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Network Optimization I: algorithms for the orchestration of UAV 6G Networks

Abstract

The main objective of 6G-SORUS is to study the integration of UAVs with RIS and vRAN. This document describes a set of algorithms and techniques to be used when orchestrating a B5G scenario with drones. The document provides a review of the state of the art and an initial subset of techniques to apply. These are divided in three groups: general algorithms to be used by UAVs (path planning, localization, etc.), orchestration algorithms (i.e., algorithms to control the overall operation of the service), and techniques and algorithms to provide communications using drones.

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Contents

List of Figures 4
List of Acronyms 5
1. Introduction 6
2. Algorithms for UAV-based networks 7
3. Operation for UAV-based networks 15
4. Communication for UAVs 19
4.1 Integration of UAV-networks via SDN/NFV 21
5. Summary and Conclusions 23
6. References 24

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List of Figures

Figure 1. Classification of the problems and algorithms in UAV-based communications........................ 7

Figure 2. Link between the orchestration and the controller of the uav 19

Figure 3. Different connections between the orchestrator and the controller of the uav. 20

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List of Acronyms

6G: Sixth Generation of Wireless Communication Technology

ACO: Ant colony optimization

APF: Artificial potential field

CNNs: Convolutional Neural Networks

IMU: Inertial measurement unit

MAS: Multi-Agent System

MPC: Model Predictive Control

MPC: Model predictive control

NMPC: Nonlinear Model Predictive Control

PID: Proportional-Integral-Derivative

PSO: Particle swarm optimization

RL: Reinforcement Learning

RNNs: Recurrent Neural Networks

SLAM: Simultaneous Localization And Mapping

SVMs: Support Vector Machines

UAV: Unmanned Aerial Vehicle

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1. Introduction

Unmanned Aerial Vehicle (UAV) networks involve using multiple UAVs to carry out coordinated tasks like surveillance, monitoring, mapping, search and rescue, or communication. There are several advantages and disadvantages to using UAV networks, which we'll explore below.

Advantages:

1. **Quick deployment:** UAVs can be deployed rapidly, making them ideal for setting up communication networks in hard-to-reach areas or where traditional infrastructure is unavailable.
2. **Flexible:** UAVs are easy to move around, making them well-suited for emergency response situations or events where communication networks need to be established quickly.
3. **Wide coverage:** UAVs can provide communication coverage to large areas, making them ideal for creating networks in remote or rural regions.
4. **Resilient:** UAVs can establish communication networks in disaster-stricken areas where traditional infrastructure may be damaged or non-existent.
5. **Cost-effective:** UAV-based networks can be cost-effective compared to traditional infrastructure, particularly in remote areas where laying cables or building towers is expensive.

Disadvantages:

1. **Limited battery life:** UAVs have a restricted battery life, which can limit their usefulness in establishing communication networks for long periods.
2. **Limited payload capacity:** UAVs have a limited payload capacity, restricting the number and type of communication equipment they can carry.
3. **Weather-dependent:** UAV-based networks require favourable weather conditions and may not be suitable for use in adverse weather conditions.
4. **Limited bandwidth:** The communication network created by UAVs may have limited bandwidth, which could negatively impact communication quality.
5. **Regulatory challenges**: UAV-based networks may face regulatory hurdles, particularly in areas with restrictions on UAV use or where the airspace is congested.

In summary, UAV-based networks offer benefits such as quick deployment, flexibility, wide coverage, resilience, and cost-effectiveness. However, they also have limitations such as limited battery life, payload capacity, weather-dependence, bandwidth limitations, and regulatory challenges. These disadvantages should be taken into account when deciding whether to use UAVs for establishing communication networks.

In what follows, we present an updated review of the state of the art considering algorithms for the operation of drones in B5G scenario. It has been done by performing a literature review of the most recent scientific works published, which have been ranked by their relevance, and then classifying them in three groups: general algorithms to be used by UAVs (path planning, localization, etc.), Orchestration algorithms, and techniques and algorithms to provide communications using drones.

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2. Algorithms for UAV-based networks

There are several algorithms used for unmanned aerial vehicles (UAVs) that allow them to perform different tasks and missions. We present in the next figure some problems for UAVs and the algorithms to address them.

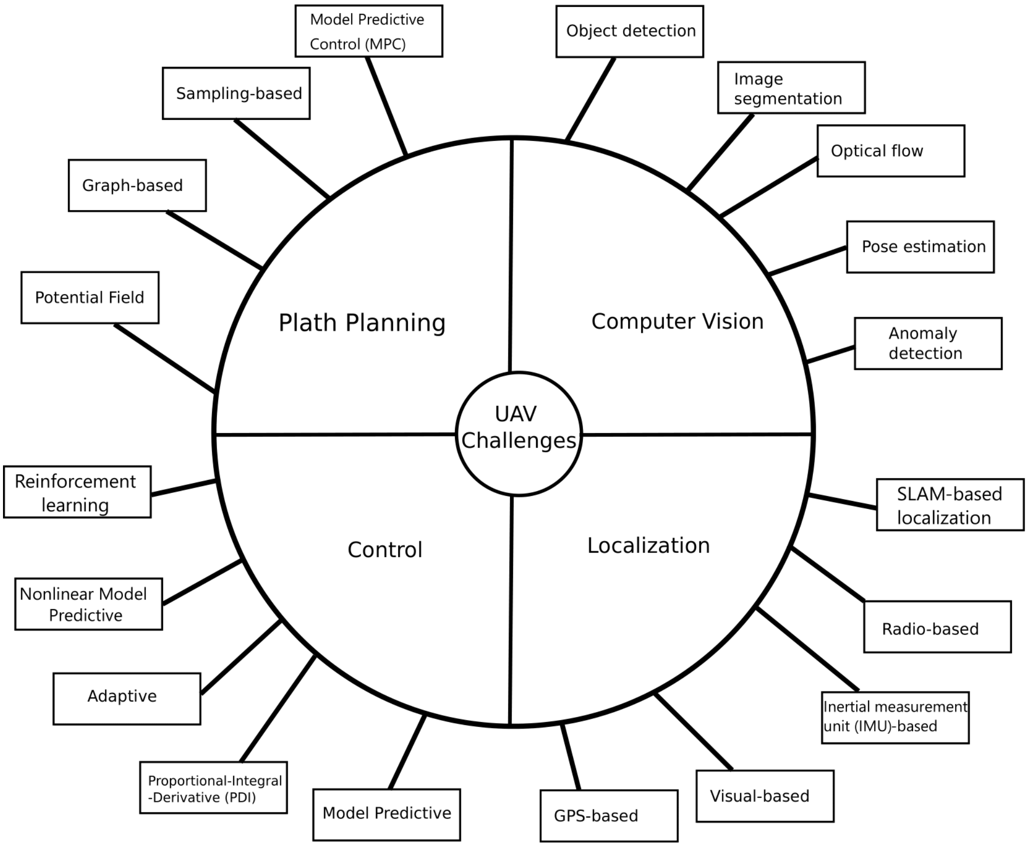

FIGURE 1. CLASSIFICATION OF THE PROBLEMS AND ALGORITHMS IN UAV-BASED COMMUNICATIONS

We next provide an in-depth exploration of each of these algorithms, delving into their strengths and limitations. Additionally, we also address the upcoming challenges that lie on the horizon.

Path planning algorithms for UAVs

These algorithms are designed to find an optimal or near-optimal path for the UAV to follow in order to complete a mission. This can include tasks such as surveillance, inspection, search and rescue, and more. The algorithm must take into account various factors such as terrain, obstacles, energy consumption, and time constraints.

Path Planning		
Algorithm	Challenge	Approach
Potential Field [CWH17, CSQ13]	Imagine a search and rescue mission in a disaster-	This algorithm creates a virtual field around the UAV,

	stricken area, and you have a team of UAVs tasked with locating survivors in a partially collapsed urban environment. The UAVs need to navigate through the debris, buildings, and other obstacles to find and mark the locations of survivors.	with attractive forces guiding the UAV towards its target and repulsive forces pushing it away from obstacles.
Graph-based [LCC20]	Imagine a scenario where you have a network of UAVs tasked with optimizing their connectivity to ensure efficient communication and data sharing among them. The UAVs are deployed in a large, remote area with various obstacles and terrain features that affect their communication range. The goal is to design a network topology that maximizes connectivity while minimizing energy consumption.	This algorithm represents the environment as a graph, with each node representing a location in the environment and each edge representing a possible path between nodes. The algorithm then searches for the shortest path from the UAV's current location to its destination.
Sampling-based [KF13]	Imagine a scenario where you have a team of UAVs tasked with monitoring a forested area for potential fires and, if a fire is detected, suppressing it by dropping water or fire retardant. The forest is dense and filled with trees of varying heights, making navigation challenging. The UAVs must find efficient paths through the forest to monitor the entire area and respond quickly to any fire detections.	This algorithm generates a random set of points in the environment and connects them to create a graph. The algorithm then searches for the shortest path from the UAV's current location to its destination using this graph.

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Model Predictive Control (MPC) [KLP17, GRW13].	Imagine a precision agriculture scenario where you have a fleet of UAVs tasked with optimizing the distribution of fertilizers or pesticides in a large agricultural field. The goal is to minimize resource usage (e.g., chemicals, fuel) while maximizing crop yield by precisely targeting areas that require treatment.	This algorithm predicts the UAV's future movements based on its current state and environmental conditions and generates a path accordingly. The algorithm continually updates the path based on changes in the UAV's state and environmental conditions.

Path planning algorithms play a crucial role in enabling UAVs to navigate through complex environments and complete their missions safely and efficiently. As seen above, current solutions rely on different techniques such as building a graph or virtual fields, and could be used to plan the temporary coverage to be provided in a deployment using UAVs.

<u>Computer vision algorithms for UAVs</u>

Computer vision algorithms play a critical role in enabling unmanned aerial vehicles to analyse images and videos in real-time to identify objects, recognize faces, and detect anomalies. These algorithms enable UAVs to process visual information and make decisions based on what they "see".

Computer Vision		
Algorithm	Challenge	Approach
Object detection [RTO19, LZX16]	Imagine a wildlife conservation project in a vast natural reserve or national park. The goal is to monitor and protect endangered species while collecting data on their behaviour and habitat.	This algorithm allows the UAV to detect and recognize objects in its environment, such as people, cars, buildings, and more. It can use various techniques such as deep learning and image processing to detect objects.
Image segmentation [YGL19]	Imagine a precision agriculture scenario where you have a fleet of UAVs tasked with monitoring the health of crops in a large agricultural field.	This algorithm separates an image into different regions or segments based on similarities such as colour, texture, and shape. It can be used to detect and

	The goal is to assess crop health, detect diseases or stress, and provide targeted treatments to improve crop yield while conserving resources.	identify objects in an image and extract useful information.
Optical flow [CCW02]	Imagine a scenario where you have a UAV tasked with navigating autonomously through an indoor environment or a densely populated urban area where GPS signals are unreliable or unavailable. The UAV needs to fly safely and avoid obstacles while reaching a specified destination.	This algorithm analyses the motion of objects in an image sequence, allowing the UAV to estimate the motion of its surroundings. It can be used for tasks such as tracking moving objects, detecting changes in the environment, and avoiding obstacles
Pose estimation [ZLH19, FMS18]	Imagine a scenario where you have a UAV tasked with autonomously navigating and mapping the interior of a large industrial facility or warehouse. The goal is to inspect the environment, locate specific objects, and build a detailed map for subsequent analysis or maintenance.	This algorithm determines the 3D position and orientation of an object in an image or video. It can be used to track the UAV's own position and orientation, as well as to detect and track other objects in the environment
Anomaly detection [AA18, CK20]	Imagine a scenario where you have a fleet of UAVs responsible for monitoring a network of pipelines and critical infrastructure, such as power lines, railroads, or water supply systems. The goal is to detect anomalies, including leaks, damages, or unauthorized access, to ensure the integrity and security of the infrastructure.	This algorithm detects unusual or unexpected events in an image or video sequence. It can be used for tasks such as identifying potential security threats, monitoring for changes in the environment, and detecting anomalies in infrastructure

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Computer vision algorithms are essential for enabling UAVs to make sense of the visual information they capture and to perform a variety of tasks, from surveillance and inspection to search and rescue and more.

Localization algorithms for UAVs

Localization algorithms for unmanned aerial vehicles (UAVs) are designed to determine the UAV's position and orientation accurately in real-time. Accurate localization is critical for enabling the UAV to navigate through its environment, avoid obstacles, and complete its mission successfully.

Localization		
Algorithm	Challenge	Approach
GPS-based localization [WLL19]	Imagine a precision agriculture scenario where you have a fleet of UAVs tasked with mapping a large agricultural field and performing precision farming operations, such as planting, fertilizing, or pest control. The goal is to optimize crop yield by applying treatments and resources precisely where needed.	This algorithm uses GPS signals to determine the UAV's position. It requires a GPS receiver on the UAV and a sufficient number of GPS satellites in view. However, GPS signals can be affected by factors such as signal interference and obstacles, which can reduce the accuracy of the UAV's position
Inertial measurement unit (IMU)-based localization [KN18]	Imagine a scenario where you have a UAV tasked with exploring and mapping the interior of a large and complex indoor environment, such as a warehouse, factory, or underground facility, where GPS signals are unavailable. The goal is to create a detailed map of the environment and navigate autonomously.	This algorithm uses measurements from an IMU, which typically includes accelerometers and gyroscopes, to estimate the UAV's position and orientation. IMUs are often used in combination with GPS to improve localization accuracy, especially when GPS signals are weak or unavailable
Visual-based localization [FCW18, CST19]	Imagine a search and rescue mission in a complex and cluttered environment, such as an urban disaster area or a densely	This algorithm uses visual features in the UAV's environment, such as landmarks or objects, to

	forested region. The goal is to locate and rescue survivors or missing persons in challenging conditions.	determine the UAV's position and orientation. It can use various techniques such as feature extraction, image processing, and machine learning to estimate the UAV's position
Radio-based localization [KMN16, SMM14]	Imagine a scenario where you have a UAV tasked with monitoring and collecting environmental data in remote and dense forests where GPS signals are unreliable or non-existent. The goal is to gather data about the forest's health, wildlife, and environmental conditions.	This algorithm uses radio signals, such as Wi-Fi or Bluetooth, to estimate the UAV's position. It requires a network of radio beacons to be installed in the environment, and the UAV's position is determined based on the strength and timing of the radio signals
SLAM-based localization [AVT+16]	Imagine a scenario where you have a UAV tasked with autonomously exploring and mapping the interior of an unknown and potentially hazardous underground mine. The goal is to create a detailed map of the mine's layout and environmental conditions while ensuring the safety of the UAV.	This algorithm uses simultaneous localization and mapping (SLAM) techniques to create a map of the UAV's environment while simultaneously estimating the UAV's position and orientation. It can use various sensors such as cameras, LiDAR, and IMUs to create the map and estimate the UAV's position

Localization algorithms are critical for enabling UAVs to navigate through their environment accurately and perform a variety of tasks, from surveillance and inspection to search and rescue and more.

Control algorithms for UAVs

These algorithms are designed to control the motion of the UAV and ensure that it flies safely and efficiently. These algorithms take input from various sensors such as accelerometers, gyroscopes, GPS, and cameras, and generate commands to control the UAV's motors or servos.

Control

Algorithm	Challenge	Approach
Proportional-Integral-Derivative (PID) control [IMI17, MB08]	Imagine a scenario where you have a UAV equipped with a high-resolution camera and LiDAR sensor, tasked with capturing aerial images and generating accurate 2D or 3D maps for surveying and mapping purposes. The goal is to capture images with minimal motion blur and ensure precise coverage of the survey area.	This algorithm uses a feedback loop to adjust the UAV's motion based on its current state and desired state. The algorithm calculates an error signal, which is the difference between the desired state and the current state, and generates a control output based on this error signal.
Model Predictive Control (MPC) [BKD18]	Imagine a scenario where you have a racing UAV that needs to complete a challenging course with precision manoeuvres, such as navigating through tight turns, flying through gates, and avoiding obstacles. The goal is to complete the course as quickly as possible while adhering to safety constraints and optimizing the UAV's trajectory.	This algorithm predicts the UAV's future state based on its current state and environmental conditions, and generates a control output accordingly. It takes into account various factors such as energy consumption, time constraints, and environmental obstacles to generate an optimal or near-optimal control output.
Nonlinear Model Predictive Control (NMPC) [LBT11]	Imagine a scenario where you have a UAV tasked with autonomously inspecting and monitoring complex structures such as bridges, tall buildings, or wind turbines. The goal is to navigate the UAV to inspect specific areas of the structure, capture visual data, and make real-time decisions to ensure safe and effective inspection.	This algorithm is similar to MPC, but it uses a nonlinear model of the UAV's motion and dynamics to generate the control output. NMPC can handle nonlinear dynamics and constraints, and is often used for controlling UAVs in challenging environments

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Adaptive control [HMS05, TD13]	Imagine a scenario where you have a UAV tasked with performing autonomous missions in extreme weather conditions, such as strong winds, turbulence, heavy rain, or snow. The goal is to ensure safe and stable flight, maintain mission objectives, and adapt to unpredictable weather variations.	This algorithm adjusts the control output based on changes in the UAV's dynamics and environmental conditions. It uses feedback from various sensors to continuously update the control output, allowing the UAV to adapt to changing conditions such as wind gusts or changes in payload weight.
Reinforcement learning [DHG+20, TZZ+21, SWJ+20].	Imagine a scenario where you have a UAV tasked with autonomously patrolling and monitoring a large area, such as a perimeter fence around a secure facility. The goal is to detect and respond to potential intrusions while optimizing patrol routes and conserving energy.	This algorithm uses a trial-and-error approach to learn the optimal control output for a given task. It uses feedback from the environment to adjust the control output and can learn to navigate complex environments and perform tasks such as obstacle avoidance and target tracking.

Control algorithms are critical for enabling UAVs to fly safely and perform a variety of tasks, from surveillance and inspection to search and rescue and more.

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3. Operation of UAV-based networks

In this section we describe some of the main orchestration techniques used in unmanned aerial vehicle (UAV) networks.

Centralized orchestration

Centralized Orchestration involves a centralized controller that oversees and coordinates the activities of all UAVs in the network. This controller can either be a human operator or an automated system, and it communicates with the UAVs through wireless communication links such as Wi-Fi or cellular networks [ZCR19, RLC18].

Through these links, the central controller assigns tasks, monitors progress, and adjusts behavior as needed. The UAVs themselves are equipped with various sensors and cameras that capture data and enable tasks such as mapping, inspection, and surveillance. They can also communicate with each other to coordinate activities and share information.

In a Centralized Orchestration scenario, the central controller can optimize the UAV network's performance using algorithms and protocols. It assigns tasks based on UAV location, capabilities, and availability and adjusts behavior to account for environmental changes such as weather or obstacles.

Centralized Orchestration is particularly useful in scenarios requiring a high degree of coordination and control, such as large-scale search and rescue operations or military missions. However, it can be resource-intensive, as it necessitates a central controller to manage and monitor all UAV activities in the network.

Distributed orchestration

Distributed Orchestration is an alternative approach to coordinating unmanned aerial vehicle (UAV) networks, in contrast to Centralized Orchestration. In a Distributed Orchestration scenario, the UAVs work together as a team and communicate with each other to achieve a common goal [ZWW+16, SSZ+19].

Each UAV has some degree of autonomy and can make decisions based on local information and feedback from other UAVs in the network. For example, UAVs can communicate with each other through wireless links, such as Wi-Fi or cellular networks, and share information about their location, altitude, and speed. They can also share sensor data, such as images or video feeds, to build a more comprehensive understanding of the environment.

In a Distributed Orchestration scenario, each UAV can be responsible for a specific task or area of coverage, such as surveillance or mapping. The UAVs can use algorithms and protocols to coordinate their activities, such as avoiding collisions or maximizing coverage of the area of interest. They can also adapt their behavior based on changing conditions in the environment, such as wind or obstacles.

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Distributed Orchestration can be particularly useful in scenarios where a high degree of flexibility and adaptability is required, such as in environmental monitoring or precision agriculture. However, it can also be more challenging to coordinate and monitor the activities of the UAVs in a distributed system, as each UAV has some level of autonomy and can make its own decisions. To address this, some distributed orchestration systems may still have a central controller to provide high-level guidance and coordination to the UAVs.

Hybrid Orchestration

Hybrid Orchestration is a combination of both Centralized and Distributed Orchestration techniques, which attempts to harness the advantages of both approaches while mitigating their disadvantages.

In a Hybrid Orchestration scenario, some UAVs may operate under Centralized Orchestration, while others may operate under Distributed Orchestration. For example, a subset of UAVs may be assigned specific tasks by a central controller, while the remaining UAVs may work together as a team and communicate with each other to achieve a common goal [IGL19, AYS+20].

The Centralized Orchestration component of the system can provide high-level guidance and coordination to the UAVs, while the Distributed Orchestration component can provide flexibility and adaptability to changing conditions in the environment. The UAVs can use wireless communication links, such as Wi-Fi or cellular networks, to exchange information with each other and with the central controller.

The Hybrid Orchestration approach can be particularly useful in scenarios where a mix of tasks and objectives are required. For example, in a search and rescue operation, some UAVs may be responsible for mapping the area and searching for survivors, while others may be responsible for delivering medical supplies or providing communication links to first responders. By combining Centralized and Distributed Orchestration techniques, the UAV network can be optimized to meet all of these objectives.

However, implementing a Hybrid Orchestration system can be more complex than using just one orchestration technique. It requires careful design and integration of the various components of the system, and can also require more resources and computational power to manage both centralized and distributed components.

Multi-Agent Systems Orchestration

Multi-Agent System (MAS) orchestration is a process of coordinating multiple agents (in this case, unmanned aerial vehicles or UAVs) to achieve a common goal. In the context of UAV networks, MAS orchestration involves managing the interactions and behaviors of multiple UAVs to carry out a specific mission, such as surveillance or package delivery.

Here are some steps that might be involved in orchestrating a MAS of UAVs:

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1. **Mission Planning**: The first step is to define the mission objectives and constraints, such as the area to be covered, altitude restrictions, and safety requirements. The mission planner uses this information to develop a high-level plan for the UAVs, including their flight paths, tasks, and roles [MKM19].
2. **Task Assignment:** Once the mission plan is in place, the task assignment module allocates specific tasks to each UAV based on their capabilities and availability. For example, one UAV might be assigned to collect visual data, while another is assigned to transport cargo [SLK19].
3. **Communication and Coordination**: The UAVs need to communicate with each other to co-ordinate their actions and avoid collisions. The communication protocol used must be reliable and secure, and the coordination module must be able to handle conflicts and adjust plans in real-time [BAL19].
4. **Control and Monitoring:** The control and monitoring module is responsible for ensuring that the UAVs are following their assigned tasks and that their performance is within acceptable limits. This involves monitoring their flight path, speed, altitude, and battery level, and adjusting their behavior as needed [MSB+17].
5. **Fault Detection and Recovery:** In case of a malfunction or loss of communication, the MAS must be able to detect and recover from faults. This involves identifying the affected UAVs, re-assigning their tasks, and coordinating with the other UAVs to compensate for the loss [DLZ+19].

MAS orchestration is a complex process that requires sophisticated algorithms and technologies to manage the interactions and behaviors of multiple UAVs. However, with the right tools and techniques, it can enable efficient and effective operation of UAV networks in a variety of applications.

<u>Machine Learning Orchestration</u>

Machine learning orchestration is a process of managing the deployment, training, and optimization of machine learning models in a complex system such as unmanned aerial vehicles (UAVs) networks. In the context of UAVs, machine learning can be used for a variety of tasks, such as object detection, navigation, and anomaly detection.

Here are some steps that might be involved in orchestrating a machine learning system for UAV networks:

1. **Data Collection:** The first step in machine learning orchestration is to collect relevant data that can be used to train and test the machine learning models. This might include visual data from cameras mounted on the UAVs, sensor data, and other information [AYA+19].
2. **Model Selection:** Once the data is collected, the next step is to select the appropriate machine learning model(s) to use for the specific task(s) at hand. This might involve choosing from a variety of models such as deep neural networks, decision trees, or support vector machines [KCA+19].
3. **Training and Testing:** The selected model(s) must be trained and tested on the collected data. This involves partitioning the data into training and testing sets, and then using the training data to train the model and the testing data to evaluate its performance [ZGL+19].

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4. **Deployment:** Once the model is trained and tested, it can be deployed to the UAVs in the network. This might involve installing the model on the UAVs or on a central server that communicates with the UAVs [ZWW+19].
5. **Monitoring and Optimization:** After the model is deployed, it must be monitored to ensure that it is performing well and making accurate predictions. If the model's performance is not satisfactory, it may need to be retrained or replaced with a different model [SV18].
6. **Integration with MAS Orchestration:** Finally, the machine learning model must be integrated with the Multi-Agent System (MAS) orchestration to coordinate the actions of the UAVs. This might involve using the model's predictions to adjust the UAVs' flight paths or tasks in real-time [BPN14].

Machine learning orchestration is a critical component of UAV networks, enabling the UAVs to perform complex tasks and adapt to changing environments in real-time.

It is worth mentioning that the choice of orchestration technique depends on the specific requirements of the UAV network and the tasks that need to be performed. Some tasks may require centralized control and coordination, while others may benefit from a more distributed or hybrid approach. Machine learning orchestration can be particularly useful in complex environments where the UAVs need to adapt to changing conditions and learn from their experiences.

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4. Communication for UAVs

In this section, we delve into the synergy between UAVs and orchestration, specifically focusing on connectivity. We provide a visual representation of this connection in the following figure. While the orchestrator-controller link was briefly mentioned in the previous deliverable (6G-SORUS-DRONE), we now explore it in depth.

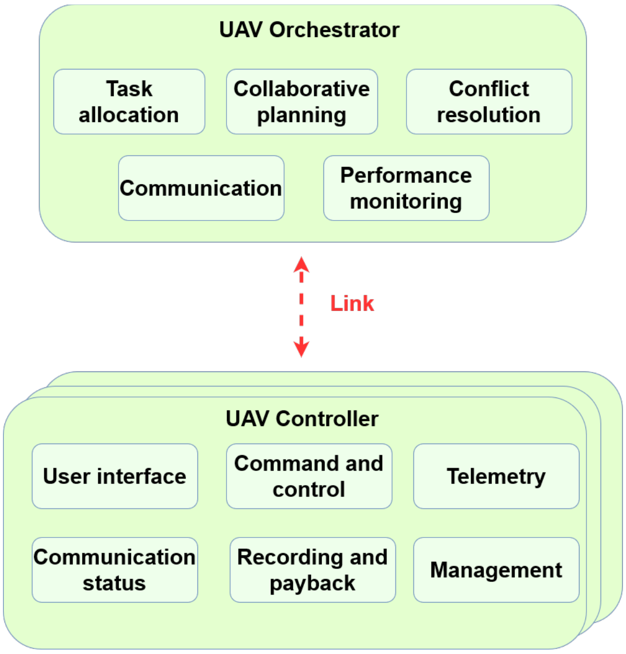

FIGURE 2. LINK BETWEEN THE ORCHESTRATION AND THE CONTROLLER OF THE UAV

If we zoom in the link, we find several components that empower the connection between the UAV and the orchestrator. These component are mainly: Communication Protocol, Telemetry Data Stream, Command and Control Interface (RESTful API), Mission Planning and Execution Module, Waypoint Management, Safety and Emergency Procedures, Data Encryption and Security, Error Handling and Recovery and Remote Control Override.

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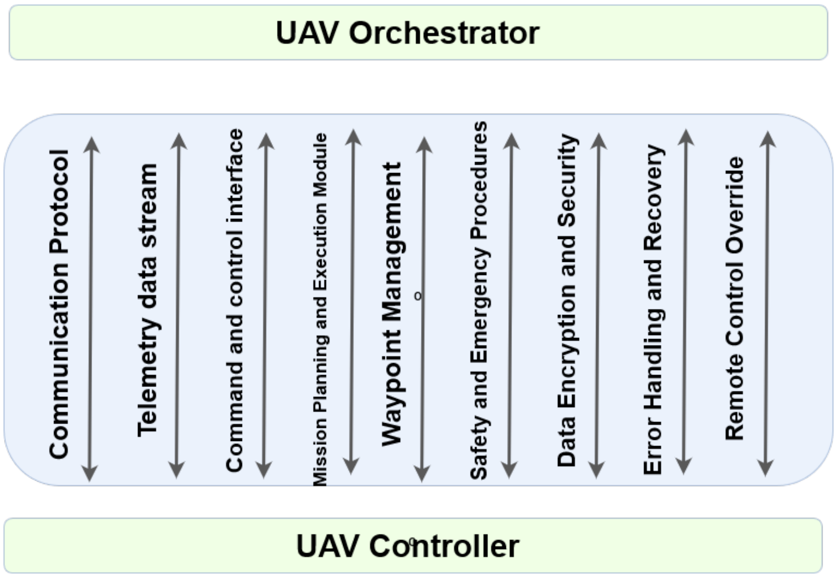

FIGURE 3. DIFFERENT CONNECTIONS BETWEEN THE ORCHESTRATOR AND THE CONTROLLER OF THE UAV.

1. **Communication Protocol:** This establishes the rules and format for data exchange between the UAV and the orchestrator. Common protocols include MQTT, RESTful APIs, and UDP, ensuring efficient communication.
2. **Telemetry Data Stream:** This continuous flow of data from the UAV to the orchestrator provides critical information such as GPS coordinates, altitude, battery status, sensor readings, and overall UAV health.
3. **Command and Control Interface:** It serves as a standardized method for the orchestrator to send commands to the UAV. This interface allows for actions like takeoff, landing, waypoint navigation, and altitude adjustments to be initiated.
4. **Mission Planning and Execution Module:** Within the UAV, this module interprets high-level mission plans from the orchestrator. It employs algorithms like a pathfinding to plan routes, avoid obstacles, and adapt to changes in real-time.
5. **Waypoint Management:** The UAV controller manages a list of waypoints provided by the orchestrator. These waypoints guide the UAV to specific locations, ensuring it follows the desired path.
6. **Safety and Emergency Procedures**: These predefined procedures, such as return-to-home (RTH) in low battery situations, enhance UAV safety and allow it to respond to critical issues promptly.
7. **Data Encryption and Security:** Security measures, including AES-256 encryption and TLS/SSL protocols, protect data integrity and confidentiality during communication between the orchestrator and UAV.
8. **Error Handling and Recovery**: Both the orchestrator and UAV controller employ mechanisms to handle communication failures, ensuring reliable data transfer and mission continuity.

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9. **Remote Control Override**: In cases of emergency or loss of communication, a remote-control station can take manual control of the UAV, ensuring human intervention when necessary.

4.1 Integration of UAV-networks via SDN/NFV

SDN and NFV are intricately intertwined and complement each other seamlessly. SDN plays a pivotal role in benefiting NFV by providing the capability to create programmable network connections between Virtual Network Functions (VNFs), which in turn enables more advanced traffic management. Conversely, NFV supports SDN by virtualizing components like SDN controllers, essentially treating them as VNFs that can be executed in the cloud. This virtualization facilitates the dynamic relocation of SDN controllers to optimal locations as needed.

The integration of Software-Defined Networking (SDN) in Unmanned Aerial Vehicle (UAV) networks is appealing due to its numerous advantages. UAVs are often treated as SDN switches, and this approach is well-suited to address the unique challenges of UAV networks:

1. **Resource Limitations:** UAV networks have restricted communication and resource usage capabilities.
2. **High Traffic Demands:** Specific scenarios can lead to high traffic demands, consuming more energy and overloading the network.
3. **Intermittent Connectivity:** The mobility of UAVs leads to intermittent connectivity and network fragmentation.
4. **Global Network View:** Efficient UAV deployment requires a global view of the network.

SDN integration in UAV networks offers solutions to these challenges without completely redesigning the network architecture. Key solutions include:

- **Centralized Control:** SDN's centralized control can enhance resource utilization and quality of service (QoS). It requires constant updates of network topology to maintain UAV-SDN controller connectivity.
- **Flexible Resource Allocation:** SDN enables flexible reconfiguration and allocation of radio resources among UAV swarms through ground-based centralized controllers.
- **Load Balancing:** SDN optimizes load balancing between UAVs and ground-based Base Stations (BSs).
- **Efficient Traffic Routing:** SDN controllers facilitate efficient routing of traffic among UAVs, preventing losses and network congestion.
- **Dynamic UAV Management:** SDN allows dynamic adjustment of 3D UAV movements for optimized location management, polling, and paging.

We next analyze different SDN-based architectures that aim to flexibly manage UAV networks.

1. **SDN-based routing:** it centralizes control over routing decisions, separating the control plane from the data plane. This approach allows for dynamic and flexible routing by utilizing

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a centralized controller, such as an OpenFlow controller, which maintains a global view of the network. SDN employs flow-based routing, making decisions based on packet characteristics, enabling real-time adjustments for optimal traffic management, traffic engineering for resource optimization, and policy-based routing to enforce specific rules or security requirements. Examples of SDN-based routing applications include data center optimization, dynamic routing in Software-Defined Wide Area Networks (SD-WANs), efficient Internet Service Provider (ISP) traffic management, and scalable cloud network resource allocation [RSL+17, QSK+19].

2. **SDN-based monitoring:** it leverages the centralized control and programmability of Software-Defined Networking to gain deep insights into network traffic, performance, and security. In SDN, monitoring functions can be orchestrated and applied dynamically, allowing network administrators to collect real-time data and respond to network events more effectively. For instance, using SDN, one can implement traffic analysis tools that monitor specific flows or applications, detect anomalies, and reroute traffic for security purposes, such as isolating a compromised segment of the network. Additionally, SDN-based monitoring facilitates Quality of Service (QoS) assurance by continuously monitoring and optimizing traffic flows to meet service-level agreements (SLAs), ensuring a high-quality user experience [ZSG+18, CLT+18].
3. **SDN-based coverage:** This approach is particularly valuable in wireless and mobile networks, such as 5G and IoT deployments. For instance, in a 5G network, SDN can dynamically allocate resources to ensure consistent and efficient coverage for connected devices. It can intelligently reroute traffic and adjust network parameters to address coverage gaps or interference. In IoT applications, SDN-based coverage can prioritize and manage communication for a vast number of devices efficiently. Furthermore, in rural or remote areas, SDN can enable cost-effective deployment by allowing network operators to adapt and scale coverage as needed, improving connectivity in underserved regions [AEL+17, SPD+13]

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5. Summary and Conclusions

The deployment of UAV-based networks presents various challenges that require the development of sophisticated algorithms to address them. The state-of-the-art algorithms for UAV-based networks include deployment, mobility, routing, and resource allocation algorithms. These algorithms aim to optimize network coverage, capacity, and efficiency while minimizing energy consumption and interference. However, several challenges and open research issues remain, such as the integration of UAV-based networks with existing infrastructure, the management of interference, and the security and privacy concerns. Further research and development in algorithm design and optimization are crucial to overcome these challenges and fully realize the potential of UAV-based networks.

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