Networking of Internet of UAVs: Challenges and Intelligent Approaches

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Abstract

Internet of unmanned aerial vehicle (I-UAV) networks promise to accomplish sensing and communication tasks quickly, robustly, safely, and cost-efficiently via effective situation awareness and cooperation among UAVs. To achieve the promising benefits, the crucial I-UAV networking issue should be tackled. This article argues that I-UAV networking can be classified into two categories: quality-of-service (QoS) driven networking and quality-of-experience (QoE) driven networking. Each category of networking poses emerging challenges that have severe effects on the safe and efficient accomplishment of I-UAV missions. This article elaborately analyzes these challenges and expounds on the corresponding intelligent approaches to tackle the I-UAV networking issue. Besides, considering the uplifting effect of extending the scalability of I-UAV networks through cooperating with high altitude platforms (HAPs), this article gives an overview of the integrated I-UAV and HAP network and presents the corresponding networking challenges and intelligent approaches.

Introduction

The sixth-generation (6G) wireless communication networks are desired to provide ubiquitous and seamless geographical communication coverage to meet diverse use cases in many scenarios including villages and motorways [1]. It’s difficult to achieve the above-mentioned ambitious goal with terrestrial networks (TNs) alone. TNs are vulnerable to natural disasters and severe ground disruption. As a result, ground (mobile) users will experience communication interruptions. Since the interruptions are either temporary or unexpected, it will be timely and financially infeasible to construct TNs to recover communications. In this case, resorting to the assistance of non-terrestrial networks (NTNs) is a promising choice in cost-effectively and rapidly implementing the above goal. Actually, in the 6G era, the integration of TNs and NTNs is a global consensus, and demonstrations on the integration have been initiated in many countries.

NTNs consist of many heterogeneous and interconnected flying platforms deployed at different altitudes, including satellites, high altitude platforms (HAPs), and unmanned aerial vehicles (UAVs). These platforms have advantages and disadvantages concerning such aspects as cost, persistence, responsiveness, vulnerability, footprint, and overflight [2]. Owing to the advantages in cost, flexibility, responsiveness, and communication latency, UAV-assisted communications have recently received extensive attention. UAVs mounted with diverse devices have also been applied to accommodate some typical use case demands, such as the UAV-base station (BS) for ubiquitous coverage and the UAV-relay for distant users’ connection [3, 4].

Despite the many promising advantages, the design of a network consisting of a single UAV faces many tricky challenges caused by unreliable communication links, weak survivability, a small footprint, mission completion time, size, weight, and power (SWAP) constraints, and so on. To meet these challenges when accomplishing a mission (e.g., sensing and communication), one needs to construct a network architecture of the Internet of UAVs (I-UAVs) involving many cooperative UAVs [5]. Some UAVs in I-UAV networks can act as aerial Internet-of-Things (IoT) devices to execute sensing or integrated sensing and communication tasks.

The cooperation among UAVs is crucial for I-UAV networks and inspires the potential advantages of I-UAV networks in providing sensing and communication services. The robustness of I-UAV networks can be enhanced by UAV cooperation, which keeps the network organized even in the event of link or node failure. Thus, the probability of successful sensing and transmission can be significantly improved. I-UAV networks can accomplish such tasks as sensing and communication faster through cooperation among UAVs. For example, via the UAV cooperation, a UAV needs not fly close to a communication point first to meet the QoS requirements, which will cause extra latency. The requirement for sensing frequency in sensing applications can be satisfied by exploring task scheduling and offloading strategies among multiple cooperative UAVs. The lifetime of a UAV can be significantly extended without establishing a long-distance link to the destination node. In non-cooperative multi-UAV networks, each UAV is required to independently accomplish several sensing and communication tasks, the process of which will occupy a significant...
amount of radio resources (e.g., frequency and power). I-UAV networks, however, can achieve resource optimization through cooperative radio resource management [6]. Further, I-UAVs enable UAVs to perceive UAV local situations (e.g., flight, payload, and battery states) and surrounding environmental situations. In summary, cooperation, integrated sensing and communication, and situation awareness are significant characteristics of I-UAV networks.

Nevertheless, to achieve the above-mentioned promising benefits, the crucial I-UAV networking problem must be solved. The goal of constructing or deploying I-UAV networks is to accomplish some tasks like sensing and communication safely and efficiently. From the perspective of accomplishing a communication task, we can classify the I-UAV networking into two categories: quality-of-service (QoS) driven I-UAV networking, quality-of-experience (QoE) driven I-UAV networking.

The primary task of QoS-driven I-UAV networking is to guarantee the QoS requirements of users, which are usually characterized by users’ achievable data rates. Because of the dynamic stochastic deployment environment and user mobility, the problem of I-UAV networking has to be formulated as a sequential and uncertain situation-aware constrained problem (e.g., UAV energy consumption and link outage probability). This problem is confirmed to be high-dimensional and difficult to solve using some conventional optimization approaches [7].

As reported by Cisco, mobile video traffic is expected to occupy roughly 79 percent of global mobile data traffic by 2022. Besides, 80 percent of mobile video traffic comes from hotspot contents (e.g., FIFA World Cup, American Super Bowl), whose coverage is one of the typical use cases for deploying I-UAVs. That is, performing I-UAV networking to deliver video streams for ground users will be a key mission of I-UAV networks. However, how to deploy I-UAVs to guarantee users’ QoE requirements is challenging.

First, QoE is an application layer indicator in the multimedia transmission field, which is particularly subjective and is quite different from the indicator QoS. One usually characterizes QoE using video quality, freezing, latency, and smoothness. However, finding an appropriate QoE model that can exactly correlate with low-layer and controllable resources is non-trivial. Second, reliable and low-latency propagation links are desired for video transmission. Yet, random channel fluctuations in I-UAV networks may result in playback buffer starvation and then frame freezing.

Additionally, UAVs are deployed in complex and shared three-dimensional (3D) airspace. Situation information must be considered when performing I-UAV networking to ensure the safe flight of UAVs and efficient video stream transmission, and so on. However, the investigation on the situation awareness of I-UAV networks is difficult. First, the dynamic stochastic 3D environment with multiple and uncertain scenarios happen in the burst will threaten the computing capability and the safety of I-UAV networks. In this case, how to correctly sense and fuse local situations built by a UAV is challenging. Second, there are many UAVs in I-UAV networks, which generate a large amount of situation information. How to share local situations and generate global situations in I-UAV networks is therefore difficult.

Since intelligent approaches can effectively solve some dynamic and high-dimensional problems, this article aims to present an overview of intelligent I-UAV networking. Besides, considering that HAPs can overwhelm UAVs regarding communication persistence, service abilities, and footprints, the integration of HAPs and UAVs has attracted much attention. For example, the network framework for integrating HAPs with UAVs for edge computing was discussed in [8, 9]. This article also envisions the integration of HAPs and I-UAVs. The main contributions of this article are summarized as follows: This article elaborately analyzes the challenges of I-UAV networks in channel modeling and situation awareness and proposes some promising intelligent I-UAV networking and situation awareness approaches. Supported by the channel models and situation information of I-UAV networks, this article summarizes the challenges of QoS-driven and QoE-driven I-UAV networking and expounds on corresponding intelligent methods to address the two types of I-UAV networking problems. Two use cases are also studied to verify the effectiveness of the developed intelligent networking methods. Finally, this article discusses the integration of I-UAVs with HAPs, analyzes the technical challenges of the integrated I-UAV and HAP network in channel tracking and situation awareness, and presents potential intelligent approaches for handling these challenges.

**Applications of I-UAV Networks**

As shown in Fig. 1, I-UAV networks consist of multiple cooperative fixed-wing and rotary-wing UAVs flying at altitudes of tens to hundreds of meters. Depending on the roles of UAVs, I-UAV networks can provide different applications that are summarized in Table 1. UAVs in the network can act as flying base stations (BSs) with BS functional modules being mounted on them. The I-UAV networks can then be applied in several emergency communication scenarios. UAVs can also act as flying access points (or relays) when fronthaul/backhaul hubs are mounted on them. The I-UAV networks can then form an airborne fronthaul/backhaul hub network that collects fronthaul/backhaul traffic from ground BSs and forwards aggregated traffic back to a ground gateway.

Except for installing a BS or a hub, each UAV in the network can be equipped with multiple types of sensors and computing and communication modules for stabilization, navigation, positioning, (integrated) sensing and communication, and so on. The sensors include an IoT device, a three-axis accelerometer, a three-axis gyroscope, a magnetometer, a barometer, GPS, and an electro-optical pod, and so on. For the computing module, it’s responsible for analyzing and fusing sensed data, for example, target detection and recognition. The communication module will support two types of communication links, that is, a control and non-payload communication (CNPC) link and a payload communication link. The CNPC link is established to ensure the safe operation and efficient control of I-UAV networks. As shown in Fig. 1, in I-UAV networks, a CNPC
Efficient and secure I-UAV networking requires the guidance of situation information of I-UAV networks. Compared to well-studied ground communication channels, channels of I-UAV networks have some unique characteristics, and one needs to explore intelligent approaches to model them accurately.

Intelligent Channel Modeling and Situation Awareness of I-UAV Networks

The channel model is the foundation for mathematically formulating and analyzing the networking problem of I-UAV networks. Efficient and secure I-UAV networking requires the guidance of situation information of I-UAV networks. Compared to well-studied ground communication channels, channels of I-UAV networks have some unique characteristics, and one needs to explore intelligent approaches to model them accurately.

Intelligent Channel Modeling of I-UAV Networks

From the kinds of UAV links, one can know that I-UAV networks include three types of communication channels, that is, the UAV-to-UAV (UtU) channel, the UAV-to-ground user (UtG) channel, and the UAV-to-base station (UtB) channel. This subsection then presents the potential of modeling UtU, UtG, and UtB channels by exploring intelligent approaches.

UAV-to-UAV Channel:

Owing to UAVs’ flexible and controllable flight in 3D airspace, they can easily establish line-of-sight (LoS) links. Correspondingly, many works leverage LoS propagation models (e.g., Friis transmission equation) to characterize the UtU channel. Except for receiving LoS signal components, however, a UAV may receive complicated non-line-of-sight (NLoS) signal components, for example, reflection signals from terrain and high-rise buildings and scattering signals from the atmosphere when the UAV works in the S-band. Therefore, both LoS and NLoS signal components should be considered when modeling the UtU channel so that more realistic channel characteristics can be reflected.

Additionally, the UtU channel may experience the Doppler frequency shift, the amount of which is closely related to UAVs’ relative velocities. Nevertheless, the consideration of NLoS components and the Doppler frequency shift may result in a complicated UtU channel expression intertwined with many parameters. In this case, the subsequent problem of I-UAV networking may become theoretically intractable.

To tackle this issue, deep neural networks (DNNs) can be explored. DNNs have a well-
known, powerful nonlinear approximation ability. The universal approximation theorem asserts that a neural network (NN) with one hidden layer and enough hidden neurons is sufficient to approximate a continuous mapping. DNNs with deeper layers can approximate more complex continuous mappings. As a result, by training DNNs using measured channel coefficients, a complicated channel expression can be approximated by a simpler one as a function of UAVs’ relative velocities and the distance between any two UAVs.

**UAV-to-Ground User Channel:** The UtG channel modeling is a hot research topic in UAV communications. Owing to the surrounding complicated reflection, diffraction, and scattering environments, ground users will receive signals from many propagation paths. Motivated by this observation, a geometry-based stochastic channel model was developed by considering the signal scattering and reflection on some geometric shapes (e.g., cylinder, sphere, and ellipsoid). Yet, the mathematical expression of the channel gain or channel impulse response (CIR) of this type of channel model is rather complex. To simplify the theoretical expression of the UtG channel gain, statistical analysis methods (e.g., fitting and estimation) were explored. Specifically, given channel coefficients, statistical analysis methods will derive a mathematical expression to approximate or average the channel coefficients. Nevertheless, the statistical channel model is closely related to a particular UAV deployment environment, and one statistical channel model cannot fit all UAV deployment environments.

Exploring machine learning (ML) and artificial intelligence (AI) approaches to approximate the UtG channel dynamically will be a promising route for UtG channel modeling. For example, this article simulates an urban propagation environment using the ITU local building model and the 3GPP 36.777 multipath model and explores an intelligent channel estimation approach (exactly, DNNs) to approximate the propagation channel. Each DNN has 512 neurons in its 1st hidden layer and 256 neurons in its 2nd hidden layer. To demonstrate the generalization ability of the intelligent approach, the DNN pre-training process is performed in the LoS propagation environment while the online DNN training process is performed in the simulated urban propagation environment. In Fig. 2e, the obtained mean absolute percent error (MAPE) values of the first 436 episodes and the later 500 episodes illustrate the estimation accuracy of DNNs during the pre-training and online training phases. Besides, from Fig. 2, we can observe:

- In Fig. 2a, it is interesting to observe that the MAPE value increases when the online training is activated. Nevertheless, the MAPE value decreases as more fresh experience is collected and utilized to train DNNs.
- In Fig. 2b, there is an updating interval where DNNs cannot approximate channel coefficients well. This is because the channel samples collected in the DNN pre-training stage are quite different from those collected during the online training stage. However, the experience replay technique, which reduces the training complexity via randomly sampling a minibatch of channel samples for training, is leveraged to train DNNs. DNN estimation errors gradually decrease as more fresh experience is accumulated.

**UAV-to-Base Station Channel:** In many related works, UtG channel gain models are directly adopted to model the UtB channel. This is inappropriate because the characteristics of the UtB channel differ significantly from those of the UtG channel. Compared with a UtG channel, a UtB channel suffers from much fewer multipath and shadowing fading as a BS is usually located at a high altitude and its surrounding environment contains much less scattering than that of a ground user. Additionally, for a BS with full-dimensional large arrays, it can leverage the massive multiple-input and multiple-output (MIMO) technique to mitigate interference and significantly enhance the network spectral efficiency.

To benefit from this advanced technology, the

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**TABLE 1. Applications of I-UAV networks**

| Applications                              | UAV’s role                          | Allocated frequency (in GHz) |
|------------------------------------------|-------------------------------------|------------------------------|
| Emergency communications                 | Flying BS                           | CNPC link: 0.96–1.164, 2.4–2.4835, 5.03–5.091, 5.47–5.875, 10.95–14.5, and 17.3–30 |
| Airborne fronthaul/backhaul hub network  | Flying access point (or relay)      | Payload link: 2.4–2.4835, 5.47–5.875, and 1.32 |
| (Integrated) sensing and communication   | Flying sensor, computing, and communication node |                             |
| Mobile edge computing                    | Flying computing and communication node |                             |

**FIGURE 2.** Channel estimation accuracy of DNN-based method: a) MAPE of DNNs for UtG channel gain coefficient estimation b) instantaneous energy efficiency with DNN-based channel estimation vs. perfect CSI
One can leverage a statistical distribution to model the global situation and impose a local constraint on the local situation perceived by each UAV using the statistics of the distribution. By exploring FL, each UAV constructs and shares its local gradient model over statistics with a centralized controller without collecting all local situations from each UAV for generating global situations.

Intelligent Situation Awareness of I-UAV Networks

UAVs are usually deployed in relatively low altitude 3D airspace and will share the airspace with other low altitude flying platforms. Owing to the existence of some obstacles, such as high-tall buildings, mountains, and high voltage lines, the low altitude airspace environment is complex. As a result, when conducting I-UAV networking, it is critical to consider the live, multi-domain situations of the entities in I-UAV networks as well as the environment so that UAVs can complete missions safely and efficiently [12].

Multi-domain situations refer to the evolution status of entities in time, frequency, spatial, and network domains, including the UAV network status (e.g., network backbone nodes and links), UAV flight status, UAV safety, and threat status. To guide the I-UAV networking with situation information, both the perception of local situation information and the generation of global situation information are required. However, the accurate perception of local situations and the generation of global situations are extremely difficult. For instance, there are many dangerous small targets (e.g., high voltage lines and birds) with unobvious features in low altitude airspace. The performance of traditional target recognition approaches will be catastrophically degraded without the support of obvious and accurate target features, and then accurate local situation perception cannot be guaranteed. Additionally, local situation information perceived by a typical UAV needs to be shared by the remaining UAVs in the I-UAV networks so that the global situation can be generated. However, one cannot ensure the accuracy of the generated global situation by exchanging local situations in the dynamic I-UAV networks. Besides, the frequent exchange of a large number of local situations in the dynamic networks will occupy a lot of resources and produce severe signal interference, which thus results in the degradation of the network’s performance.

One can then leverage some ML/AI approaches to tackle these challenging issues. In terms of local situation awareness, ML/AI approaches can be utilized to perform single-frame coarse detection of dynamic small targets, which will recognize some candidate targets. Next, one can analyze the changes in the shapes or attitudes of candidate targets and extract the spatial and temporal correlation features of targets to perform fine detection. As a result, fast and accurate detection of dynamic small targets can be achieved. Using ML/AI approaches, one can also accurately detect stationary small targets based on a detection process that ranges from coarse detection to fine detection. In the stage of coarse detection, one can recognize a candidate target based on extracted unobvious features in the stage of fine detection, and then identify the candidate target as an auxiliary object and detect the auxiliary object surrounding the target. Obtain the spatial association features between the candidate target and the auxiliary object, and then utilize a Bayesian association detection model to complete the fine detection of the target.

In terms of generating global situations, joint statistical ML and emerging federated learning (FL) approaches that do not require exchanging a large amount of local situation information can be designed. One can leverage a statistical distribution to model the global situation and impose a local constraint on the local situation perceived by each UAV using the statistics of the distribution. By exploring FL, each UAV constructs and shares its local gradient model over statistics with a centralized controller without collecting all local situations from each UAV for generating global situations. Each UAV estimates local statistical parameters using some statistical ML approaches (e.g., maximum likelihood estimation (MLE), maximum a posteriori (MAP), and expectation maximum (EM)). The controller aggregates all local gradient models and then broadcasts the averaged or global model to each UAV. Besides, considering the existence of intermittent links in I-UAV networks, the operation of sharing local gradient models with the controller can be conducted in an asynchronous manner, which significantly reduces network overhead and signal interference.

Intelligent I-UAV Networking

Supported by the channel models and situation of I-UAV networks, this section explores the issues of QoS-driven and QoE-driven I-UAV networking. Specifically, the emerging challenges of investigating these types of networking are highlighted, and the corresponding intelligent networking approaches are expounded.

QoS-Driven Intelligent I-UAV Networking

Challenges and Intelligent Approaches to QoS Optimization

Satisfying the QoS requirements of ground users is a significant goal of I-UAV networking. Generally, the QoS of a user is characterized by its achievable data rate. During the past five years, plenty of works related to the I-UAV networking in two-dimensional (2D) airspace were published. Considering the time-varying characteristics of I-UAV networks, most of them propose to formulate the I-UAV networking problem as a sequence-dependent problem. The primary objective of the problem is to accommodate users’ QoS, subject to computing, networking, and storage resource constraints in I-UAV networks. Fortunately, the Lyapunov technique can be explored to decompose the sequential decision problem, and iterative and approxima-
tion schemes can then be leveraged to solve the decomposed problem [13].

In practice, UAVs can flexibly fly in 3D airspace; thus, increasing attention has been paid to the case of I-UAV networking in 3D airspace. Nevertheless, the formulated 3D I-UAV networking problem is far more difficult to solve than the 2D I-UAV networking problem. First, higher dimensional decision variables need to be optimized. Second, the 3D locations of UAVs are complicatedly coupled in an UtG channel model, which poses a challenge to the theoretical tractability. In this case, it’s difficult to solve the formulated problem using some optimization methods. Reinforcement learning (RL), which can effectively eliminate the risk of combinatorial explosion, has been demonstrated as an efficient way of handling complex control problems in continuous and high-dimensional state spaces. Thus, many researchers turn to leverage RL methods to solve the 3D I-UAV networking problem.

**Case Study:** Let us consider a communication scenario where I-UAV networks with J UAVs are centrally controlled to fly in 3D airspace continuously to provide energy-efficient data delivery services for N quasi-stationary users. These users are uniformly distributed in a geographical area of 2.5 × 2.5 km². At each time slot, a UAV can connect to at most one user, and a user can be served by at most one UAV. The connection between a UAV-user pair is considered to be established only if the user’s QoS requirement is satisfied. Then, the continuous movement control problem of I-UAV networks can be formulated as a sequence-dependent problem aiming at implementing fair and energy-efficient communication coverage, subject to constraints on users’ QoS requirements, UAVs’ flight airspace, and the connectivity of I-UAV networks. To solve this problem, a new deep reinforcement learning (DRL) method is developed, where all the actor and critic networks are composed of fully-connected feedforward NNs. The state space consists of communication coverage indicators, UAV energy consumption, and communication coverage fairness. The action space consists of UAVs’ moving distances, pitch and yaw angles. The actions resulting in the violation of airspace boundary or network connectivity constraints will be penalized. The reward is defined as the ratio of the product of the fairness index and the total data rates to the total UAV energy consumption. Figure 3 illustrates the tendency of the obtained energy efficiency with a constant UAV transmit power $P_T = 24$ dBm and the number of users $N = 100$. The 1st and 2nd hidden layers have 400 and 300 neurons, respectively. The minimum and maximum allowable UAV deployment altitudes are 100 m and 800 m. It’s observed from Fig. 3 that the proposed DRL method can effectively solve the UAV movement control problem, although the deployment of more UAVs will make the problem more difficult to solve. The proposed method can also significantly improve the energy efficiency of the communication coverage of I-UAV networks.

**QoE-Driven Intelligent I-UAV Networking**

**Challenges and Intelligent Approaches to QoE Optimization:** It’s widely considered that providing high-quality mobile video services for ground users is another important goal of deploying I-UAV networks. The quality of received videos by users is quantified by their QoE. From the perspective of video transmission, the QoE of a user is defined as its subjective measurement toward perceived video streams, which is primarily affected by network status (e.g., bandwidth, latency, and throughput) and content configuration factors (e.g., coding, resolution, and sampling rates) [14].

The video transmission has stringent low transmission latency and high-reliability requirements. Owing to the movement of users and the time cost of configuring I-UAV networks (including network topology and resource configuration), ML/AI approaches can be explored to realize proactive I-UAV networking so that transmission latency is reduced. To guarantee transmission reliability, one can leverage ML/AI approaches to predict network status. With the network status being proactively obtained, the dynamic adaptive streaming over HTTP (DASH) technique can be collaboratively explored to change source coding rates to adapt to the network status.

Additionally, LoS UtG links can be established via UAVs’ mobility in I-UAV networks to significantly improve the quality of mobile video services. UAVs’ mobility, however, will lead to time-varying I-UAV network status, which poses a challenge to accommodate users’ QoE requirements. For example, unreliable UtG links will dramatically degrade video demodulation quality, and a single packet loss may result in frame freezing for several seconds. Time-varying UtG links may lead to network congestion, resulting in large packet transmission latency. Therefore, it’s urgently required to solve the time-varying I-UAV networking problem to guarantee the stringent QoE requirements of users. To this end, ML/AI approaches can be explored. For instance, one can leverage ML/AI approaches (e.g., an echo state network (ESN) and long short-term memory (LSTM)) to predict stochastic packet arrival processes. With the predicted results as one of the routing metrics, novel UAV routing protocols can capture the packet accumulation status of each

![Energy efficiency vs. number of UAVs with DRL-based UAV movement decision vs. random and greedy movement decisions](image-url)
UAVs and HAPs cannot realize efficient computing in a short period of time. Prioritizing data and predicting changing trends in the data by resorting to ML/AI approaches will be promising ways of addressing this issue.

**Case Study:** Let us imagine a communication scenario where I-UAV networks with J UAVs are deployed to sense a disaster area and transmit sensed video streams back to a GCS for analysis. To accomplish the transmission task, we design an intelligent routing method and characterize QoE using latency. A typical UAV \( j \) will choose UAV \( k \) in its communication range as a forwarding node (also known as the next-hop node) to alleviate network congestion. Whether UAV \( k \) will be selected is determined by its queue backlog length \( l_k \), the transmission latency \( d_k \) between it and UAV \( j \), and its minimum hop-counts \( h_k \) toward the GCS. Since the packet arrival rate (PAR) determines the queue backlog length and directly reflects packet arrival processes, an LSTM approach is explored to predict future PARs and the corresponding queue backlog length according to historically observed PARs. Then, the UAV \( k \) with the minimum weighted sum of normalized \( l_k \), \( d_k \), and \( h_k \) will be the UAV \( j \)'s next-hop node. Compared to routing methods without PAR prediction, the novel routing method will significantly reduce the packet backlog. This is illustrated in Fig. 4 with a constant UAV communication radius \( r = 10 \) m. Figure 4 shows that the novel UAV routing protocol outperforms the shortest path routing protocol and the queue backlog-based routing protocol in decreasing the average packet transmission latency.

This article investigates the networking of I-UAVs using ML/AI approaches. It’s noteworthy that generalization ability is a bottleneck in the development of AI. To improve the generalization ability of AI, some mechanisms should be adopted to prevent overfitting. For instance, one can exploit regularization methods and increase the batch size to prevent overfitting. One can reduce the training cost to a certain extent by storing similar experience in advance and retraining NNs based on stored experience. Besides, the generalization ability of AI can be increased through data augmentation and expanding training datasets.

**INTEGRATION OF I-UAVS WITH HAPS: CHALLENGES AND INTELLIGENT APPROACHES**

Compared to UAVs, HAPs have longer communication persistence, stronger service abilities, and larger footprints. Meanwhile, compared to satellites, HAPs are much closer to UAVs, which can significantly reduce the path-loss and have shorter propagation latency and lower cost while having faster responsiveness and higher flexibility. Therefore, it’s essential to integrate I-UAVs with HAPs to significantly boost the communication coverage and enhance the service robustness [8, 9]. However, many challenging issues need to be addressed to achieve efficient integration of such a heterogeneous network. In previous literature, some issues like infrastructure design, network connectivity, layer interworking, and unified routing protocol design for heterogeneous HAP and UAV networks have been studied. Unlike previous studies, this article discusses the issues of intelligent I-UAP channel modeling and situation awareness, which remain almost untouched but will greatly benefit efficient network integration.

From the perspective of channel estimation and tracking, the HAP-UAV wireless channel differs from the UAV-UAV channel due to the unique propagation environment and transceiver antenna configuration. First, the ITU Radio Communication Sector (ITU-R) has allocated the frequency band in the Ka-band (28–31 GHz and 37–42 GHz) for HAP communications. Signals in the Ka-band are sensitive to time-varying atmospheric conditions such as oxygen, rain, and turbulence [15]. Further, the HAP-UAV wireless channel traverses the complex atmospheric propagation environment. To address this issue, online learning methods can be explored to estimate and track the HAP-UAV channel by approximating its path-loss based on continuously measured channel coefficients. Second, a massive antenna array will be mounted on an HAP to significantly increase the HAP-UAV link capacity. The directivity and channel sparsity of massive antenna array, however, pose a great challenge to HAP-UAV channel estimation and tracking. Third, owing to the long-distance propagation, the slight disturbance in the flight attitude of an HAP may cause the HAP-UAV pair to be misaligned. To tackle these issues, prediction methods combined with compressed sensing (CS) should be investigated to estimate and track the HAP-UAV channel. ML/AI approaches can be explored to predict the flight attitude of the HAP, and a CS method can recover sparse signals and corresponding channel coefficients with guaranteed estimation errors.

In view of the situation awareness of the integrated network, it’s more challenging than that of I-UAV networks. In contrast to UAVs, an HAP can be deployed at an altitude ranging from 17 km to 22 km, implying that the integrated network must generate larger and more complex airspace situations. Generating situations in such airspace raises more serious data and scene explosion concerns. This is because more data (especially videos, images, and radar data) in the airspace will be sensed and stored. To tackle the challenging issue, one should shift the way of information delivery and sharing from a raw data-centric one to a knowledge-centric one by exploring ML/AI methods. HAPs that have a wide-area sensing capability and are far from targets can send coarse knowledge to UAVs. With the assistance of or a reference to coarse knowledge, UAVs that are close to targets can generate meticulous and accurate predictions.
knowledge. Meanwhile, the scenes are prone to sudden changes in such vast airspace, which poses a great challenge to accurate sensing. Furthermore, these explosion issues put a strain on the UAV’s and HAP’s computing power. UAVs and HAPs cannot realize efficient computing in a short period of time. Prioritizing data and predicting changing trends in the data by resorting to ML/AI approaches will be promising ways of addressing this issue. For this aim, joint statistical ML (e.g., Bayesian decision) and deep learning approaches can be explored to prioritize data, which, in deep learning approaches, can classify and recognize data and statistical ML approaches can determine the priority of the classified and recognized data with the minimum Bayesian risk. Based on current and previous collected data or experience, ML/AI approaches (e.g., various types of NNs) can also be leveraged to train models for predicting changing trends in the data. Finally, envisioning the potential for significantly improving the integration efficiency of I-UAVs with HAPs, the in-depth study on the situation awareness and situation application of the integrated I-UAV and HAP network deserves more attention in the future.

Conclusion

An overview of I-UAV networking was presented in this article, including the applications of I-UAV networks, the intelligent channel modeling and situation awareness of I-UAV networks, and the challenges and intelligent approaches of I-UAV networking. Nevertheless, some key technological bottlenecks are still in the process of being addressed, and there is a need for better understanding and accurate situation awareness and the generation of global situations should be made before the critical situation-assisted I-UAV networking could contribute to intelligent I-UAV networking standards. Lastly, the potential and challenges of integrated I-UAV and HAP networking were introduced. We hope that the discussion on the intelligent I-UAV and integrated I-UAV and HAP networking in this article will inspire researchers’ interest in the I-UAV and integrated I-UAV and HAP networking and pave the way for them to design and build I-UAV and HAP-integrated networks in the future.

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