSN) in the pre disaster period. Fog nodes can be disrupted over the city and form a mesh network to process WSN data in real time and report back to control stations [10, 11]. Fog node can be deployed with some machine learning algorithms to act upon, and learn from, the data collected from WSN. Hence, fog nodes will be able to make intelligent and powerful networked systems for natural disaster forecasting [1, 12]. Although fog nodes can be very useful for pre disaster system processes, they are least effective/important in post-disaster processes as they might be collapsed/damaged by the disaster. However, they might able to indicate that a particular area might be affected.

This chapter highlights the importance of UAVs and fog in serving natural disaster management systems. UAVs can work independently or in collaboration with fog nodes in the monitoring processing by involving the cameras and WSN to collect and analyse huge amounts of data in real time. Fog nodes assist the UAVs in processing data due to UAVs on-board micro-processors limited capacities. The remainder of this chapter is organised as follows: Sect. 2 provides an overview of the disaster management related technologies of IoE, UAVs and fog computing. Section 3 addresses the general technical connectivity of deploying both UAVs and fog nodes for disaster management. Section 4 presents the stages of a natural disaster along with the use of UAVs and fog nodes in disaster monitoring, early warning and planning search and rescue missions. Finally, Sect. 5 concludes this chapter.

2 Background

Smart cities (SC) are cities that adopt and invest in smart solutions and recent technologies to improve the quality of life (QoL) for the citizens. SC vision is not only to enhance the QoL by creating efficiency, improve sustainability, servicing needs and better utilising resources, but also to reduce the negative impact on the environment [1] by early warning for natural disasters. The SC concept integrates information and communication technology (ICT), and various physical devices connected to the network to optimise the efficiency of SC operations/services and make the citizens connected [4, 13]. SC technologies allow infinite control for administrators and services to interact directly with both community and infrastructure to monitor what is happening in the surrounding community/environment as well as managing urban flows and allow real-time responses [4]. Therefore, SC could be more prepared to respond to challenges (e.g., disasters) than normal cites with a simple traditional relationship with its citizens, community and environment [14]. Important properties of SC systems and applications are the robustness, resource efficiency, being adaptable and cooperativeness. Thus, SC systems bring together the power of internet of everything (IoE), unmanned aerial vehicles (UAVs) and fog computing to serve public needs and improve the QoL.

2.1 Internet of Everything

Internet of everything (IoE) is the network of physical devices which is able to establish connections among each other and exchange data. In IoE area, the concept of $Everything$ refers to anything able to connect to the Internet and exchange data over this IoE network, thus, this could point to a diversity of devices (e.g., wearable), vehicles (e.g. smart cars), smart home appliances (e.g., smart appliances), and so forth.

Cisco IBSG estimated that approximately 50 billion sensors will be connected to the IoE as soon as 2020 [10, 15]. According to IBM, currently we are creating 2.5 Quintillion bytes of data every day through different sensing devices [16] worldwide. International Data Corporation predicts that from 2005 to 2020, the digital universe will grow from 130 exabytes to 40,000 exabytes, or 40 trillion gigabytes (i.e., more than 5200 gigabytes for every human on earth in 2020) [16]. It is clear that we are entering the era of "Big Data" which is accelerated by unmanned aerial vehicle (UAV) which feeds the network with heavy-weighted data packets from its on-board camera [10, 11, 17]. UAV's emerging technology becomes widely accepted for video surveillance applications/systems due to its abilities in monitoring a target from the sky using the on-board cameras and sensors to collect huge amounts of data in real time and transmit them to ground stations.

Information and communication technology (ICT) is continuously enhancing its infrastructure to provide appropriate data processing mediums to serve the massive data generated by the IoE. Thus, providing secure transformation channels, rapid processing and proper use of data. ICT-based operation models that organisations adopt have been swinging from centralisation (e.g., mainframe) to decentralisation (e.g., client–server) and vice versa. The latest swing towards centralisation embraces *Cloud* computing by making software, platform and infrastructure available to organisations as services (i.e., anything-as-a-services) or utility in return for a fee. However, research has proven that cloud may not be a feasible solution for IoE data due to several factors such as high latency [18], network bandwidth, reliability and security [18, 19]. A new swing rises toward the adoption of *fog* computing, hence developing the ICT to become the future trends, thus, attracting the Research and Development (R&D) community.

IoE-based systems bring together the power of embedded smart things (e.g., sensors and actuators) and flying-things (e.g., UAVs) along with the data processing mediums (e.g., fog and edge computing) to create intelligent and powerful networked systems.

2.2 Unmanned Aerial Vehicle (UAV)

The continuous development of robotics resulted in serious enhancements to the design and capabilities of UAVs. In varying sized inexpensive UAVs equipped with microprocessors, local data storage as well as on-board sensors, actuators and cameras. In addition, most UAVs are supported with a wireless communication device that enables UAVs to establish various types of connections with either other UAVs or ground controllers. UAVs are reliable and operate with high level of flight stability, unlike a few years ago when UAVs could lose communication or lose sustainability which leads to UAVs overturning. UAVs were mainly developed for military applications, but also numerous civil applications have recently emerged and contributed in improving UAV capabilities in a more cost-effective manner [1]. The on-board UAVs system is usually able to offer various types of services ranging from sensing and navigation to data gathering and processing besides the transformation of these data to ground stations. UAVs also called drones have received increasing interest for environmental and natural disaster monitoring [20], border surveillance, emergency assistance, search and rescue missions, and relay communications [1, 20]. UAVs are useful, especially small multi-copters, in monitoring practices due to their ease of deployment and low acquisition and maintenance costs [20].

The incredible advancement in developing small and cheap UAVs has resulted in having the UAVs deployed and adopted in different industries, also their reliability and efficiency makes it more acceptable for the public. The typical architecture of a UAV consists of number of inter-connected components and sub-systems that allow UAVs to operate to such high performance. The main systems and components are flying control systems including landing processes, communication control system, monitoring system, sensors, actuators and data processing system.

Table 1 Most common technologies used in UAVs networking [9]

Technology	Type	Available at
VHF, UHF	915 MHz (UHF)	[24]
IEEE 802.11 (Wi-Fi)	IEEE 802.11a	[25]
	IEEE 802.11b	[26, 27]
GPRS, 3 G, LTE		[28–30]
Satellite		[30, 31]
Airmax		[32]

There are two main types of UAVs, the types are identified by the actual architecture of the UAV, it can be either fixed-wing UAVs architecture or rotary-wing UAVs architecture [21]. Fixed-wing UAVs are airplane-like vehicles. These UAVs perform horizontal takeoff-and-landing operations, such as passenger airplanes, while the rotary-wing UAVs perform vertical takeoff-and-landing. Hence, they can hover on a specific location during the flight, this feature is especially important for surveillance UAVs. Some UAVs that are generally formed as wireless ad-hoc network are called aerial ad-hoc networks (AANETs) [22, 23]. AANET vehicles have the ability to move at high speed or, on the contrary, to maintain specific positions when it is needed [9], this type can be found in helicopter-like architecture. Moreover, UAVs make advantage of the fact that air-to-air communications usually are less affected by disruptions than ground-to-ground communication links [9].

Different technologies have been used for communications within the UAV networks to establish sustainable communication among UAVs or between a UAV and base stations. Table 1 presents some of the most common technologies used in UAVs. It is worth noting that several UAVs development do not rely on only one technology but multiple ones are adopted. This is extremely important for UAVs to have backup plan when one UAV system is not available due to failures. Thus, there is still the possibility to use an alternative one for the connection with the other UAVs or ground station. The IEEE 802.11 is always the main choice for designing UAVs networks due to its massive use in commercial wireless devices as it can offer high bandwidth [9]. However, IEEE 802.1 technology would only support star or multi-star topologies. Other technologies would be required to implement the ideal case of hierarchical or flat mesh networks [9, 33].

2.3 Fog Computing

Smart city system applications rely mostly on data provided from sensors, actuators and other wireless devices. These applications and systems are normally integrated with a cloud-based data centre to perform the required processing and analysis of the data for various purposes. Cloud-based approach is adopted for long term now and it is good enough for data storage, powerful processing and advanced services. However, with the emerge of IoE and UAVs the generated data every second becomes much bigger than it used to be, hence a greater demand on developing and new data processing mediums becomes essential. Nevertheless, integrating IoE applications with the cloud has many restrictions as the cloud cannot deal with the essential characteristics and requirements of IoE applications such as highly heterogeneous devices, mobility, low-latency responses, location and context awareness [1, 10]. Fog computing was proposed by CISCO [10, 17] to overcome these restrictions.

Fog computing can improve the cloud computing paradigm by offering smaller platforms located at the network edges closer to the IoE devices and networks. Fog computing offers the ability to extend the storage, networking and computing capabilities of the cloud but with better positioning within the network in relation to the end-devices, such as IoE smart objects, that require this data with low latency [10, 17]. Fog computing is not a replacement to cloud, but only extends the services to the edge of the network with the ability to reduce latency and improve availability to the end-users. Using fog computing, an application in a certain area can utilise an architecture that uses a dedicated computer available locally. This provides access to computing and storage services at a smaller scale, but very close to the application, thus reducing response times and providing localised services. As a result, access to cloud services can be minimised, yet efficiently accessible when needed [1, 10].

A new paradigm of UAV-based fog computing was introduced recently [12]. This paradigm brings together the power and advantages of fog computing and UAVs to better support IoE systems and applications by utilising UAVs services along with the support of fog nodes services to achieve certain tasks forming UAV-Fog networks. UAV-Fog computing can provide flexibility, mobility and fast deployment features to support IoE systems in a smart city. UAV-Fog can be used for different purposes, such as disaster management systems. For example, in disaster situations, UAV-Fog can be deployed to support search and rescue operations.

3 UAV-Fog Collaboration and Coordination

This section of the chapter discusses the network between UAVs and fog nodes, including both collaboration and coordination modes for the networked UAVs and fog nodes, see Fig. 1. Simply put, the horizontal networking among UAVs (e.g., UAV-2-UAV) or fog nodes (e.g., $\mathscr{F}$og-2-$\mathscr{F}$og) is a collaboration mode. This collaboration mode triggers when two or more networked objects (i.e., UAV or fog) are networked to serve one user or works toward achieving one task. For example, two UAVs monitor the two sides of a long-bridge and report to each other upon hazard detection to take action like informing the rescue team or closing down a bridge, while the vertical networking among UAVs and fog nodes (e.g., UAV-2-fog or fog-2-UAV) is a coordination mode. This coordination mode triggers when a UAV networks with a fog node or vice versa. Such mode occurs when a process needs to be carried out over several steps. For example, due to the limited processing capabilities of the UAVs, they will not be able to process live images taken by its

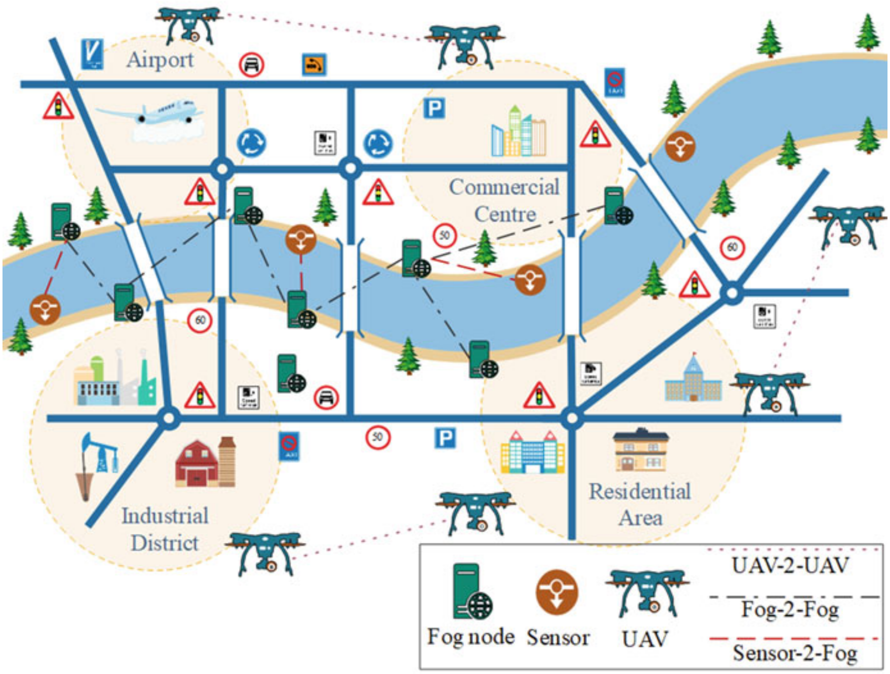

Fig. 1 Smart City with UAVs and Fog computing

on-board camera, therefore, fog will help in performing image processing for these images and report back to the UAV.

3.1 Collaborative UAVs

The minimal design requirement of any UAV must include a micro-controller and wireless transceivers [34]. UAVs are equipped with a micro-controller to process received commands and allow to be externally controlled via remote controller where desired. In addition, the wireless transceivers are embedded in UAVs to allow UAVs communication among themselves and with other objects on the ground, such as fog nodes. When two or more UAVs are communicating among each other to achieve one task, they are forming a so-called UAV ad-hoc network. The advances in ad-hoc communication paradigm among UAVs suit the main requirements of UAV systems, which are: (1) node mobility and (2) adaptive network topology. The ad-hoc network allows data packets to be shared among networked UAVs with no delay (i.e., in real time) [34–36]. Thus, the shared data packets are routed through the networked UAVs with a path taken depending on the used routing protocol. According to [34, 37], there are two main routing protocols, proactive routing protocol and reactive routing protocol. In proactive routing, the networked UAVs know the shortest network path to each other. Thus, the shortest data is logged locally and updated frequently upon UAVs location updates. Hence, due to the big amount of packets transmitted over the network regularly to maintain connectivity, the overall available network bandwidth will be reduced. In reactive routing, the shortest paths need to be known only when data packets need to be sent among UAVs. Thus, reactive routing requires more time compared to proactive routing that knows paths ahead of time which allows a low end-to-end time delay for sending data packets. Therefore, when choosing a routing protocol, a trade-off must be made between time-delay and available bandwidth.

Most systems that adopt UAVs technologies are notable with their rapid changes in either the network topology and/or the networking connectives, hence, UAVs are adopted based on their abilities to operate in a highly dynamic environment [8]. For example, as most UAVs are self-programmed during the time of operation, some mission conditions may change for various reasons, such as weather condition changes that may affect UAV connectivity, and thus it requires the UAV to act accordingly. In such a scenario, if a UAV has no opportunity to establish an ad-hoc network with other UAVs to regain signal to complete the initial mission or return to ground, the UAV will be highly unreliable [38]. Therefore, the adoption of the ad-hoc network in UAV systems will feature the connectivity among UAVs, and hence enhances the reliability of the UAVs [38]. In addition, UAVs battery life is another important reason where the collaboration among UAVs is important. Networked UAVs could help in reducing the drawback of UAV limited time of operation by triggering the UAV to outsource the processes to another UAV before it goes offline. The majority of UAVs have about 20–30 min of flight time [39], and the way to extend network lifetime is by alternating network responsibilities among UAVs through the ad-hoc network.

Due to the ad-hoc nature of UAVs, the topology of the network may change over time. Also, UAVs consist of different types of UAVs organised in different hierarchies [8, 9]. Such that, a sub-group of UAVs may only be equipped for long-range communication services in order to communicate with external networks, while another sub-group of UAVs maybe designed for sensing and monitoring tasks only [40], hence carrying some specific sensors and cameras. Each group would share the data packets with their equal UAVs within the group, but they also can send the information to other sup-group when required [9]. This flexibility, in terms of topology and hierarchy, allows UAVs to adapt to a variety of system's needs. The most common wireless technology used for UAV-2-UAV communication is the IEEE 802.11 standards, while IEEE 802.115.4 is used for other UAV communications with other connected objects [9].

3.2 Collaborative Fogs Computing

This section discusses the network model that supports $\mathscr{F}$og-2-$\mathscr{F}$og collaboration. The collaboration between fog nodes is about gathering multiple fog nodes to perform/achieve a specific task in a certain situation or scenario. Fog computing becomes members of a federation because of their capabilities that satisfy the needs and requirements of a situation assigned to this federation for handling. Hence, fogs are described and discovered for federation and then selected for a particular federation according to *planned* and *ad-hoc* federations [41].

- Planned federation, formed at design-time, all its fog nodes participants are already identified and ready to act according to a task's needs and requirements.
- Ad-hoc federation, formed at run-time, fogs are joined together according to certain occasions where each fog can empower the federation with various types of processing and controls that enhance.

Consider a scenario where a fog node accepts a data-processing request from a UAV. Fog will process the request and respond back to the UAV in real time. However, when the fog node is busy processing other UAV's requests, it may only be able to process part of the payload and offload the remaining parts or offload the whole request to other fog nodes. Therefore, either *planned* or *ad-hoc* should be supported by the fog so it can collaborate with the other fog nodes in the network to serve the request sent from the UAV. Hence, there are two approaches to model interactions among fog nodes. (1) the centralised model, which relies on a central node that controls the interactions among the fog nodes in one domain. (2) the decentralised model, which relies on a universal protocol that allows direct interactions among fog nodes so that each fog identifies the best fog node to collaborate with. In the decentralised fog model, the fogs are distributed as a mesh network, hence there is no need for a centralised fog node to share the state of fog nodes and its location. Instead, each fog node runs a protocol to distribute their updated state (e.g., load and location) information with the neighbouring nodes. Thereafter, each fog node will hold a list of best fog nodes which can be updated periodically. The decentralised model is more suitable for scenarios where a UAV system is in operation as fog node can cope with the mobility of UAVs, hence more flexibility in data acquisition. The process of selecting and sorting the best neighbouring fog nodes is based on the possibilities of collaboration between the fog nodes and able to provide data processing with low latency and high reliability. More details on such $\mathscr{F}$og-2-$\mathscr{F}$og collaboration can be found in [10].

3.3 Coordination of UAV and fog

Integrating UAVs with the fog computing paradigm can boost the reliability of service times and availability, thus enabling many applications to have advanced services utilisation in smart cities. Fog computing can provide powerful services for the operations of the UAVs. For example, using a fog-based system to process and analyse the image taken by the UAV camera in real time [42, 43].

Having the coordination between UAVs and fog nodes is extremely important when it comes to the systems where large amount of data is collected every millisecond. The coordination of UAV and fog nodes is useful for rapid data processing, thus fog nodes will act as external processing unit for the data captured by UAV, such as sensed data or regular stream of live images. This huge amount of data will require immediate processing before its importance vanishes. Moreover, sensed data is generally have different types and can be collected in different time-interval, such as images or sensors data streams at defined time intervals, critical location data, and mission's commands. Hence, UAVs on-board processors are not powerful enough to cope with all these data types especially when it comes to systems where real-time data processing is essential for decision making [1]. Therefore, the coordination of UAV and fog is especially important in the dissemination of critical data. Important events should be transmitted reliably at all costs. Therefore, the aim is to achieve low latency, high reliability, and a high success ratio of data delivery in UAVs and fog nodes data routing in mission-critical applications, such as disaster prediction systems.

Effective coordination among UAVs and fog nodes relies on timely information sharing. However, the time varying flight environment and the intermittent link connectivity pose great challenges to message delivery. The main objective of UAVs and fog coordination is threefold:

- System latency: The objective of the coordination networking among UAVs and fog nodes is to minimise latency from timely sensitive application, such as disaster hazard monitoring systems where the time between the hazard detection and the delivery of message to rescue team is very critical.
- System reliability: This is about the success ratio of data packets delivery.

  In UAV-Fog packets delivery, the minimal packets losses and faster sharing-time, the higher is the reliability. Therefore, in the scenario of disaster systems, providing reliable communication for critical data is essential to ensure that the sensed data is being transmitted to the desired destination successfully.
- System self-adaption: The networking protocols should be able to deal with the mobility of UAVs. Hence, UAVs must always maintain a good connectivity with the nearest fog nodes to transmit its data. It is worth noting that this process could be an energy-intensive process.

During UAVs time of operation, the weather condition may change and some of the UAVs may be disconnected. If the ad-hoc UAV system cannot support this scenario, it can maintain the connectivity through fog computing. This connectivity feature enhances the reliability of the UAVs system. Therefore, in a UAV-Fog network all UAVs will be connected to a ground fog node via wireless communication.

To provide robust UAV network control and information acquisition, emphasis must be placed on communication security. Malicious attacks are closely related to UAV network operation, so robust communication protocols play a critical role.

The coordination between UAVs and fog nodes also helps in ensuring privacy and trust within the UAVs systems by monitoring all the privacy policy for the shared data. For example, video footage that is recorded by a UAV during the disaster response may contain sensitive frames (e.g., dead or wounded people) that should be censored [44]. Indeed, this will raise a number of important questions about the information privacy and trust when using UAVs to gather multimedia information (e.g., live images) about the people who affected by a natural disaster [44]. Thus, fog nodes could have the abilities to run extensive image processing to determine whether the shared images may breach any privacy policies.

4 UAV-Fog for Environment Disasters Management

Natural disasters occur frequently worldwide and they are considered as a factor that affects human life and development [7]. Natural disasters are significant adverse incidents resulting from some natural processes of the earth (e.g., earthquakes and floods) or geological processes (e.g., volcano) [45]. A natural disaster can severely impact the environment and people's lives and infrastructures [46], such as telecommunication systems. This raises big challenges to traditional disaster monitoring systems and makes the rescue actions harder to achieve and sometimes ineffective. However, natural disaster severity highly depends on the affected population's resilience (i.e., the ability to recover) as well as the infrastructure available to handle such events.

In natural disasters, such as flood, the rescue and emergency response management is very challenging. Hence, early efforts in event/circumstances monitoring, analysis, rescue operations and emergency arrangements are extremely important [1]. In most of these state of affairs, rescue teams cannot easily and quickly enough reach vulnerable people and also most of the infrastructures, such as communication systems, may be damaged because of the impact of the disasters [47]. Thus proper management and early actions are significantly required for such circumstances.

Utilising UAVs and fog computing can effectively improve the disaster monitoring/prediction in such circumstances of a natural disaster [1, 48, 49]. Fog computing and UAVs can be used as flexible and reliable networking infrastructure for data sharing and monitoring the situation in real time. In addition, they are very safe tools for monitoring the current situation without risking human lives dealing with the disaster.

4.1 Disaster Management Stages

It is important to understand the nature of a disaster and its stages to effectively respond to them and to develop a feasible disaster management and prediction

Fig. 2 Natural disaster stages

method. The disaster stages concept has been used in the past decades to describe and examine disasters and to organise emergency management processes [7]. The continuous process of disaster management known as disaster management cycle [7, 50] is the most common stage of a disaster management cycle shown in Fig. 2, thus they cover the following processes [51]:

- Predicting and planning before a disaster can happen. The goal is to minimise the effects of a disaster by giving early warning and identifying risk zones. Also, planning and preparedness on how to respond to a disaster.
- Rescue operations and response to emergencies when a disaster happens. The goal is to minimise the hazards formed by a disaster.
- Recovering after the disaster. The goal is to assess the damages created by a disaster. Also, acquire some knowledge that can be used to prepare and evaluate a prediction model for such disasters.

Response time to disaster hazard during a natural disaster is key in saving human lives, especially those who live/work in the affected areas. UAV-Fog can assist disaster management processes, thus they can improve the processes of acquiring real-time data from the environment, through the embedded environmental sensors connected to the fog nodes, or data from the sky, through the sensors and camera connected to the UAVs. UAV-Fog can assist with the following processes of a disaster management:

1. Disasters monitoring, preparedness and early warning.
2. Situational awareness, logistics, and evacuation.
3. Search and rescue missions

Each disaster management process imposes a set of UAVs and fog nodes tasks. Each task may require different lengths of time and with varying priority levels [44]. Therefore, a static network of fog nodes and UAVs is no longer sustainable for disaster management processes. Instead, the network must continuously evolve in topology and capability, having reasonable capabilities of networking coordination between UAVs and Fog nodes as well as collaboration features among them (i.e., UAV-2-UAV and $\mathscr{F}$og-2-$\mathscr{F}$og), so they can be self-adapted with situations, when a disaster is progressing.

4.2 Disasters Monitoring, Preparedness and Early Warning

At this stage of disaster management processes, the UAVs and fog systems are classified into three main groups: monitoring, preparedness and early warning systems. This classification follows the disaster management phases, where the forecast group of systems refers to the prevention, preparedness and rescue operations for a natural disaster. The prevention covers the monitoring of a disaster through all stages as UAV-Fog system will provide disaster information during all the phases, while the preparedness includes all procedures required for how to deal with a disaster hazard, and the rescue operations refer to a disaster response and recovery.

4.2.1 Disasters Monitoring

The UAVs technologies and advanced wireless sensor network (WSN) technology that often used with fog computing have recently gain more attention and improvement, thus it is being used for many disaster management systems, especially in disaster monitoring systems.

Some disaster monitoring systems require the WSN sensed data to be transmitted in real time to a control station through a multi-fog communication. For example, when a hazard detected by a sensor, such as a flood sensor, the fog nodes should be able to acquire this data from sensors in real time and transmitted straight to the disasters control station (either fog-2-station or multi-fog-2-station) where admins/operators can make decisions and arrangements. However, some disaster monitoring systems are delay tolerant and do not require the WSN sensed data to be transferred to the desired destination in real time. These types of systems normally collect the data for historical data archiving and disasters pattern creation/recognition. For example, systems that monitor infrastructure-health and environmental changes. In such scenarios, UAVs and fog computing can be used as data collectors from these distributed sensors to transfer them to the main stations [1, 52, 53] when they are not busy with higher priority tasks that require real-time/instant attention. In flood disaster scenarios, multiple deployed WSN collect physical information, such as the water level at the monitored bank and vibration/displacement on the territory. Thereafter, the data gets transmitted to connected fog nodes, where the information is logged and processed.

In disaster monitoring events, the objective is to monitor certain areas in a given time-period and with a given update-frequency to assist rescue reams and operations. Hence, the UAVs establish communication links among UAVs and links with other higher level networks (e.g., fog nodes) and ground base stations. Some research to enhance communication links among UAVs, UAVs and WAS and/or fog can be found in nodes [1, 54, 55]. Thus, it is common to find UAVs-to-ground communication links in order to transmit data from the UAVs for fog nodes and/or ground stations. The UAVs can pass over WSN and wirelessly collect their sensed data. Thus, this way they can save the WSN energy by reducing the communications and extend the battery life of WSN [1, 56]. Although the UAVs are efficient for monitoring purposes and situational awareness, there are different regulations that apply to the usage of UAVs, depending on the country [44]. However, during a disaster, special authorisations are granted to UAVs to help first disasters monitoring and assessing the situation [44].

4.2.2 Preparedness and Early Warning

The preparedness processes for a disaster have no predefined duration and could start before or within the actual occurrence of a disaster. During the preparedness stage, the data acquisition from WSN is normally used by the connected fog nodes to perform some processing and analysis to assess the probability of disaster occurrences, thus, using UAVs as source of live data from the sky, such as live images. UAVs have limited use at this stage as the processes during this stage is more like identifying the suitable methods to achieve the minimal effects of a natural disaster, including the rescue operations required to elevate the hazards caused by a disaster. However, the WSN could have the most use for ground-based environment measurements, because the operational time of WSN can be sufficient to capture the different trends in the sensed environment natural parameters that could help for disaster early warning.

Early warning systems (EWS) represent the essential part of the preparedness towards natural disasters [7], hence, there are lots of efforts focused on developing an efficient EWS. For example, the UrbanFlood[1] is a European project that aims to investigate the use of sensors within flood embankments to support an online EWS, and real-time emergency management. EWS uses the data from both UAVs and fog's connected WSN to predict and forecast a natural disaster by processing and analysing the structural and environmental monitored data. Hence, the goal of most EWS is to create a connected service's platform that can be used to link WSN data with predictive models and emergency warning systems. Thus, the warnings and information produced by these platforms can be accessible by all people within an area that in a high-risk of a threaten natural disaster attack.

[1] http://www.urbanflood.eu/.

4.3 Situational Awareness, Logistics and Evacuation

The start of this stage occurs as soon as a disaster takes place in which parts of the environment and topographical region are damaged and become unusable for vehicular traffic or people habitation. The employment of UAVs and fog computing at this stage can be useful in reporting real-time data from the area affected by a hazard. The critical tasks carried by the UAVs during this stage involves the process of establishing ground communication processes with the affected people, then transferring the gathers data to the control station and/or rescue team raise awareness about vulnerable people. This monitoring processes at this time of the disaster will help in assessing the situation as UAVs and fog nodes are able to provide a real-time data for the surrounding that can help in accurate assessment of the situation/hazard. For example, the UAVs fly over an affected region by a flood and send live images to the rescue teams about any possible vulnerable people as per Fig. 1.

4.3.1 Situational Awareness

Situational awareness is part of the disaster management processes where the main goal is to gather enough information when a disaster is progressing. Gathered data will significantly help in providing safe and secure recommendations to the vulnerable people who are endangered from the disaster, as well as the rescue teams deployed on the disaster area [39]. Both UAVs and fog connected WSN can be used during this stage to transfer information about the affected areas as well as the vulnerable people. Although, some fog nodes and their connected WSN may also be affected by a disaster, they still used as indication that particular area might be affected by a disaster in which caused the damage for the planted fog nodes and WSN. The fog nodes and it connected WSN infrastructure that is partially in operational can be used in conjunction with the operated UAVs. Hence, video/images collected present an overview of the situation. Also, affected people might also use various social-media or forward messages and/or images via the UAVs observing them, to the rescue team or control centre so they can get help.

4.3.2 Logistics and Evacuation

UAVs could have more advantages during the logistics and evacuation processes compared to fog nodes and WSN. The UAVs can be significantly useful due to their ability of movement and flying to a targeted area. UAVs can be used for delivering first-aid equipment in very convenient way for all areas that are hard or not accessible due to the infrastructure damages caused by a disaster, also rural areas that are surrounded by forests. This will be significantly crucial to deliver the logistical services which are delay-sensitive [9] and it is important to deliver to affected people as soon as possible, such as delivering medication or medical resources. In addition, UAVs can maintain connectivity with vulnerable people and direct them to safe areas and evacuation routes based on the information gathered during the disaster progression.

4.4 Search and Rescue Missions

The main goal of search and rescue (SAR) missions is to search for and to rescue the unfortunate people that happen to be lost, trapped by debris or injured during a natural disaster. The first 72 h after a disaster is the most critical [7, 39, 44] as SAR operations are on its peak where the rescue teams need to safely find the survivors in disaster situations as well as give them right assistance. Hence, the goal of SAR is to help in taking quick actions to preserve people's lives.

To increase the effectiveness of SAR missions and rescue teams, different technologies must be used at the same time, such as WSN, social networks, autonomous UAVs, data processing mediums (e.g., fog nodes) and satellite observations [7]. Therefore, UAVs and fogs can be used to help in SAR operations significantly as they are able to provide instant and real-time data about the surrounding environment. UAV and fog connected WSN are used in disaster situations where continuous updates are needed or where rescue teams cannot reach easily and/or safely to the target area due to debris or other obstructions. UAVs provide a great surveillance tool as it can fly over the targeted area and relay information, such as capturing images and video for a specific target, back to the rescue workers to keep them updated. In such event, UAVs network must maintain both connection and throughput between individual UAVs within the network and the ground station or the fog nodes forming the UAV-2-UAV, UAV-2-station and/or UAV-2-fog. However, the videos or images footage collected by UAVs are different substantially from images acquired on the ground [57], therefore, such aspect should be taken into account when designing the image processing algorithm for the UAVs use for SAR missions.

5 Conclusions

Smart cities (SC) adopt and invest in smart solutions and recent technologies, such as UAVs and fog computing, to improve the quality of life for the citizens. SC main goal is to enhance the QoL by creating efficiency, improve sustainability, better services utilisation as well as reducing the negative impacts on the environment, such as early warning systems for natural disasters. UAV and fog computing have been introduced recently to bring together the power and advantages of fog computing and UAVs to better support IoE systems and application by utilising UAV services along with the support of fog nodes services. UAV-Fog computing can provide flexibility, mobility, and fast deployment features to support IoE systems in smart cities. Also, UAV-Fog has significant advantages for disaster management systems as it helps in disaster situations to deploy services supports for all pre-disaster monitoring, forecasting and all search and rescue operations. During disasters, UAVs fly over affected regions to collect live images and videos to help in assessing the situation and relay to the rescue teams about any possible vulnerable people. UAV in conjunction with fog computing presents a promising future technology for disaster management systems.

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Drone of IoT in 6G Wireless Communications: Technology, Challenges, and Future Aspects

B. D. Deebak and Fadi Al-Turjman

1 Introduction

Drone of Internet of Things (D-IoT) is known to design a layered network framework that mainly accesses the coordinates of unmanned aerial vehicles (UAVs) not only to operate the airspace but also to offer the navigation services. D-IoT extends its services for various application domains such as search and rescue operation, aerial surveillance, traffic, and environment monitoring [1]. From aeriform navigation to discover–rescue operation to deliver the legal transfers, the UAVs are highly exploded. According to the Federal Aviation Administration (FAA) report, the drone fleets is expected to be 2.4 million units in 2022 [2]. Moreover, it is evident that more frameworks will emerge to fuel the growth of the UAVs. Importantly, the frameworks associate with UAVs to telephone networks that ensure superior communication and control mechanism to evolve the business opportunities, i.e., for mobile operators. Of late, third Generation Partnership Project (3GPP) has overseen the standard accomplishments of mobile networks that equip the operator to handle the challenges of UAVs.

This emerging technology has led the world in the development of sixth-generation (6G) network to characterize the key factors of telecommunication infrastructure. It is designed to support more user/device connectivity that highly demands the Internet access to conform the performance standards. In order to extend the influence of business framework, Internet of Things (IoT) emerged. It is aimed to connect more devices to provide the reliable applications such as smart city, smart agriculture, and smart factory. In general, they are involved to sense,

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_9

collect, and analyze the environment data to meet the expectation of business IoT model. Due to design limitation and intrinsic experience, the terrestrial network infrastructure could not guarantee the typical key performance indicators of 6G. Transmission coverage forms a terrestrial infrastructure to build an economical network that offers high technological resilience and quality of experience (QoE). In 6G, UAVs and satellite communication integrate the IoT as a benefit tool to increase the bandwidth utilization.

It is essential to perform a reliable packet delivery activity such as Amazon Prime Air [3], which transforms Boeing's drone into a submarine [4]. IoT can properly equip as an intellectual gateway to collect the sensing data, i.e., from IoT sensors. In 6G, the coverage range authorizes the users to access the data over wireless channel. The user positions and its related mobility may arbitrarily exchange the coverage area to cover data generation, customization, and infrastructure overhead. In addition, IoT has a chance to act as an intermediate node, which is completely depending on payload hardware to provide technological solution. Satellite communication has widely been deployed for the extension of Internet access. Currently, it is deploying to support global connectivity through the act of low Earth orbit (LEO) satellite [5, 6]. In the literature, the introductory studies have exploited the use of satellite communication for IoT devices. They are envisioned to perform data exchange between end users and IoT networks via satellite [6]. It may be connected as an intermediate node to offer dynamic deployment and network connectivity.

1.1 IoT Wireless Technologies

Generally, IoT determines the essential quality of data exchange between devices and sensors over wireless channel, i.e., free from human interference. It is nowadays applied in various industrial environments, namely, smart automation, smart metering, and smart weather forecasting. As from the insight report, it is expected to grow from 23.14 billion in 2018 to 75.44 billion in 2025 [6]. Broadly speaking, IoT technologies are classified into short- and long-range communication.

Table 1 summarizes commercial market solution for short-range and long-range approaches. IoT uses wireless technologies to transmit the data to the broadband gateway residing at physical and data link layer, which encapsulates the application data. As the technologies are highly involved of protocol specification for the broadband connectivity, each network gateway proactively applies the application protocol stack to convert the IoT data. Moreover, it would tactfully enforce the layer conversion to suit the end user applications. Figure 1 shows long-range commercial solution for IoT applications [7]. IoT environment standardizes the commercial market to promote the special groups such as the Third Generation Partnership Project, the European Telecommunications Standards Institute, and the Institute of Electrical and Electronics Engineers. Importantly, the proposed solution addresses the category of low power wide area (LPWA) protocol [8].

Table 1 Summary of short-range and long-range approaches and its related market solution

Wireless specification	Short range			Long range		
	Bluetooth	Zigbee	WiFi	LoRaWAN	SigFox	Ingenu
Modulation method	G-FSK/ D-QPSK/ D-PSK	B-PSK/ O-QPSK	IEEE 802.11 a/b/g	Chirp spread Spectrum	D-BPSK (upload) G-FASK (download)	RPMA DSSS (upload) CDMA (download)
MAC interface	FDMA/ TDMA	CSMA/ CA	CSMA/ CA	Unslotted MAC	Unslotted ALOHA	CDMA-Like
Transmission rate	3 Mbps	250 Kbps	7 Gbps	0.3 – 50 Kbps	100 bps (upload) 600 bps (download)	78 Kbps (upload) 19 Kbps (download)
Network coverage	~30 m	~100 m	~100 m	~5 km (urban) ~15 km (rural)	~10 km (urban) ~50 km (rural)	~15 km (urban)

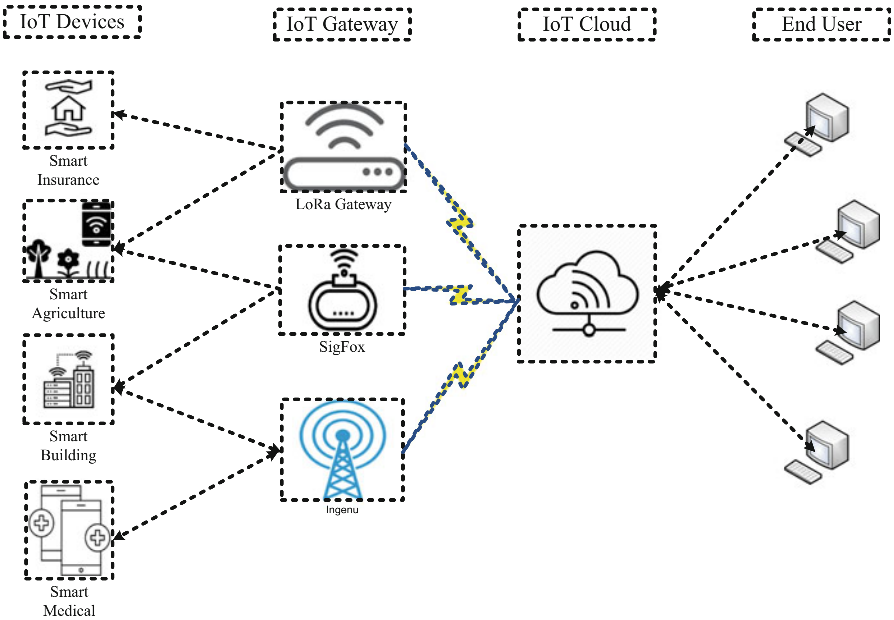

Fig. 1 Long-range commercial solution for IoT applications

It is evident that the commercial IoT applications present the broadband gateway to substitute the activity of cellular base station. The effective communication ensures between the IoT devices to guarantee the business objectives of IoT networks. The application layer relies on end-to-end data exchange [9], which invokes a typical publish–subscribe model to categorize the message pattern. The major message classes are as follows:

1. CoAP is expressed as constrained application protocol, which is put into service for IoT applications standardized by Constrained RESTful Environments, IETF [10, 11].
2. XMPP is defined as eXtensible Messaging and Presence Protocol that makes working for a particular purpose of instant messaging (IM) standard, IETF.
3. MQTT is represented as Messaging Queueing Telemetry Transport (MQTT) that integrates the embedded devices and the communication networks to link through application and middleware.
4. Data Distribution Service (DDS) is an object-oriented group (OOG) to provide a scalable data exchange between the real-time systems [12, 13].
5. AMQP is denoted as Advanced Message Queuing Protocol, which is an open communication standard to provide an effective data transmission between the applications or organizations.

1.2 UAVs with IoT Integration

UAVs are exceptionally growing to develop the market opportunities that highly demand the IoT integration to collect the information services of industrial environment such as public surveillance, air pollution [14, 15], etc. In the future, UAVs known as drone deploy its intellectual standard to meet the objectives of real-time systems, namely, automation, transportation [16], boarder,and homeland security [17, 18]. The UAV case study models are as follows:

Military: UAVs are widely used to provide a search operation in military surveillance. Importantly, they are considered as a weapon tool to destroy the opposition's military base. In 2015, Defense Advanced Research Projects Agency (DARPA) has revealed the growth of systematic approach using low-cost drones [18].

Earthquake and disaster management: The integration of IoT and UAVs is equipped to collect the necessary information, namely, gas level, video, images, etc. The collective information will be helpful to track and aid the visiting area in terms of food delivery and medicament [19].

Crowded surveillance: UAVs allow the security agent to monitor the public area. It is equipped with IoT features to capture the abnormal situation that alerts the agent to interfere physically in order to ensure the public's security and safety [19].

Real-time traffic monitoring: UAVs aviate over a specific location to collect the real-time information that will subsequently be sent to a central server to analyze the data features. Moreover, the relevant data may also be updated to navigate the route mapping, i.e., to the users.

Weather forecasting: The specialized UAVs operate over any specific area to collect the useful information such as temperature, humidity, wind speed, etc.

Moreover, the collective information is transmitted to minimize the computation complexity of weather forecasting.

1.3 UAV and IoT: A State of the Art

An exhaustive research has been carried out for the extensive use of IoT integration. In most of the real-time case, the crowdsource applications employ face recognition to exploit the integrated IoT with UAVs [20]. In LTE-A, UAVs associate the camera sensor to connect the ground station. A surveillance drone may execute a command that applies the facial recognition to analyze the suspicious behavior over a criminal track record. Yoo et al. [21] demonstrated the optimal routing and flyer path that uses location-aware multilayer mapping to explore the utility functions such as density, time, risk, and energy. Moreover, a genetic algorithm is utilized to maximize the usage of evacuation support system [22].

This system is composed of IoT device, agent,and autonomous controller that apply a suitable strategy to evacuate the people to a safe zone. Peng et al. [23] designed an intelligent home security system to monitor the environment activities such as sensing, analyzing, and controlling. The experimental result showed the effectiveness of home intelligent system. Lately, UAVs and its integral IoT play a significant role to monitor the field parameters in order to improve the quality of agriculture crops. Uddin et al. [24] designed a distributed IoT network for heterogeneous application domains that proactively examine the field parameters.

1.4 Satellite and IoT Network

IoT network has applied state-of-the-art approaches for rural environment that use the device network to monitor the terrestrial communication such as the desert, ocean, and mountain [25]. A possible IoT/satellite system uses a LEO constellation to obtain cost-efficient solution that minimizes the propagation delay and information loss in comparison with GEO satellite. Kawamoto et al. [26] utilized a data collection technique known as satellite-routed sensor system that uses distributed IoT network to send the environment data to the ground or remote station. Kawamoto et al. [27] introduced a tsunami detection technique to detect the earthquake earlier in time. In this scenario, a large number of sensor objects such as buoys are involved to sense and analyze the gathered data at a remote area.

However, there are several open challenges to address the IoT communication protocols, which have a choice of satellite communication to allow the network properly [28]. Siris et al. [29] investigated the proposed model to minimize the influences of data and control overheads when the integrated IoT supports over satellite–terrestrial networks. The employment of wireless and satellite network supports machine-to-machine or device-to-device communication that exploits several convergence technologies such as smart grid and supervisory control and data acquisition (SCADA) to investigate the pros and cons of information-centric networking [30].

Bacco et al. [31] studied the CoAP protocol to test the communication system over random-access networks in order to reduce the network traffic and congestion. Soua et al. [31] integrated satellite network and M2M communication to configure both MQTT and CoAP. Chiti et al. [32] provided a challenging solution to repress the data traffic that fulfills the energy efficiency of 6G networks.

2 UAVs, IoT, and Emerging 6G Technologies

The rapid advancement and its related application domains such as virtual reality, three-dimensional media, and Internet of Everything have led for voluminous amount of data generation. As reported in [33], global mobile traffic was recorded as 213 Exabyte per month in 2010 and is expected to be 5016 Exabyte per month. The importance of statistical improvement clearly depicts the evolution of autonomous sectors such as transport, industry, health, space, and ocean. To provide a smart automation, millions of sensing components are embedded in the real-time environments. As a result, a reliable transmission rate is highly demanded to provide smart application services. Fifth generation (5G) has widely been deployed for the application features of wireless networks. However, it could not be more competent to automation and smart intelligence [34].

In order to fulfill the smart automation and intelligence, 6G communication is nowadays evolving meticulously. The associative features of 6G may exploit the advanced spectrum management to experience better quality of services (QoS). Moreover, the technological features invoke several techniques to test the integrated licensed and non-licensed frequency band [35]. The growth of automation and data-centric system is nowadays exceeding the capabilities of 5G. In some application domains, it is even more demanding than 10 *Gbps* transmission rate such as virtual reality devices [36]. In 2030, 5G would reach its limitation to support new ventures and its related challenges. As a result, 6G is newly emerging to meet the standard goals of application features such system throughput, power consumption, and massive network connectivity.

6G networks certainly emerged the additional services such as artificial intelligence, smart sensors, three-dimensional printing, vehicle tracking, and intelligent device computation. The significant features of 6G network are massive data storage and high-speed transmission rate for the effective device communication [36]. In the future, 6G will play an important role to diversify the application features to improve the performance of service quality. It will also provide better security and data privacy to meet the objectives of global communication. It is predicted that the transmission rate will be $\sim$1 Tbps in several application scenarios to extend its connectivity 1000 times faster than 5G. In ultra-range communication, 6G will experience $\sim$1 ms latency to facilitate the exciting feature of AI.

2.1 Emerging Trends in Mobile Networks

In 1980, the first analog communication was evolved to improve the quality metrics such as network service and data traffic. Over a decade, the mobile data traffic has proportionally grown for the massive use of smart devices and M2M communication. Figure 2 shows the growth rate of mobile network connectivity. It is predicted that the growth of mobile traffic will raise 670 times in 2030 as compared to 2010 [33]. An international telecommunication union (ITU) reports that the overall data traffic will surpass 5 Zettabyte per month. The number of subscriber connectivity will arrive at 17.1 billion as compared to 5.32 billion in 2010. Moreover, the number of machine-to-machine connectivity will exponentially grow to exceed the volume of data traffic. As a result, the mobile data traffic will gain more congestion, i.e., 50 times greater than 2010. Table 2 shows the global developments in wireless connectivity.

Of late, the data-driven method has transformed into intelligent-driven approach that builds a basic structure for intelligence networks providing the AI operations [34]. The fully intelligent networks adapt the network management to drive the

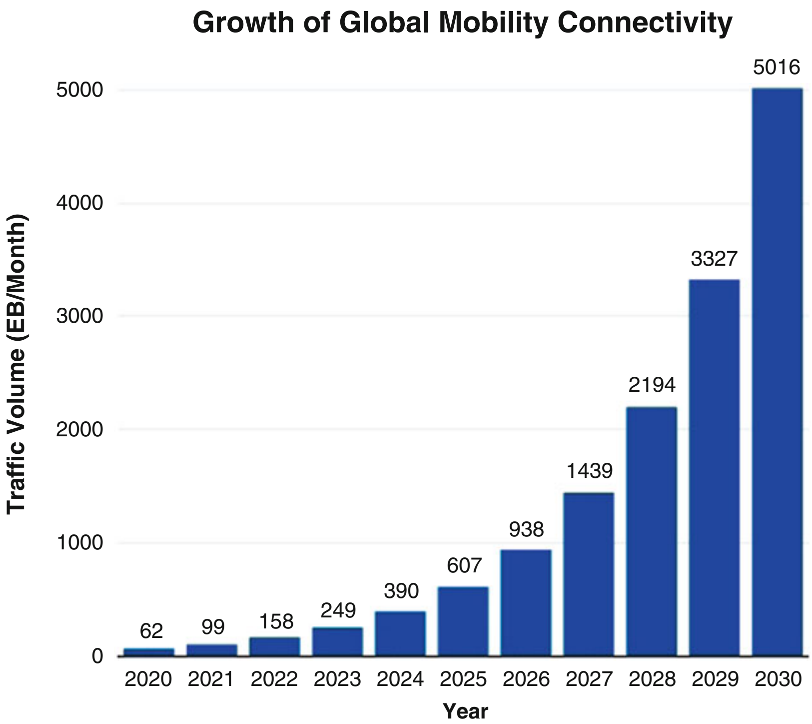

Fig. 2 Growth of global mobility connectivity

Table 2 Global developments in wireless connectivity

Network issues	2010	2020	2030	Units
Mobile user subscription	5.32	10.7	17.1	Billion
Smartphone user subscription	0.645	1.3	5.0	Billion
M2M user subscription	0.213	7.0	97	Billion
Data traffic volume	7.462	62	5016	Billion
M2M data traffic	0.256	5	622	Billion
Data traffic per subscription	1.35	10.3	257.1	Gigabyte per month

possible key features such as reliability, energy efficiency, spectrum allocation, traffic availability, communication convergence, sensing, control, computing, and localization.

2.2 *Integrated Wireless Technologies*

In 6G, the integrated AI incorporates resource management, network instrumentation, signal processing, service connection, and physical layer to promote the revolution of Industry 4.0. It has transformed the industrial engineering into digital form that envisions the architecture of 6G communication system. Some important prospects are as follows:

Ultrasmart society: 6G structures accelerate the features of smart societies such as environment analysis, industrial automation, and quality improvement that use the energy harvester and AI-based communication to make the network more efficient.

Extended reality (XR): The services such as virtual reality, augment reality, and mixed reality to signify the features of 6G communication. The key drivers such as three-dimensional (3D) objects and AI are provided to meet the standard requirements such as storage, cognition, computing, and human interaction.

Autonomous connectivity and robotics: An autonomous robot is used to investigate the activities of automotive objects that help to deploy the drone-integrated UAV. In 6G, the wireless communication can radically promote the development of self-driven mechanism, i.e., driverless car. The sensors such as radar, GPS, sonar, odometry, light detection, and ranging are grounded to support the system controller between UAV and ground station. Moreover, the integrated wireless technologies support high transmission rate and data broadcasting to the application domains such as disaster management, agriculture, product manufacture, and military surveillance.

Wireless brain–computer interaction (BCI): In medicine, a direct communication path between external devices and brain activities is continuously monitoring the brain signals to interpret the data features.

Branch of haptic communication: In haptic, a branch of nonverbal communication uses the touch sensing to support the superior features of real-time interaction.

Five-sensing information transfer: Human has five senses, namely, touch, hearing, taste, sight, and smell, to examine the data transfer. It uses the neurological process to infer the sensation through the integration of sensory systems.

Internet of Everything (IoE): This convergence technology provides seamless connectivity to the large number of computing platforms including sensor, controller, and computing devices. It integrates physical objects and wireless technologies to introduce the AI intelligence-based 6G convergence.

3 Technical Requirement and Specification

6G technologies have tactfully engaged in the trade of several challenging issues such as deployment cost, energy efficiency, delay, throughput, hardware complexity, and reliability. In order to meet the technological demand, 6G tries to fill the bridgework such as device connectivity, high data transmission rate, reliable service connectivity, latency, and machine intelligence. Moreover, it is estimated that 6G will be able to provide a simultaneous connectivity, i.e., 1000 times higher than the 5G features. In order to extend the energy harvesting, 6G will use the system intelligence.

3.1 Network Characteristics

The important network characteristics are as follows:

Integrated satellite networks: To support a global connectivity and satellite integration, 6G is highly required of system intelligence.

System intelligence: In wireless communication, 6G will advance the pervasive computing to produce a new computing paradigm.

Seamless integration and energy transfer: 6G will intellectually transfer the energy to charge the smartphone or device to integrate the wireless information and energy transfer (WIET).

3D connectivity: In 6G, the core network functionalities will access the very low Earth orbit to make the 3D connectivity ubiquitously.

3.2 General Requirements in Networks

The important characteristics of wireless network are as follows:

Small-cell network: The small cell network has improved the signaling quality for the enhancement of cellular and spectral efficiency.

Backhaul connectivity: A high backhaul network is influenced to support high-volume data traffic and capacity.

Integrated radar technology: In 6G, the network features integrate the radar technologies to support the mobile communication systems.

Virtualization and software systemization: The design features of software systemization and virtualization ensure reconfigurability, programmability, and flexibility that provide intelligence to share the physical infrastructure effectively.

4 Key Responsibilities in 6G

6G network has driven various technologies using system intelligence. The important enabling technologies are as follows:

Artificial intelligence: 6G has significantly improved the system intelligence for the support of industrial automation. The technological advancement creates more intelligent networks to improve the efficiency of real-time data.

Spectral efficiency: In 6G communication, spectral efficiency can substantially increase the bandwidth utilization to advance the multiple input and multiple out (MIMO) technologies. The key properties are high data transmission rate and path loss arising out of high frequency.

Optical wireless technologies: Optical communication is envisioned to support device-to-access network and access network-to-backhaul connectivity. However, it can be used widely to enhance the performance of wireless technologies.

Blockchain: This technology massively uses the data communication that influences a distributed ledger to distribute the computing devices. Moreover, it manages the peer-to-peer network to gather and structure the data blocks. As a result, it will extend several functional possibilities such as traceability, interoperability, and autonomic interactivity.

Quantum communication: In 6G, the networks employ unsupervised learning to build the complex representation that is operated in truly autonomous networks.

Cell-free communication: 6G network is crucial to integrate multiple frequencies and heterogeneous networks. As a result, it is claimed to provide seamless connectivity to provide better quality of services (QoS).

Big data analytics: In order to analyze the complex datasets, big data analytics is highly involved. This process discloses the hidden pattern, customer inclination, and unknown correlation to achieve better data management.

5 Challenges and Future Aspects

Several technical issues are demanded to deploy the IoT-integrated UAV in 6G networks. The possible concerns are as follows:

High propagation: A new design transceiver is operated at high frequency, i.e., *THz* communication to challenge the long-distance data transfer.

Technological complexity in resource management: 3D network extends the vertical direction to add some new dimension that significantly degrades the network performance. Thus, a new competing technique is essential to optimize the resource management and network mobility.

Hardware constraints in network heterogeneity: In 6G, various communication systems such as service delivery and network topologies are involved to access the mobile terminal effectively.

Autonomous wireless networks: In order to support the automation process, 6G will provide a reliable automation such as UAVs and Industry 4.0. To emerge the wireless networks, autonomous systems are designed.

Modeling frequencies: The key-driven factors are subjected to characterize the effects of absorption and dispersive effect. Thus, the channel modeling is relatively complex to design a perfect channel modeling.

Backhaul connectivity: The access networks are diverse in nature to support high data rate transmission that is widely used to handle the massive amount of data connectivity.

Interference and spectrum management: Due to spectrum scarcity and interference issues, 6G spectra effectively includes the innovative spectrum techniques and management to achieve maximum resource utilization.

Beam management (*THz*): The massive MIMO system provides a promising technology to support high-transmission data rate. However, seamless data connectivity and handover are so important to optimize the beam management techniques in high-speed UAVs.

6 Conclusion

This paper discusses IoT wireless technologies, UAVs with IoT integration, and satellite and IoT network to signify the application scenario of IoT technologies. The important issues related to emerging 6G technologies are rigorously studied to explore the opportunities of cellular networks. The preliminary studies are majorly pointed to highlight the significance of 6G networks. It is expected to deal with future technologies that promise public safety and individual system privacy. Moreover, this paper is envisioned to present the possible application scenario and its related technologies that clarify the vision of 6G communication systems. In the future, a new cyber-physical system will be addressed to identify the challenging aspects of UAV-based cellular systems.

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Image Processing in Unmanned Aerial Vehicles

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1 Introduction

Although they are known as unmanned aerial vehicles (UAVs) in remote sensing science, their prevalent name is drones, and they are aerial vehicles that are able to operate without a presence of a pilot [1]. They have increasing importance in every field of science and life with huge variety of applications in the last decade [2]. From entertainment to military missions or to professional photography, they assist humans and provide vision that humans are not able to see. Recent researches [2] present that drones are used for disaster management [3], geographical monitoring [4], journalism [5], and farming [6] beside entertainment and military missions.

Different viewpoints and angles of UAV cameras create estimable captured frames and scenes. In addition, applied image processing techniques to these frames make it possible to obtain valuable results for particular applications. A variety of image processing techniques and unique characteristics of each frame of each captured image is a big challenge for the determination of proper techniques for specific application. Thus, the analysis of recent researches, investigation of preferred image processing techniques, and effective classification of drone applications are required for future implementation and applications to minimize the time of image processing part of drone-captured images.

This chapter focuses on the types and applications of drones, especially by considering image processing techniques, and classifies UAV applications into different categories. Considered image processing techniques and corresponding applications are presented with recent examples.

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9_10

The organization of this chapter is as follows: Sect. 2 briefly introduces the types of UAVs, and Sect. 3 presents the application areas of these drones. Sect. 4 performs analysis of applied image processing techniques in drone-captured images, and Sect. 5 presents the discussions and conclusions of the performed analysis and drone applications.

2 Classification of UAV Types

A huge number of models and types are available for UAVs, and different classifications have been performed for UAVs by considering their diverse characteristics. US Department of Defense classified UAVs into five categories as small, medium, large, larger, and largest according to their maximum gross takeoff weight, normal operating altitude, and airspeed. However, most common classifications are based on their size, endurance, and configuration [2, 7].

In size classification, large-scale and medium-scale UAVs have a size of 10 and 5 m, respectively, while small-scale UAVs have sizes between 50 cm and 2 m and a weight of 2–10 kg. Mini UAVs are categorized by their size (1–1.4 m) without considering weight, and in micro/nano UAVs, only weight is considered and limited to 100 g [2].

In endurance classification, endurance hours and flight range are considered to classify UAVs as very low cost and close-range UAVs, close-range UAVs, mid-range UAVs, and long-endurance UAVs. Endurance of UAVs differs from 0.5 to 36 h and directly affects the flight range of UAVs.

In configuration category, UAVs are divided into three classes as fixed wing that need runway for takeoff and landing, rotary wing which is able to land and take off vertically and flapping wing that is bio-inspired UAVs. Table 1 shows classification of UAVs by their three different characteristics as size, endurance, and

Table 1 Common classification of UAVs [2, 7]

Category	Types
Size	Large-scale UAVs
	Medium-scale UAVs
	Small-scale UAVs
	Mini UAVs
	Micro/nano UAVs
Endurance	Very low-cost and close-range UAVs
	Close-range UAVs
	Mid-range UAVs
	Long-endurance UAVs
Configuration	Fixed wing
	Rotary wing
	Flapping wing

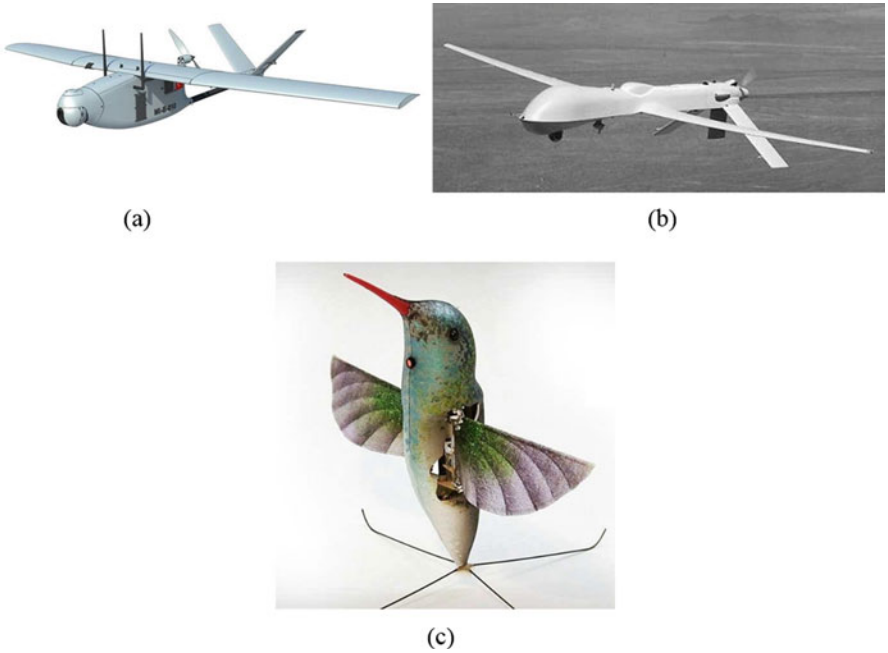


Fig. 1 Example UAVs—(**a**) mini UAV [8], (**b**) long-endurance UAV [9], and (**c**) flapping wing UAV [10]

configuration. Figure 1 shows mini UAV, long-endurance UAV, and flapping wing UAV, respectively.

3 Application Areas of UAVs

The popularity of UAVs or drones has gained an importance in the last decades [11] while their application areas become wide. Technological developments and increased capabilities of UAVs provide the use of UAVs in every field and moment of life.

It is difficult to categorize the applications of UAVs into groups and subgroups, but some of the researchers tried to separate these applications into fields according to their usage areas. Kaimaris et al. [1] categorized UAV applications into five areas according to their purposes beyond military usage as forestry and agriculture, archaeology and cultural heritage, surveying, urban and regional planning, and environmental surveying and transportation for traffic monitoring.

In forestry and agriculture, wide applications of UAVs have been recently investigated and implemented by researchers. Saadat and Sherif [12] used UAVs for forest surveillance system and applied machine learning and image processing algorithms in order to recognize the tree species in the forest. Orillo et al. [13] applied image processing techniques to drone-capture images to determine the density of green leaves. Ye Seul et al. [14] used UAVs similarly to calculate the tree heights from drone image.

Marsujitullah et al. [15] applied image processing techniques and support vector machine (SVM) to determine the growth phase of rice farms. Stavrakoudis et al. [16] implemented multiple linear regression model for multispectral drone-captured images to predict agronomic traits of rice plants. Hunt Jr. and Rondon [17] used drone images to detect potato beetle damage.

In environmental surveying, UAVs are used for mapping and interpretation [18] and for three-dimensional reconstruction of geospatial data [19].

In transportation, implementations are generally based on vehicle detection and counting to assist experts about the traffic density of the roads. Thus, object detection in images or in video frames is essentially used in these applications. Vehicle detection in UAV camera frames has been implemented by various researches [20–23].

Transportation applications in drone-captured images have similarities between other implementations such as human detection, motion detection, and object recognition in urban areas. Nguyen et al. [24] implemented convolutional neural network (CNN) for multiple human detection in drone image, and Karim et al. [25] proposed a system to detect weapons in drone-captured images in order to control street crimes. Zhu et al. [26] proposed a system for large-scale object detection and tracking.

Recent different and diverse applications of UAVs require to update the application areas by taking them into consideration. Leonardi et al. [27] performed a research to locate pothole and cracks on roads by using drone images, and Seo et al. [28] proposed principles for bridge inspection by drone-captured images. Kim et al. [29] proposed image processing techniques on drone images for concrete crack detection. Shajahan et al. [30] and Reddy et al. [31] proposed systems for monopole tower inspection and cracks and damage detection in wind turbines by using drone images, respectively. In another interesting study, Lee et al. [32] used drone-based thermal images for sinkhole detection. Drones are also used in marine environments effectively [33].

In the light of these researches, it is possible to extend the previous categories of drone applications. Table 2 shows the extended categories of UAVs applications.

4 Image Processing in UAV Images

Each of the UAV applications requires proper image processing techniques as well as machine learning models in order to make captured images significant for each application area. Thus, categorical separation of UAV applications is possible according to the purposes of their images used. These purposes can be categorized as segmentation and analysis, identification and prediction, and 3D reconstruction.

Table 2 Extended categories of UAVs applications

Category	Aim
Forestry and agriculture	Save time and resources to identify problems [1]
Archaeology and cultural heritage	Mapping or 3D modeling or archaeological sites [1]
Surveying and urban and regional planning	Create and update maps, applications, illegal constructions, etc. [1]
Environmental surveying	Monitoring water and soil resources for environment protection [1]
Transportation	– Traffic monitoring and project supervision [1] – Road security
Unmilitary rescue operations	To help humans after accidents and disasters
Construction safety	To assist engineers for the detection of damages and cracks in the buildings
Animal care	To observe and count animals to estimate the change in animal population thus as an effect of climate

Table 3 Proposed categorical applications of UAVs according to image processing purposes

Category	Definition	Application
Segmentation and analysis	Direct manipulation or segmentation of region of interest (RoI) in drone-captured images by applying image processing techniques	– Construction safety – Object detection – Animal care – Vehicle detection – Human detection – Unmilitary rescue operations
Identification and prediction	Recognition of segmented or unsegmented objects or scenes and prediction of the future using machine learning techniques	– Object recognition – Person identification – Agricultural estimation – Animal care
3D reconstruction	Reconstruction of 3D images using multiple or single 2D scenes.	– Geospatial data processing – Environment mapping

Table 3 presents proposed categorical applications of UAVs according to the purposes, and Fig. 2 shows the relationship between these categories with each other as a set.

Segmentation and analysis and identification and prediction categories are intermixed together, while some UAV applications use both of them in one application or need another step of other categories to produce superior results.

4.1 Analysis and Segmentation

Analysis and segmentation part of UAV image processing generally includes image binarization and morphological operations to separate region of interest from whole image or to provide explicit captured image of RoI.

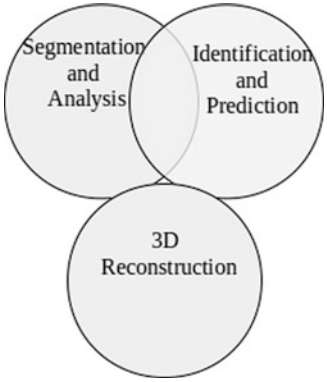


Fig. 2 Relationship between UAV categories by techniques and applications

Laliberte and Ripple [34] applied thresholding and pixel clustering in order to count snow geese. Similarly, Fang et al. [35] applied image binarization (thresholding) and morphological operations to segment and detect animals in wildlife. Vayssade et al. [36] also applied image binarization to segment goats in drone-captured images, and Canny filter and Hough transform are also applied to finalize segmentation. Segmented regions are identified by linear discriminant analysis (LDA) classifier. Figure 3 presents obtained results of thresholding and morphological operation implementations on animal detection [35].

Seul et al. [14] used lambda schedule segmentation to segment their test area for the calculation of tree height. Different test areas consist different structures, but the RoI was the trees in order to provide significant height calculation. Figure 4 demonstrates the example segmentation result of Seul et al.'s research.

Kim et al. [29] used different and basic image processing techniques such as image subtraction, median filtering, and thresholding to detect concrete cracks in images captured by UAVs.

4.2 Identification and Prediction

In different researches, identification or prediction tasks were performed either after applying analysis and segmentation algorithms or directly to the drone-captured images. Identification and prediction tasks are commonly based on machine learning models and deep learning.

Lee et al. [32] applied adaptive dual thresholding to detect candidate sinkholes and morphological operations to obtain enhanced images. They ensemble different classifiers such as random forest, boosted random forest, and convolutional neural network for sinkhole recognition.

Reddy et al. [31] implemented CNN for the detection of damages and cracks in wind tribunes, and Nguyen et al. applied Faster R-CNN for multiple human tracking in drone-captured images. Karim et al. [25] applied histogram of oriented gradient

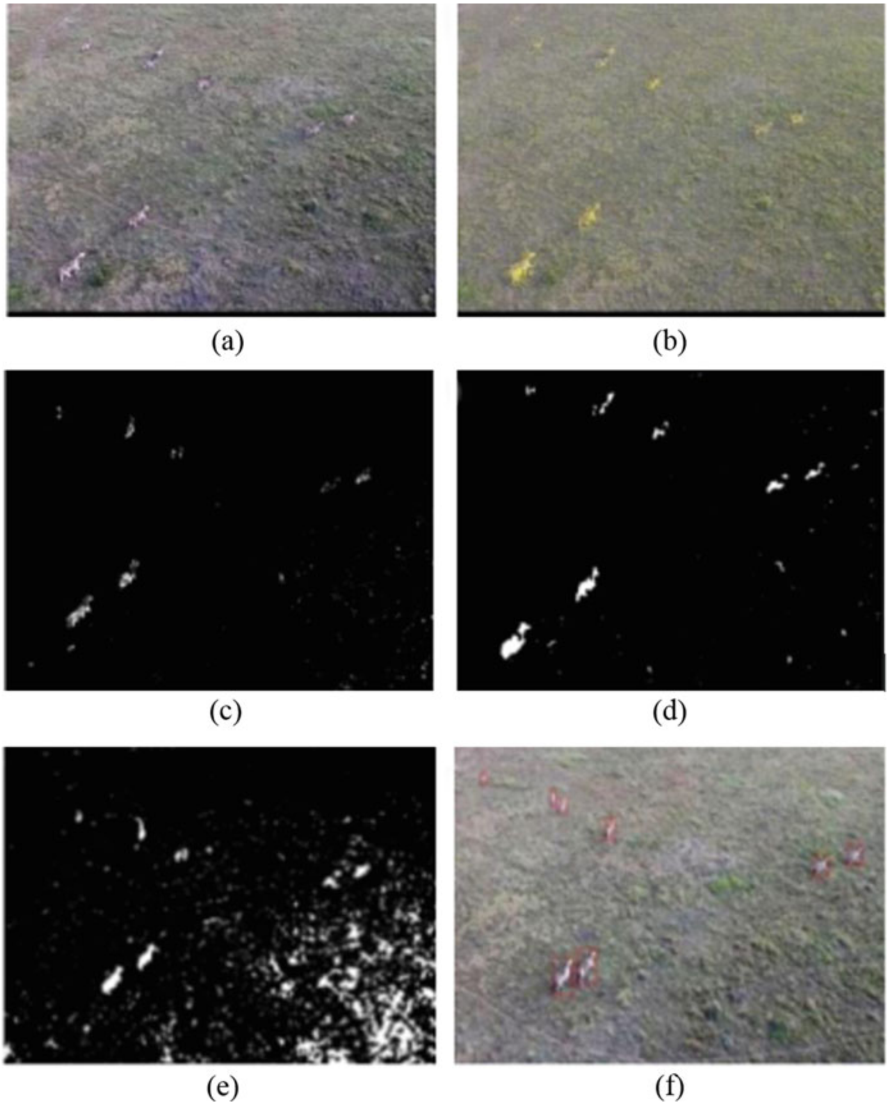
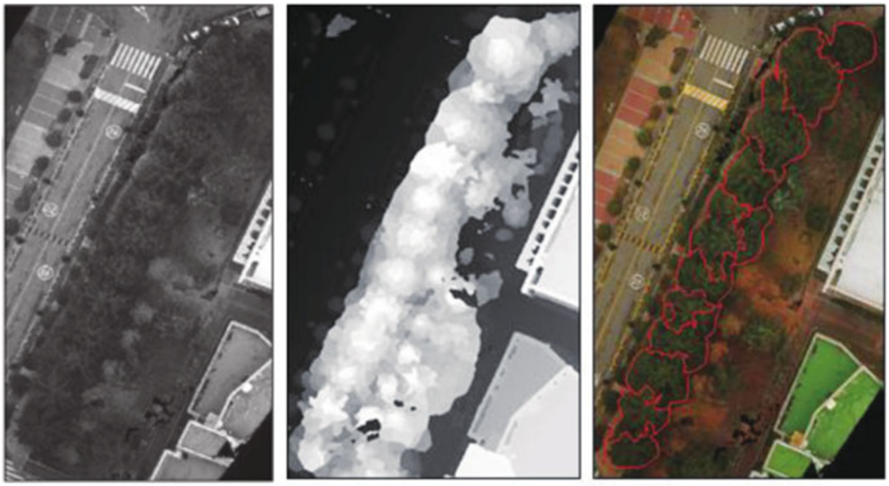


Fig. 3 Example of thresholding and morphological operations implementations on UAV image by Fang et al. [35]: (**a**) original image, (**b**) optical flow vectors, (**c**) binarized image, (**d**) morphological operations applied image, (**e**) segmentation with errors, and (**f**) detection result

(HOG) for weapon detection to control street crimes in drone images. In this study, detected weapons were classified by support vector machines.

Maria et al. [21] applied cascade classification, and Tang et al. [23] implemented CNN for the car and vehicle detection in UAVs images. Hunt et al. [17] applied rule-based classification to detect potato beetle damages. Fan et al. [37] applied



(a) (b) (c)

Fig. 4 Segmentation result of trees in UAVs images by Seul et al. [6]

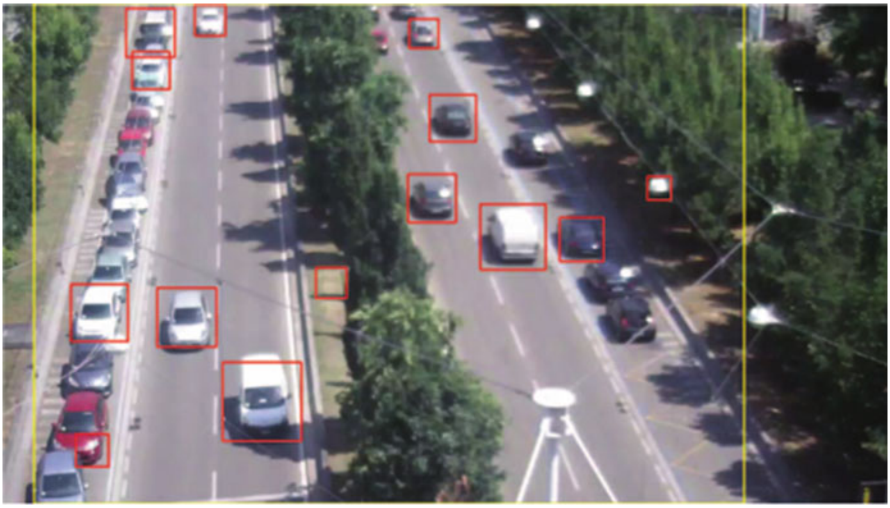


Fig. 5 Car detection in drone images by cascade classifier [21]

morphological operations, image binarization, and watershed segmentation in order to extract tobacco plant in drone images. Then, they applied CNN to recognize if extracted plants were either tobacco or not. Figure 5 shows an example of car detection in transport infrastructure [21], and Fig. 6 presents segmentation and recognition results of tobacco plant by [37].

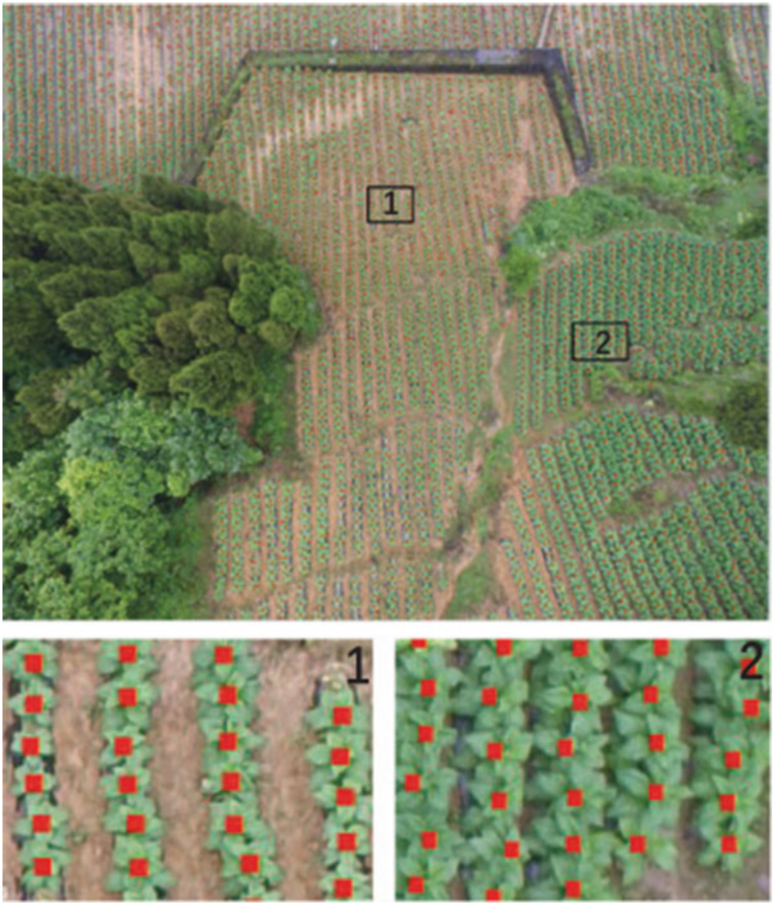


Fig. 6 Tobacco plant segmentation and recognition results [37]

4.3 3D Reconstruction

3D Reconstruction of drone-captured images can be used for every field of application to visualize 2D images and provide data for further investigation of these images. GPS, trajectory and position of camera, land position, and camera parameters have vital importance for 3D reconstruction of 2D images. Sanfourche et al. [18] presented a workflow for 3D reconstruction steps. An example of 3D-reconstructed images is shown in Fig. 7 [19].

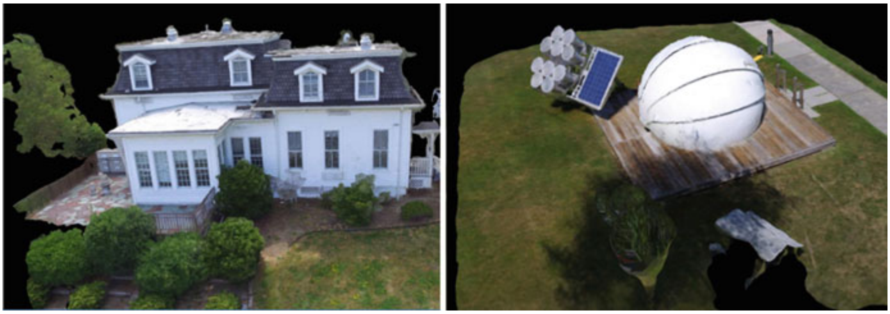


Fig. 7 Example of 3D-reconstructed image from 2D drone images [19]

5 Discussions and Conclusions

The importance of unmanned aerial vehicles is rising since the last decade. They provide a vision for humans, and also processing of these vision which are drone-captured images has a vital role in applications that increase the human life quality, effect the food sources, or make roads and streets more secure.

Drone images may analyzed directly by human experts for specific application but they mostly need implementation of image processing techniques for further analysis. Because, sometimes the characteristics of drone images may not be suitable for naked-eye inspection and need automation for rapid results.

Classification of drone applications is one of the initial challenges, and different classifications have been performed. An update of recent classification which was based directly to the application field has been performed on behalf of recent researches and applications. In addition, applications are classified according to the image processing techniques applied in these applications. These novel categories are segmentation and analysis, identification and classification, and 3D reconstruction.

Identification and classification category may use image processing techniques used in segmentation and analysis to provide more effective data for classifiers. However, 3D reconstruction class is completely independent from others and needs some parameters for efficient reconstruction.

It is obvious that automated application-specific content acquirement of drone-captured images requires proper image processing techniques where the selection of these techniques creates big challenge for scientists. Recent researches show that basic image processing techniques are still the most effective and preferred methods for drone image analyses. These are image binarization and morphological operations. On the other hand, image binarization has different types as local, global, or adaptive, and this also creates another challenge to determine which will be the proper binarization method for the application. Segmentation results that are obtained by image binarization are generally supported by morphological operations such as opening, closing, dilation, and erosion to remove noise or to fill the gaps within segmented parts of RoI. In some researches, these two fundamental image processing techniques are applied before or after other image processing techniques to obtain superior results.

Contrary to binarization and morphological operations, there are no specific segmentation or noise removal methods; however, they were independently applied to drone-captured images by trial and error to increase the accuracy of the system.

In identification and prediction, researches showed that direct feeding captured images to classifiers where the CNN and it's types are the most preferred classifiers, to obtain classification results. Therefore, the usage of fundamental image processing techniques is decreased in these types of applications. But it should also noticed that, in some applications, binarization and morphological operations were used for segmentation of RoI, then segmented areas fed to classifiers.

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F. Al-Turjman (eds.), *Unmanned Aerial Vehicles in Smart Cities*,
Unmanned System Technologies, https://doi.org/10.1007/978-3-030-38712-9

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