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Implementation of a communication system between drones and ground sensors for road traffic monitoring

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Dédicace

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Resume

Ce mémoire de fin d'études explore la mise en œuvre d'un système de communication novateur entre drones et capteurs au sol pour la surveillance du trafic routier. Face aux limitations des systèmes de surveillance traditionnels, l'intégration des Véhicules Aériens Sans Pilote (UAVs) offre des solutions prometteuses pour une gestion du trafic plus efficace.

Le document débute par une analyse approfondie des architectures des UAVs (multirotors, voilures fixes, hybrides) et de leurs caractéristiques opérationnelles (poids, endurance, portée, altitude). Il explore ensuite les protocoles de communication spécifiques aux UAVs tels que MAVLink, UranusLink et UAVCAN, en mettant en avant leurs avantages et leurs limitations, notamment en termes de sécurité et d'efficacité des ressources. Les différentes architectures de communication en essaim (centralisée, décentralisée à groupe unique, multi-groupes et multi-couches) ainsi que les protocoles de routage associés (basés sur la topologie, la position ou l'intelligence en essaim) sont également détaillés, soulignant leur impact sur la scalabilité et la robustesse.

Une partie substantielle du travail est consacrée à l'intégration de l'Intelligence Artificielle (IA) et des techniques d'apprentissage automatique (ML) pour optimiser les performances des UAVs. Cela inclut l'amélioration de la planification de trajectoire, de la gestion des missions, de la perception et de l'extraction de caractéristiques à travers des méthodes d'apprentissage supervisé, non supervisé et par renforcement (comme les Deep Q-Networks et Deep Deterministic Policy Gradient). Le mémoire aborde également les défis de sécurité cruciaux dans les réseaux d'UAVs, en identifiant les menaces (écoute clandestine, brouillage, attaques de l'homme du milieu, attaques par rejeu, portes dérobées, déni de service) et en présentant les solutions existantes pour garantir l'intégrité et la confidentialité des communications.

En conclusion, ce travail souligne que malgré les avancées significatives, des défis subsistent concernant l'endurance opérationnelle, la stabilité des communications et les cadres réglementaires. L'innovation continue dans les systèmes énergétiques, les protocoles réseau et le développement de politiques sera cruciale pour l'adoption généralisée des UAVs dans les infrastructures de transport intelligentes du futur.

Abstract

This final year project report investigates the implementation of an innovative communication system between drones and ground sensors for road traffic surveillance. Addressing the limitations of traditional traffic monitoring systems, the integration of Unmanned Aerial Vehicles (UAVs) offers promising solutions for more efficient traffic management.

The document begins with a thorough exploration of UAV architectures (multi-rotors, fixed-wing, hybrid designs) and their operational characteristics (weight, endurance, range, altitude). It then examines UAV-specific communication protocols such as MAVLink, UranusLink, and UAVCAN, highlighting their strengths and weaknesses, particularly in terms of security and resource efficiency. Various swarm communication architectures (centralized, decentralized single-group, multi-group, and multi-layer) and associated routing protocols (topology-based, geographic/position-based, or swarm intelligence-based) are also detailed, emphasizing their impact on scalability and robustness.

A significant portion of the work is dedicated to integrating Artificial Intelligence (AI) and Machine Learning (ML) techniques to optimize UAV performance. This includes enhancing trajectory planning, mission scheduling, perception, and feature extraction through supervised, unsupervised, and reinforcement learning methods (such as Deep Q-Networks and Deep Deterministic Policy Gradient). The report also addresses crucial security challenges in UAV networks, identifying threats (eavesdropping, jamming, man-in-the-middle, replay attacks, backdoor, denial of service) and presenting existing solutions to ensure communication integrity and confidentiality.

Finally, the document presents and analyzes six distinct UAV-based road traffic monitoring methods, ranging from Airborne Traffic Surveillance Systems (ATSS) to 5G integration, cooperative surveillance, emergency vehicle routing assistance systems, and collaborative hotspot selection. These case studies highlight the potential of UAVs to provide real-time, adaptive, and scalable traffic management solutions.

In conclusion, this work emphasizes that despite significant advancements, challenges persist regarding operational endurance, communication stability, and regulatory frameworks. Continued innovation in energy systems, network protocols, and policy development will be critical for the widespread adoption of UAVs in future intelligent transportation infrastructures.

Keywords — UAV, drone communication, road traffic surveillance, swarm networks, MAVLink, UAVCAN, UranusLink, routing protocols, AI, machine learning, trajectory optimization, Deep Q-Network, DDPG, security in UAVs, traffic monitoring, 5G, cooperative surveillance, intelligent transportation systems

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Contents

List of Figures

List of abbreviations

ACL	Average Connectivity Lifetime (durée de vie moyenne de la connectivité)
AI / IA	Artificial Intelligence / Intelligence Artificielle
AoI	Age of Information
APAR	Ant Colony Optimization-based Polymorphism-Aware Routing
ATSS	Airborne Traffic Surveillance System / Système de Surveillance Aérienne du Trafic
BeeAdhoc	Bee colony algorithm-based Ad hoc network
BS	Base Station / station de base
CAN	Controller Area Network
CDS	Connected Dominating Set
CHS	Collaborative Hotspot Selection
CLP	Connectivity Lifetime Path
CNN	Convolutional Neural Network
COMPID	Component ID
CRC	Cyclic Redundancy Check
DCR	Data Centric Routing
DDPG	Deep Deterministic Policy Gradient
DelayP	Transmission delay
DQN	Deep Q-Networks
DRL	Deep Reinforcement Learning
DREAM	DREAM (protocol name, no long form available)
DSDV	Destination Sequenced Distance Vector
DSR	Dynamic Source Routing
EED	End-to-End Delay
EM	Expectation-Maximization
FAA	Federal Aviation Administration
FDOT	Florida Department of Transportation
FoV	Field of View
GA-LSTM	Generative Adversarial Long Short-Term Memory
GAN	Generative Adversarial Network
GCS	Ground Control Station
GGF	Greedy Geographic Forwarding
GLS	Grid Location Services
GLSR	Geographic Load Share Routing
GMM	Gaussian Mixture Model
GMT	Greenwich Mean Time

GNSS	Global Navigation Satellite System
GPMOR	Geographic Position Mobility Oriented Routing
GPS	Global Positioning System
GPU	Graphics Processing Unit
GPSR	Greedy Perimeter Stateless Routing
G-T-G	Group-to-Group
HLS	Hierarchical Location Services
HN	Helping Node
HRP	Hybrid Routing Protocol
IAFSA	Improved Artificial Fish-Swarm Algorithm
ID	Identifier
IoT	Internet of Things
LAP	Low Altitude Platform
LEN	Payload Length
LoS	Line-of-Sight
LPR	License Plate Recognition
LR	Linear Regression
LSTM	Long Short-Term Memory
MAC	Medium Access Control
MAVLink	Micro Air Vehicle Link
MBS	Mobile Base Station
MEC	Mobile Edge Computing
MID	Message Identification
MiTM	Man-in-the-Middle
ML / apprentissage automatique	Machine Learning
MLHR	Multilevel Hierarchical Routing
MLP	Multilayer Perceptron
MLP-ARD	Multilayer Perceptron with Automatic Relevance Detection
ML-OLSR	Mobility and Load-aware OLSR
MPC	Model Predictive Control
MPGR	Mobility Prediction-based Geographic Routing
MPR	Multiple Point Relays
MSGID	Message Identifier
NS	Number of Segments Traversed
OC	Overspeeding Count
OH	Overhead
OLSR	Optimized Link State Routing
ONE	Opportunistic Network Environment
PDR	Packet Delivery Ratio
PID	Proportional-Integral-Derivative
POI	Point of Interest
PRE	Preamble
PRP	Proactive Routing Protocol
QoS	Quality of Service
R-CNN	Recurrent Convolutional Neural Network
RE	Remaining Energy
RE-DSR	Restrict DSR

REP	Residual Energy Path
RGR	Reactive-Greedy-Reactive
RLS	Reactive Location Services
RN	Reporting Node
RNN	Recurrent Neural Network
RREP	Route Reply
RREQ	Route Request
RRP	Reactive Routing Protocol
RSS	Received Signal Strength
RTM	Road Traffic Monitoring
SfM	Structure-from-Motion
SHA-256	Secure Hash Algorithm 256
SI	Swarm Intelligence
SNN	Spiking Neural Network
SPOF	Single Point of Failure
SQN	Sequence Number
STDP	Spike Time Dependent Plasticity
STX	Start-of-Frame Indicator
SVM	Support Vector Machine
SYS ID	System Identifier
TD3	Twin Delayed DDPG
TORA	Temporarily Ordered Routing Algorithm
TS	Target Service
3D	Three-Dimensional
UE	User Equipment
UE-DSR	UAV Energy DSR
UFL	University of Florida
UAV / Véhicule Aérien Sans Pilote	Unmanned Aerial Vehicle
UAVCAN	UAVCAN (protocol name)
U-T-I	UAV-to-Infrastructure
U-T-U	UAV-to-UAV
WSN	Wireless Sensor Network
ZRP	Zone Routing Protocol

General introduction

In the context of rapid urbanization and increasingly complex road networks, traffic monitoring has become a critical component of modern urban infrastructure. Traditional surveillance systems, often reliant on fixed sensors and costly installations, struggle to provide real-time, scalable, and cost-effective solutions. In response to these challenges, Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as a promising alternative for more efficient and dynamic traffic management.

This paper presents a comprehensive review of the current technologies and approaches related to the integration of UAVs in road traffic monitoring systems. It begins by examining the different UAV architectures (multirotors, fixed-wing, and hybrid configurations) along with their operational characteristics, such as weight, endurance, range, and flight altitude. The study then explores UAV-specific communication protocols (e.g., MAVLink, UranusLink, UAVCAN), assessing their strengths and limitations in terms of performance, resource efficiency, and security.

A particular focus is placed on swarm communication architectures (centralized, single-group decentralized, multi-group, and multi-layered systems) and their associated routing protocols, which significantly impact the scalability and robustness of UAV networks. Additionally, the integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques is discussed as a key enabler for performance optimization, including trajectory planning, mission management, perception, and feature extraction through supervised, unsupervised, and reinforcement learning methods such as Deep Q-Networks and Deep Deterministic Policy Gradient.

Security remains a central concern, and this work identifies major threats such as eavesdropping, jamming, man-in-the-middle attacks, replay attacks, backdoors, and denial-of-service. It also outlines current countermeasures to ensure communication integrity and confidentiality.

Finally, the paper analyzes six distinct UAV-based traffic surveillance methods, ranging from Aerial Traffic Surveillance Systems (ATSS) and 5G integration to cooperative monitoring, emergency vehicle routing support, and collaborative hotspot detection. These case studies highlight the potential of UAVs to deliver real-time, adaptive, and scalable traffic management solutions.

In summary, this review underscores the transformative potential of UAVs in intelligent transportation systems while recognizing the remaining challenges in endurance, communication stability, and regulatory frameworks. Continued innovation in energy systems, network protocols, and policy development will be crucial for the widespread adoption of UAVs in future smart mobility infrastructures. This paper aims to provide a clear picture of the current technological landscape and lays the groundwork for further research into communication systems and interoperability.

Part I

State of the art

Chapter 1

UAV Topologies, standards and Communication Protocols

Introduction

In recent years, Unmanned Aerial Vehicles (UAVs) have evolved from specialized military tools into versatile platforms used in a wide range of civilian and commercial applications. This rapid development has resulted in a variety of UAV types, each designed for specific missions and operational needs. To better understand the technological landscape of UAVs, it is essential to examine their structural configurations, classification methods, and communication systems. This chapter presents an overview of UAV architectures from both design and performance perspectives. It also explores the key standards and communication protocols that enable their operation. The objective is to provide a clear picture of the current technological state of UAVs and their potential for integration into advanced systems.

1.1 UAV Classification

Unmanned Aerial Vehicles (UAVs) have recently exhibited significant diversity in terms of design, functionality, and mission-specific adaptability. As their use expands across both civilian and military sectors, a robust classification framework becomes essential for understanding and optimizing their deployment. UAVs can be broadly categorized based on two major axes: **performance metrics** and **design architectures**.

Performance-based classification involves measurable operational characteristics such as *weight*, *endurance*, *range*, *speed*, *altitude*, *wing loading*, and *engine type*. These parameters are critical in determining how well a UAV meets specific mission requirements, such as long-range reconnaissance or high-speed target tracking.

In contrast, *design-based classification* provides a structural perspective, focusing on aspects such as the *aerodynamic configuration*, the *number and arrangement of rotors or motors*, and the overall *geometrical form*. This classification helps in understanding the UAV's flight behavior, stability, payload capacity, and maneuverability in various environments.

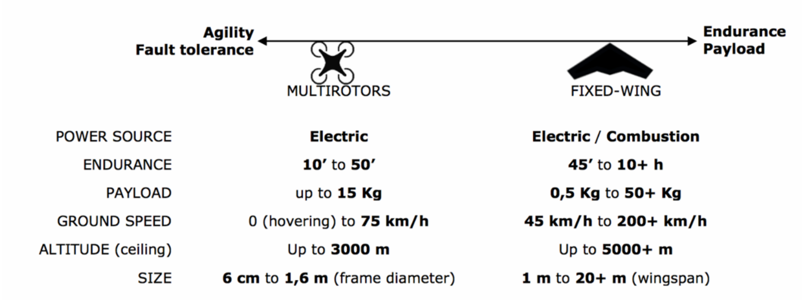

Figure 1.1: Capabilities of fixed-wing/multi-rotors (adapted from: (Khan et al., 2024))

1.1.1 Design-Based Classification

Design architecture plays a pivotal role in UAV functionality. UAVs can be structurally categorized into the following primary types. Figure 1.2 provides an overview of the primary UAV types based on design architecture.

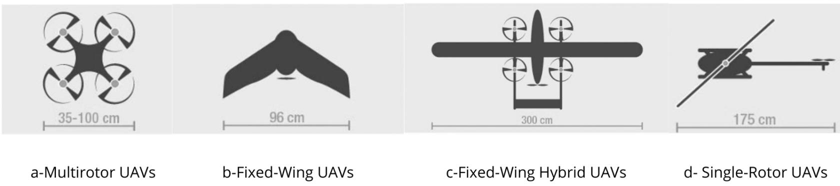

Figure 1.2: Illustration of UAV Types Classified by Design)

- **Multirotor UAVs:** This category includes the most common drones used in commercial and consumer applications, featuring multiple rotors that allow for vertical lift, precise control, and stable hovering. Multirotor UAVs are typically employed in aerial photography, inspection, and surveillance tasks. The main types of multirotors are as follows:

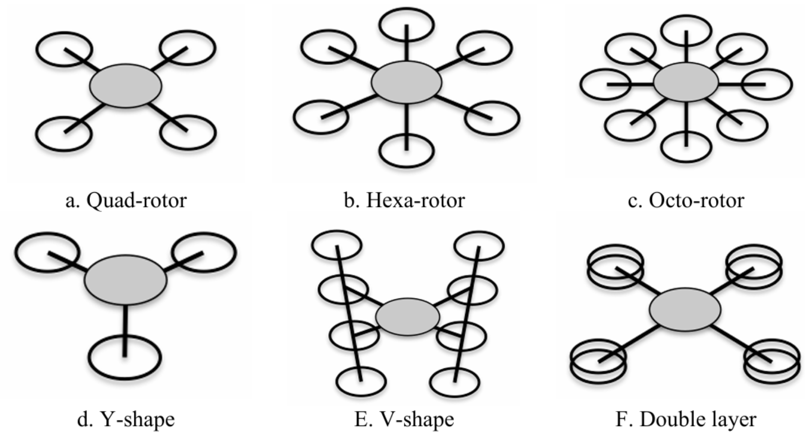

Figure 1.3: Multi-rotors Layout (adapted from: (S. Chen et al., 2016))

- **Quad-rotor (4 Rotors):** Most common and cost-effective, offering stability for light-to-medium payloads. Limited redundancy single motor failure can destabilize flight. (Ucgun et al., 2021a)
- **Hexa-rotor (6 Rotors):** Improved redundancy and payload capacity over quadcopters. Can tolerate one rotor failure but consumes more power. (Ucgun et al., 2021a)
- **Octo-rotor (8 Rotors):** Highest redundancy and payload capacity, suited for critical missions. Sacrifices flight time due to high power demand. (Ucgun et al., 2021a)
- **Y-shape Layout:** Three-rotor design for space efficiency. Lower redundancy and stability compared to quad/hexa configurations. (Ucgun et al., 2021a)
- **V-shape Layout:** Aerodynamic efficiency for longer flight times. Compromises redundancy and stability. (Ucgun et al., 2021a)
- **Double Layer Configuration:** Stacked rotors enhance lift in compact designs. Increases complexity and power usage. (Ucgun et al., 2021a)

• **Fixed-Wing UAVs:** Fixed-wing UAVs generate lift via rigid wings, offering high efficiency for long-distance missions like mapping and surveying (Ucgun et al., 2021b). They excel in speed and endurance but require runways for takeoff/landing, lacking VTOL capabilities. Compared to multirotors, they cover larger areas faster, making them ideal for large-scale data collection. Typical applications include military, agricultural, and scientific operations requiring extended flight times and higher payloads.

• **Fixed-Wing Hybrid UAVs:** Fixed-wing hybrid UAVs merge fixed-wing efficiency with rotary-wing VTOL capabilities, enabling flexible operation without runways. Their dual design allows long-range flight and quick deployment in confined spaces, ideal for search-and-rescue or surveillance. However, they are more complex and heavier than pure fixed-wing or multirotor UAVs.

- **Single-Rotor UAVs:** Single-rotor UAVs, like helicopters, use a main rotor for lift and a tail rotor for stability. They are more energy-efficient than multirotors, especially for heavy payloads, but have higher complexity and maintenance costs. Their advantages include longer flight times, better wind resistance, and suitability for cargo transport, surveying, and industrial inspections.

This classification provides a clear understanding of the different UAV types and their specific use cases based on design. Whether the goal is to achieve high endurance, heavy payload capabilities, or versatility in flight control, selecting the appropriate UAV design is essential for optimizing performance in various applications.

1.1.2 Performance-Based Classification

Complementing the structural design perspective, UAVs can also be evaluated based on core operational parameters:

0. **Weight:** Influences lift requirements, battery life, and legal classifications.

   UAVs span a wide spectrum of weights from micro UAVs under 5 kg to large strategic drones like the *Global Hawk*, which exceeds 11 tonnes. Based on their take-off weight, UAVs can be classified into five categories:

Category	**Weight Range**	**Examples**
Micro UAVs (MAV)	<5 kg	Dragon Eye, FPASS, Pointer
Lightweight UAVs	5-50 kg	-
Medium UAVs	50-200 kg	Raven, Phoenix
Heavy UAVs	200-2000 kg	Outrider, Fire Scout
Super Heavy UAVs	>2000 kg	Global Hawk, X-45, Predator B

   Table 1.1: UAV Weight Classifications and Implications

   These categories influence design decisions across multiple domains: *heavier UAVs require greater lift and thrust*, often leading to increased wingspan and a shift in engine technology (e.g., electric motors for light UAVs, turbojets or turbofans for super heavy ones).

0. **Endurance and Range:** Critical for determining the mission duration and operational area.

   Endurance and range are often interdependent and essential for mission planning, especially in military and surveillance operations. UAVs can be grouped based on their time aloft:

   These parameters directly impact logistical planning, including launch site placement and refueling intervals.

0. **Maximum Altitude:** Defines the UAV's vertical operational limit, often constrained by regulatory frameworks.

   Maximum flight ceiling is critical in both civilian airspace integration and military stealth operations. UAVs are divided into:

Category	Duration	Examples
Short Endurance	<5 hours	"Over-the-hill" reconnaissance UAVs
Medium Endurance	5-24 hours	Shadow 600, Predator
Long Endurance	≥24 hours	Global Hawk (1500-22000 km range)

Table 1.2: UAV Endurance Classifications

Category	Altitude Range	Examples
Low Altitude	Below 1,000 m	FPASS, Pointer, Dragon Eye
Medium Altitude	1,000-10,000 m	(Most common UAVs)
High Altitude	Above 10,000 m	X-45, Predator B, Global Hawk

Table 1.3: UAV Altitude Classifications

0. **Wing Loading:** Affects aerodynamic performance, especially in varying weather conditions.

   Wing loading is defined as the UAV's weight divided by its wing area. It influences flight stability, speed, and maneuverability:

Propulsion	Application	Advantages
Electric	<50 kg UAVs	Zero emissions, simple control
Piston	50-2000 kg UAVs	Fuel flexibility, proven reliability
Turbofan/Turbojet	>2000 kg UAVs	Supersonic capability, high altitude
Turboprop	500-5000 kg UAVs	Efficient cruise performance

Table 1.4: UAV Propulsion Systems by Performance Characteristics

   High wing loading tends to enhance performance in strong winds but may reduce lift efficiency at lower speeds.

0. **Engine Type:** Determines propulsion efficiency, noise levels, and maintenance needs.

   UAV engines vary widely based on mission needs. Common engine types include:

   Engine type is often interrelated with weight, endurance, and range. Proper selection can significantly improve mission performance and energy efficiency.

   This ratio reflects how efficiently a UAV can generate thrust relative to its weight. High thrust loading implies better climb rates and maneuverability, crucial in tactical and high-speed operations. Conversely, low thrust loading may indicate endurance-focused platforms optimized for loitering rather than agility.

UAV performance depends on weight, endurance, altitude, wing loading, and propulsion. These factors determine mission capabilities, from short-range electric drones to long-endurance turbine-powered systems. Each design choice involves trade-offs between speed, stability, and efficiency.

Propulsion	Application	Advantages
Electric	<50 kg UAVs	Zero emissions, simple control
Piston	50-2000 kg UAVs	Fuel flexibility, proven reliability
Turbofan/Turbojet	>2000 kg UAVs	Supersonic capability, high altitude
Turboprop	500-5000 kg UAVs	Efficient cruise performance

Table 1.5: UAV Propulsion Systems by Performance Characteristics

1.1.3 Discussion

The two classification approaches design-based and performance-based offer complementary perspectives for UAV analysis. Design determines fundamental capabilities, while performance metrics define operational limits. Hybrid designs bridge gaps but introduce trade-offs in complexity.

Design dictates how a UAV flies, while performance defines how well it executes missions. Together, they form a framework for selecting UAVs tailored to specific applications, balancing structural advantages with operational requirements.

1.2 UAV Characteristics

Unmanned Aerial Vehicles (UAVs) come in a variety of configurations and are designed for different purposes, including surveillance, reconnaissance, and commercial applications. The performance of a UAV depends on several characteristics such as speed, flight time, payload capacity, range, and altitude. These parameters play a crucial role in determining the UAV's efficiency, mission capability, and operational limits. This section discusses the key characteristics of UAVs, providing an overview of the factors that influence their behavior and utility.

1.2.1 Speed and Flight Time

The speed and flight time of UAVs are critical factors that determine their performance during operations. Smaller UAVs typically have a lower maximum speed, often less than 15 m/s, while larger UAVs can reach speeds up to 100 m/s. Speed plays an essential role in optimizing the energy consumption of UAVs, especially when following a specific trajectory designed for spectral or energy efficiency. As discussed in (**ref52**), there is a trade-off between a UAV's turning agility and its speed, which should be considered when planning flight paths.

Flight time, on the other hand, refers to the maximum duration a UAV can remain airborne before its battery is drained. Factors such as the UAV's size, weight, and external weather conditions significantly affect battery life. Larger UAVs generally have the capability to fly for several hours, while smaller UAVs may only remain in the air for 20–30 minutes. The autopilot system and GPS functionality can also influence flight time. With the growing demand for UAVs in various industries, improving their flight time is essential. Thus, ongoing research focuses on overcoming the limitations of battery life, which is crucial for the wide-scale deployment of UAVs in both military and commercial sectors.

1.2.2 Payload

The payload capacity of a UAV refers to its ability to carry various loads, such as sensors, cameras, and other equipment. Payloads typically range from a few grams to hundreds of kilograms, depending on the UAV's size and design. The payload directly impacts the UAV's performance, as carrying heavier loads generally reduces its flight time, increases battery consumption, and requires a larger frame. For instance, UAVs often carry sensors and video cameras for surveillance, reconnaissance, or commercial purposes.

Additionally, UAVs can transport cellular user equipment (UE), such as mobile phones or tablets, with a weight of less than 1 kg. It is important to note that while heavier payloads can reduce flight time, UAVs with larger surface areas and additional motors can store more power, potentially extending flight duration. Therefore, the design of the UAV and the quality of the payload play a crucial role in determining its operational efficiency and endurance.

1.2.3 Range and Altitude

The range and altitude of a UAV are key performance indicators that affect its operational capabilities. Range refers to the distance over which a UAV can be controlled remotely, varying from just a few meters for small drones to several hundred kilometers for larger UAVs. Altitude, on the other hand, defines the maximum height a UAV can achieve during flight. UAVs are typically categorized based on their operating altitude into two primary categories: low altitude platforms (LAPs) and high altitude platforms (HAPs).

Low Altitude Platforms (LAPs): LAPs are designed to support cellular communication systems and are typically deployed for quick and cost-effective operations. They offer line-of-sight (LoS) paths, which significantly enhance communication performance (**ref54**). These platforms are ideal for short-range missions and are often used in urban environments or areas with limited infrastructure.

High Altitude Platforms (HAPs): In contrast, HAPs, such as balloons, provide broader coverage and are used for more extensive communication or Internet connectivity services. The deployment of HAPs is more complex and generally requires advanced technology and infrastructure. While HAPs are capable of covering vast areas, they are typically utilized in more specialized applications, including large-scale communications or satellite-like coverage.

1.2.4 UAV Principal Movements

UAVs rely on specific movements to navigate and perform tasks effectively. These movements are influenced by the design of the UAV and its control systems. The principal movements of UAVs can be broadly categorized as follows:

1. Pitch: The pitch movement refers to the rotation of the UAV around its lateral axis, which runs from one side of the aircraft to the other. A positive pitch angle results in the UAV's nose rising, while a negative pitch angle causes the nose to descend. This movement is crucial for controlling the altitude and vertical trajectory of the UAV.

2. Roll: Roll is the rotation of the UAV around its longitudinal axis, which runs from the nose to the tail of the aircraft. When the UAV rolls, one wing moves upward while the other moves downward, allowing the UAV to bank and change direction. Roll is essential for maintaining stability and adjusting the UAV's course during flight.

3. Yaw: Yaw refers to the rotation of the UAV around its vertical axis, which runs perpendicular to both the pitch and roll axes. A positive yaw rotates the UAV to the right, while a negative yaw rotates it to the left. Yaw is primarily responsible for controlling the UAV's heading and orientation.

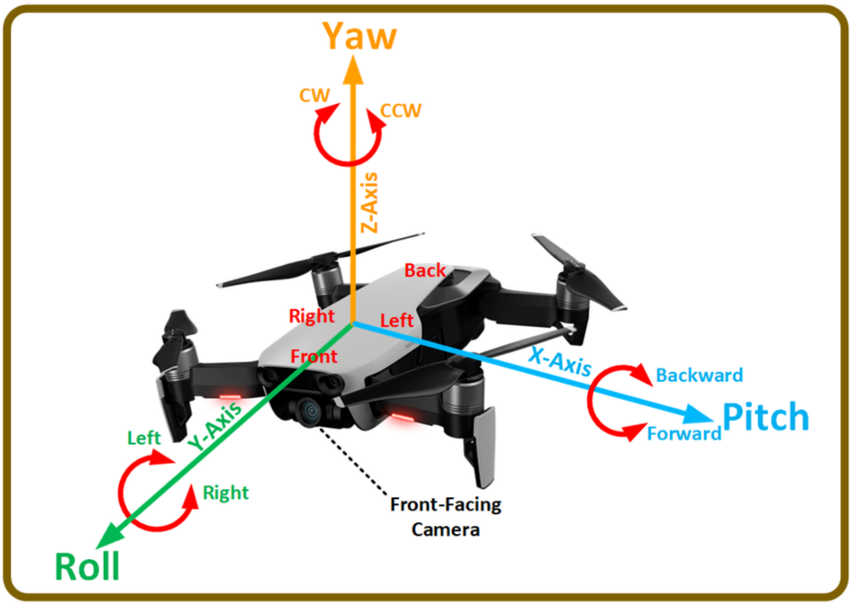

Figure 1.4: Principal Movements of a UAV in 3D Space (adapted from: (Almahamid & Grolinger, 2024))

The characteristics of UAVs-such as speed, flight time, payload capacity, range, altitude, and principal movements are fundamental to their overall design and performance. Each characteristic impacts the UAV's ability to carry out specific tasks, whether it's surveillance, communication, or commercial applications. Understanding and optimizing these factors is essential for advancing UAV technology and ensuring the successful deployment of UAVs across various industries. As research continues to improve UAV designs, advancements in battery life, payload efficiency, and flight stability are expected to enhance the capabilities of UAVs, enabling them to perform more complex and longer-duration missions.

1.3 Communication protocols for UAVs

Communication between the UAV and the Ground Control Station (GCS) relies on established communication protocols. However, existing protocols are not well-suited to the UAV environment. Due to the limited resources and the highly dynamic nature of unmanned systems, these protocols often fail to function efficiently according to (Larrieu, 2014).

This issue becomes even more critical when considering security measures, as UAVs typically operate with constraints such as limited battery life, restricted real-time processing power, and autonomous control requirements. Limited energy resources, communication bandwidth, and computational capacity make traditional protocols like TLS and Kerberos impractical for UAV networks.

Various communication protocols have been specifically developed for Unmanned Aerial Vehicles (UAVs). In this section, we will discuss these protocols in detail.

1.3.1 UranusLink Protocol

UranusLink supports both unreliable and reliable packet-oriented communication, defining the packet structure and the format in which data is transmitted. The protocol's overall mechanism and detailed description are provided by Kriz et al. (Kříž & Gábrlík, 2015). In this study, we adopt their packet structure, as illustrated in Table 1.6. Each packet comprises six fields: **Preamble** (PRE), **Sequence Number** (SQN), **Message Identification** (MID), **Data Length** (LEN), **Data**, and **Checksum** (CS).

PRE	**SQN**	**MID**	**LEN**	**DATA**	**CS**
1 B	2 B	1 B	1 B	1–252 B	1 B

Table 1.6: UranusLink packet structure. (adapted from (Kříž & Gábrlík, 2015))

The UranusLink protocol is tailored for radio communications, where data loss and corruption are frequent. Each packet begins with a **preamble (PRE)** byte `0xFD`, which seldom occurs in payloads, ensuring reliable packet boundary detection. Following this is an even-valued **sequence number (SQN)**, used to detect lost or out of order packets any packet with an SQN lower than the last accepted is discarded and a **checksum (CS)** to validate integrity. The sizes of PRE and CS balance robustness against overhead, taking link conditions and capacity into account.

The **MID** field specifies how to interpret the payload. Currently there are eight UAV to ground and sixteen ground-to-UAV message types; the two critical ones establish and maintain the connection in each direction.

Two UAV modes are supported: **flight mode**, in which the rotors spin, and **configuration mode**, used on the ground. A "robot mode switch" message triggers transitions, and only these mode-switch packets are acknowledged other messages are sent unacknowledged to minimize overhead. The ground station tracks SQNs of mode switch requests so it can determine the UAV's current mode even if acknowledgments are lost.

Compared to MAVLink which can incur up to 33 % extra overhead and offers no built-in security UranusLink achieves much lower overhead while providing essential reliability and mode-switch acknowledgment.

1.3.2 UAVCAN protocol

UAVCAN is an open-source, masterless publish–subscribe protocol for secure connectivity over CAN buses in aerospace and robotics. It carries long payloads in a single CAN frame (e.g. GNSS fixes, 3D vectors), supports multiple nodes and interfaces for high-safety applications, and offers standard services such as network discovery, node configuration and firmware upgrade, status monitoring, time synchronization, and adaptive node-ID allocation. Lightweight and real-time–capable, UAVCAN is ideal for resource-constrained UAVs and is released under the MIT license (Kříž & Gábrlík, 2015).

Based on the CAN bus, originally created for automotive multiplex wiring, UAVCAN enables host-free communication between devices and microcontrollers (Kříž & Gábrlík, 2015). Each node is assigned a unique ID in the range 1–127 (ID 1 typically denotes the autopilot; 126–127 are for debugging). To avoid mismatches, any MAVLink component communicating over UAVCAN must use the same Component ID (COMPID) as its UAVCAN Node ID commonly both set to 1 so that every MAVLink message's COMPID field matches its UAVCAN node ID (Kříž & Gábrlík, 2015).

1.3.3 MAVLink protocol

MAVLink is an open and efficient communication protocol tailored for lightweight, real-time interactions between Unmanned Aerial Vehicles (UAVs) and Ground Control Stations (GCSs). Developed by Lorenz Meier and first released in 2009 under the LGPL license, MAVLink 1.0 quickly became popular thanks to its streamlined design and operational simplicity (Allouch et al., 2019; Koubâ et al., 2017). A significant evolution of the protocol occurred in 2017 with the introduction of MAVLink 2.0, which is currently the preferred version. It maintains backward compatibility with MAVLink 1.0 while offering improvements in extensibility, robustness, and security features.

MAVLink messages are broadly categorized into two types: those originating from the GCS to issue commands or control instructions to UAVs, and those transmitted by UAVs to the GCS, typically conveying telemetry data such as geographical coordinates, altitude, system heartbeat, and operational status. To meet the demands of real-time systems, MAVLink was designed with minimal communication overhead to ensure high efficiency (Allouch et al., 2019). The following sections provide a comparative overview of the header structures used in MAVLink 1.0 and its successor, MAVLink 2.0.

MAVLink 1.0 header protocol

The comprehensive survey by Koubaa et al. (Koubâ et al., 2017) remains the only detailed study focused on the MAVLink protocol's architecture and operational principles. As part of their contribution, the authors present the header structure for MAVLink 1.0. Below, we describe the structure of a MAVLink 1.0 frame, which consists of eight primary fields, as illustrated in Figure 1.5.

The first byte, labeled **STX**, has a fixed value of `0xFE`, which identifies the start of a MAVLink 1.0 message frame. The second field, **LEN**, encoded in one byte, indicates the length of the payload. The third field, **SEQ**, is also one byte and stores a sequence number ranging from 0 to 255. Once 255 is reached, it rolls over to 0. This sequence number helps in detecting lost packets.

To distinguish between multiple UAVs managed by a single Ground Control Station, the fourth field, **SYS ID**, is used. This field also spans one byte, limiting the addressable systems to 254 UAVs, since ID 255 is typically reserved for the GCS. The fifth field, **COMP ID**, identifies the specific component (e.g., autopilot, gimbal) transmitting the message. Finally, the sixth byte marks the beginning of the payload section, which contains the message-specific data.

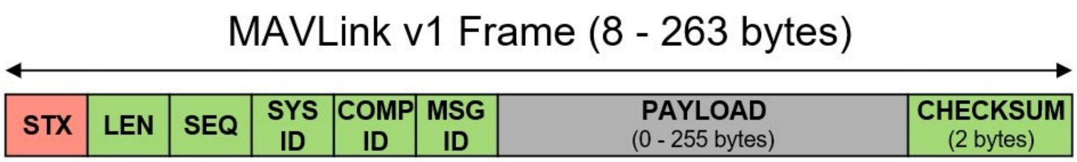

Figure 1.5: Structure of a MAVLink 1.0 packet (MAVLink Development Team, 2024).

In summary, the MAVLink 1.0 protocol employs a lightweight and efficient packet structure that balances low bandwidth usage with sufficient message integrity. The use of fixed-length headers, flexible payloads up to 255 bytes, and a robust CRC-based checksum mechanism ensures reliable communication between UAVs and ground stations. Understanding the role of each header field, especially the `Message ID`, is essential for correctly

Table 1.7: MAVLink 1.0 header structure and byte size. (adapted from (Koubâ et al., 2017))

Field	Size	Description
STX	1 B	Start-of-frame indicator (0xFE in MAVLink 1.0).
LEN	1 B	Payload length (0–255 bytes).
SEQ	1 B	Packet sequence number (0–255, wraps after 255). Used to detect packet loss.
SYS ID	1 B	System identifier (e.g., UAV ID). Value 255 is typically used by the GCS.
COMP ID	1 B	Component identifier (e.g., autopilot or camera module).
Message ID	1 B	Indicates the type of MAVLink message.
Payload	0–255 B	Actual message data depending on message type.
Checksum (CRC)	2 B	Verifies the integrity of the packet (LSB to MSB order).

interpreting messages and extracting relevant data from the payload.

MAVLink 2.0 Protocol

MAVLink 2.0 was introduced in early 2017 (Allouch et al., 2019; Khan et al., 2020), offering enhancements over MAVLink 1.0 while maintaining backward compatibility. This section presents the MAVLink 2.0 header structure and compares it with MAVLink 1.0. The MAVLink 2.0 header is shown in Fig. 1.6, and Table 1.8 explains the additional fields in the MAVLink 2.0 header compared to MAVLink 1.0.

MAVLink 2.0 retains all fields from MAVLink 1.0 but adds new fields and expands some existing ones. The first byte (0xFD) marks the start of the message, differing from MAVLink 1.0's 0xFE. The payload length field remains unchanged. Two flags appear before the sequence number (SEQ): the incompatibility flag, which indicates if the packet is signed, and the compatibility flag, which does not affect the message structure.

Figure 1.6: MAVLink 2.0 Header Structure.

Table 1.8: Additional MAVLink 2.0 Header Fields (compared to MAVLink 1.0).

Field	Size	Description
STX	1 B	Start-of-frame indicator (0xFD in MAVLink 2.0).
Incompatibility Flag	1 B	Indicates whether the message is signed (e.g., 0x01 indicates signed message).
Compatibility Flag	1 B	Indicates compatibility options that can be ignored by parsers if not recognized.
MSGID	3 B	Message identifier, expanded from 8 bits in MAVLink 1.0 to 24 bits in MAVLink 2.0, allowing up to 16,777,215 different message types.
Signature	13 B	Used for message authentication, ensuring integrity and authenticity, including LinkID, Timestamp, and the actual Signature field.

The SEQ (sequence number), system ID, and COMPID fields in MAVLink 2.0 are identical to those in MAVLink 1.0. The MSGID field is expanded from 8 to 24 bits, increasing the number of possible messages to over 16 million. The payload field can carry up to 255 bytes. The checksum in MAVLink 2.0 remains the same as in MAVLink 1.0.

MAVLink 2.0 introduces a 13-byte field for message authentication, improving security over MAVLink 1.0. The message signature is appended when the incompatibility flag is set to 0x01. This addition significantly enhances security by ensuring message integrity and authenticity.

The 13-byte message signature contains the following fields:

- **LinkID:** A one-byte field representing the link (channel) used to send the packet. The link refers to any telemetry device (e.g., Wi-Fi). Each channel used to send information has a unique LinkID.
- **Timestamp:** Encoded as 6 bytes in 10-microsecond units, the timestamp represents the time since January 1, 2015 GMT. The timestamp increases with each message sent over the channel and helps prevent replay attacks.
- **Signature:** This field covers the full message, the secret key, and the timestamp. It is encrypted into 6 bytes for the message. The first 6 bytes (48 bits) of a SHA-256 hash applied to the MAVLink 2.0 message are included in the signature. A 32-byte shared symmetric key is stored on both ends, i.e., the autopilot and the ground station or the MAVLink API.

Messages are discarded if: (1) they are received earlier than a previous packet from the same tuple (LinkID, SystemID, ComponentID); (2) the signature does not match; or (3) the timestamp exceeds one minute compared to the local system time (Koubâ et al., 2017).

1.3.4 Disscussion

UAV operations depend critically on communication protocols that remain vulnerable despite widespread use. Current protocols like MAVLink, UranusLink, and UAVCan (compared in Table 1.9) each compromise between functionality, maturity, and crucial security features.

Protocol	Pros	Limitations
UranusLink	• Open-source • Lightweight • Aerospace/robotic focus • Redundant transports	• Limited language support • No concurrency • Not scalable • Lacks security
UAVCan	• Open-source • Lightweight • Low latency • Data loss recovery	• Limited language support • No concurrency • Not scalable
MAVLink	• Widely accepted • Scalable • Multi-language • Concurrent systems • Proven performance	• No payload security • Weak encryption • Small data only • Open format

Table 1.9: Comparison of UAV Communication Protocols

As evidenced in Table 1.9, current UAV protocols prioritize lightweight operation and low latency at the expense of robust security - particularly MAVLink, whose widespread use in critical operations contrasts sharply with its lack of payload encryption and authentication (Khan et al., 2020). These security gaps create attack vectors for message spoofing, data interception, and even UAV hijacking, with potentially catastrophic consequences for sensitive operations ranging from military reconnaissance to emergency response missions. The protocol limitations underscore an urgent need for security-enhanced communication frameworks that maintain performance while addressing these vulnerabilities.

1.4 UAVs Architectures

The communication architecture is essential for enabling intelligent control and autonomous collaboration in UAV swarms. Initially, centralized architectures an extension of traditional single-UAV systems were used, with a single ground station managing all UAV communication. However, as swarm size and mission complexity grew, decentralized architectures emerged as more scalable alternatives, reducing dependency on central nodes (Cao et al., 2012). Many studies have since explored different swarm communication models. This section reviews the main architectures, summarizing their characteristics, strengths, and limitations.

1.4.1 Centralized Communication Architecture

The **centralized communication architecture**, adapted from single-UAV systems, was later applied to UAV swarms. As shown in **Figure 1.7**, it relies on a central node, such as fixed network infrastructure, connecting all UAVs through direct one-to-one links without intermediary relays. This setup offers routing simplicity, stability, and efficient performance at small scales. It is best suited for missions with limited swarm size, coverage, and complexity. A notable implementation is the **"UAV-GCS Centralized Data-Oriented Communication Architecture"** used in crowd surveillance (X. Chen et al., 2020).

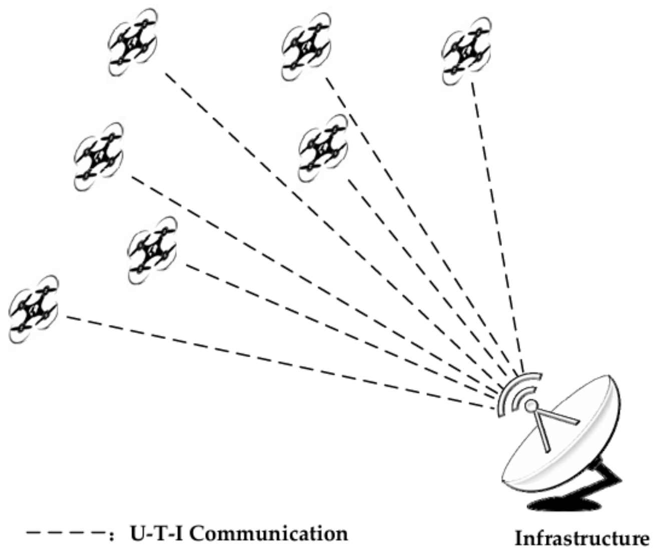

Figure 1.7: centralized communication architecture (X. Chen et al., 2020)

Despite its simplicity, this architecture presents key limitations. All inter-UAV communication must pass through the infrastructure, making the **UAV-to-Infrastructure (U-T-I)** distance typically longer than the **UAV-to-UAV (U-T-U)** distance, resulting in increased latency. Moreover, the high mobility of UAVs and growing coverage requirements render the system unstable. A major weakness is its **Single Point of Failure (SPOF)** if the ground station or satellite fails, the entire network collapses. As a result, centralized architectures are unsuitable for large-scale or high-risk missions.

1.4.2 Decentralized Communication Architecture

Given the high operational speeds of UAVs and the extensive coverage demands of missions, network connectivity often fluctuates as UAVs dynamically join and leave the network. This variability makes ad hoc networking ideal for UAV swarms. In decentralized architectures, UAVs establish real-time, self-organizing connections, eliminating the need for fixed infrastructure and overcoming traditional communication range limitations (X. Chen et al., 2020).

Single-Group Swarm Ad Hoc Network

In a single-group swarm ad hoc network (1.8), communication occurs independently of fixed infrastructure, with a gateway UAV linking the swarm to external systems and other UAVs acting as relay nodes to distribute data. This structure supports real-time information sharing among swarm members, improving operational efficiency. The gateway UAV uses two transceivers: a short-range, low-power unit for intra-swarm communication and a long-range, high-power system for external links (X. Chen et al., 2020). This design enables the use of lightweight transceivers in regular UAVs, extending coverage and accommodating smaller UAVs. However, the system requires uniform flight patterns, making it well-suited for homogeneous small UAV groups. When applied to heterogeneous swarms with different UAV types, variations in operational characteristics prevent close formation flying, leading to the development of more adaptable multi-group and multi-layer architectures for complex mission needs.

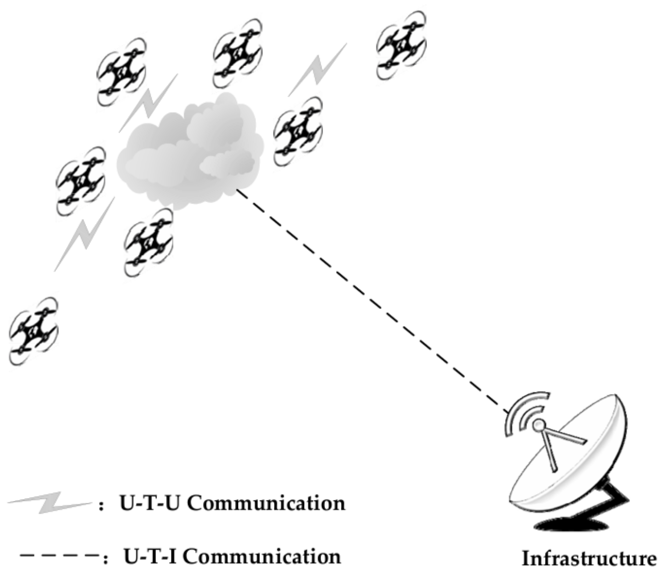

Figure 1.8: single-group swarm Ad hoc network (X. Chen et al., 2020)

Several intra-swarm communication configurations (1.9) have emerged:

- **Ring Architecture**: Forms a closed communication loop where any UAV can serve as gateway, providing redundancy but limited scalability

- **Star Architecture**: Centralizes communication through a gateway UAV, creating a single point of failure vulnerability
- **Meshed Architecture**: Combines ring and star advantages, allowing any UAV to function as a gateway with multiple routing paths

While meshed architecture has become the standard for its flexibility, mission diversity increasingly requires swarms to incorporate varied UAV sizes and capabilities, pushing the development of more advanced network topologies.

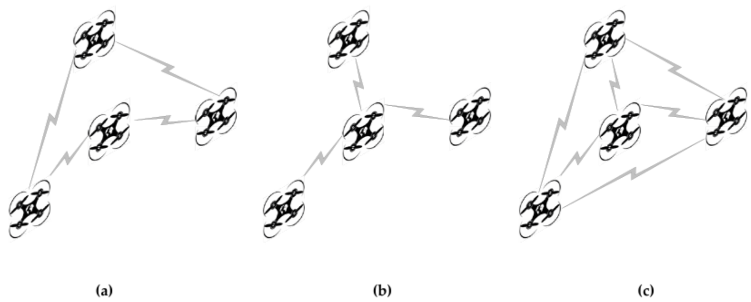

Figure 1.9: intra-swarm communication architecture: (a): ring rchitecture, (b) star architectue, (c): meshedarchitecture. (X. Chen et al., 2020)

Multi-Group Swarm Ad hoc Network

The *multi-group swarm Ad hoc network* (Figure 1.10) combines elements of both centralized and *single-group swarm Ad hoc network* architectures to address the limitations of the latter. Each group, depending on its mission, operates in an Ad hoc manner for intra-group communication, while inter-group communication (Group-to-Group or G-T-G) relies on the infrastructure, with gateway UAVs handling communication with the central infrastructure. This architecture is semi-centralized, and while it can accommodate diverse UAV types for complex missions, it still suffers from high latency in G-T-G communications. The *multi-group swarm Ad hoc network* is particularly suitable for applications like multi-theater joint operations in military scenarios, where a central control center coordinates UAV swarms that approach the mission area from various directions (Kaleem et al., 2019).

Multi-layer Swarm Ad hoc Network

The *multi-layer swarm Ad hoc network* architecture, as depicted in Figure 1.11, is a more advanced version of the *multi-group swarm Ad hoc network*. In this architecture, UAVs of the same type form an Ad hoc network at the first layer, enabling intra-group communication. At the second layer, gateway UAVs facilitate Group-to-Group (G-T-G) communication between different UAV groups. The third layer consists of the gateway UAVs communicating with the infrastructure. Notably, UAVs in the same group can communicate directly without infrastructure relay, while inter-group communication passes through the gateway UAV (X. Chen et al., 2020) Data packets move through the first

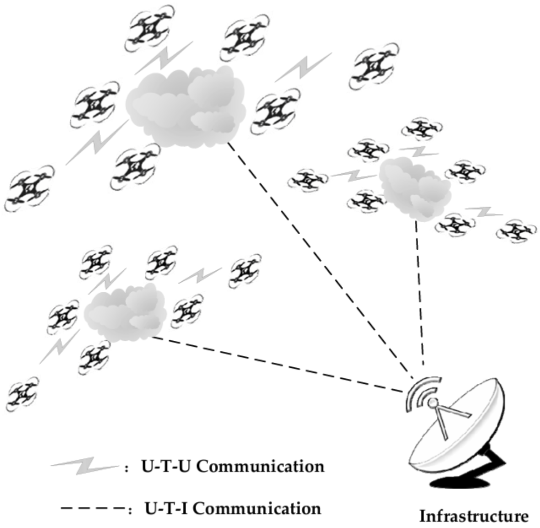

Figure 1.10: multi-group swarm Ad hoc network (X. Chen et al., 2020)

and second layers sequentially, ensuring there is no single point of failure (SPOF). This multi-layer structure offers increased robustness compared to other architectures.

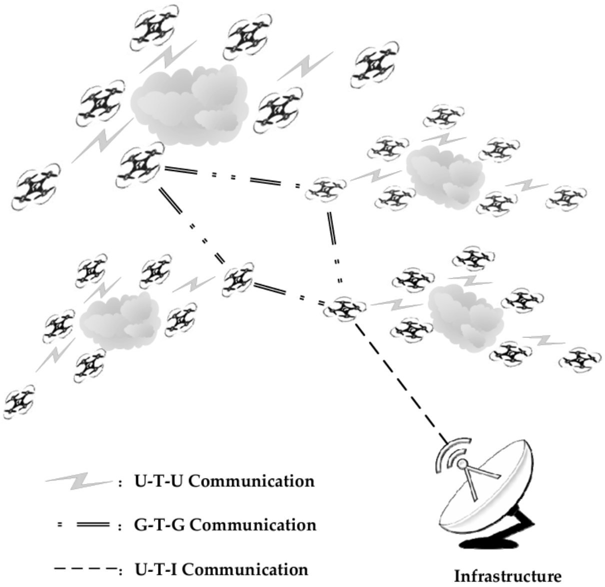

Figure 1.11: multi-layer swarm Ad hoc network (X. Chen et al., 2020)

The *multi-layer swarm Ad hoc network* architecture adapts to changes in UAV numbers, enabling quick network reconstruction. It is ideal for complex missions with dynamic network topologies and frequent UAV communication. Future improvements may include adding more layers to enhance task coverage and network robustness.

1.4.3 Discussion

UAV swarm communication architecture has advanced significantly, with various options for different mission scenarios. Centralized architecture suits small, simple missions with long-range communication to infrastructure (X. Chen et al., 2020). Decentralized architecture extends coverage via multi-hop networks and gateway UAVs for UAV-to-infrastructure communication. The *single-group swarm Ad hoc network* works for homogenous UAVs, while the *multi-group* and *multi-layer swarm Ad hoc network* architectures are better for diverse UAV types, though the former may face delays in inter-group communication. The *multi-layer swarm Ad hoc network* is more robust, eliminating single point of failure (SPOF).

Features	**Centralized**	**Decentralized**	**Single-Group**	**Multi-Group**	**Multi-Layer**
Multi-hop Communication	x	✓	✓	✓	✓
UAVs Relay Traffic	x	✓	✓	✓	✓
Different Types of UAVs	x	✓	x	✓	✓
Self-configuration	x	✓	✓	✓	✓
Limited Coverage	✓	x	x	x	x
Single Point of Failure	✓	x	x	x	x
Robustness	x	✓	✓	✓	✓

Table 1.10: Summary of UAV Swarm Communication Architectures (✓= supported, x = not supported) (X. Chen et al., 2020)

UAV swarm communication architectures must balance high coverage and connectivity. Coverage is key for intelligence gathering, while connectivity ensures real-time communication. However, dynamic environments make maintaining connectivity challenging due to signal attenuation. To avoid disruption, UAVs must stay within a suitable distance for effective communication. Nature-inspired behaviors can improve positioning, and advancements in 4G and 5G networks offer potential solutions for better connectivity across wide areas.

1.5 Routing Protocols

This section reviews common UAV swarm communication routing technologies, classifies routing protocols based on their underlying techniques, and provides a detailed overview of each category, highlighting their pros and cons. Building on prior comparisons of current architectures where the multi-layer swarm Ad hoc network showed the best overall performance it emphasizes the critical role of routing in ensuring reliable U-T-U communication, despite challenges like UAV mobility, unstable links, limited resources, and varying QoS needs. Traditional Ad hoc protocols require adaptation, making the design of suitable routing protocols a key research focus.

1.5.1 Routing Technologies

Routing technologies form the foundation for implementing routing protocols, which are often built by enhancing or combining these basic techniques. Since UAV swarm Ad hoc networks evolve from traditional Ad hoc networks, conventional routing methods can still be applied after suitable analysis and adaptation. The six common routing technologies used include store-carry-forward, greedy forwarding, path discovery, single-path, multi-path, and predictive routing (X. Chen et al., 2020).

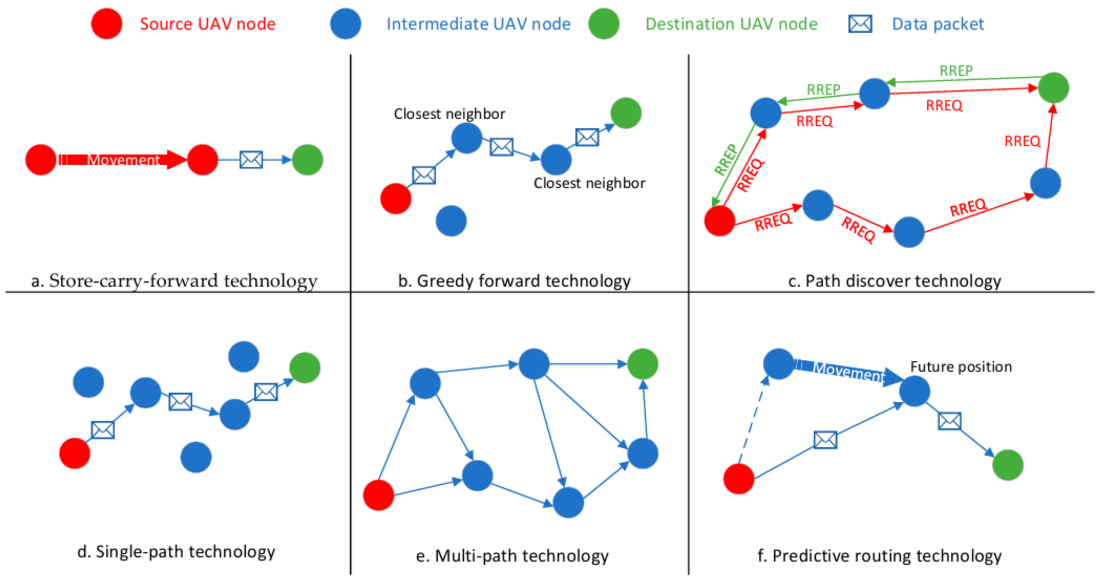

Figure 1.12: The rationales for common routing technologies of UAV ad hoc network.(X. Chen et al., 2020).

0. **Store-carry-forward:** When no relay is available, the node stores and carries the data until it finds one. Suitable for intermittent networks but causes high delays.
0. **Greedy forward:** Selects the neighbor closest to the destination as the next hop. Works well in dense UAV deployments but may fail if no closer neighbor exists requiring backup strategies.
0. **Path discovery:** Uses flooding (RREQ) to find routes, improving path availability when location info is lost. However, it consumes significant bandwidth.
0. **Single-path:** Sends data through one route, conserving bandwidth but lacking robustness no backup path if a failure occurs.
0. **Multi-path:** Maintains several routes to improve reliability. If one path fails, others can take over. However, shared path failures can cause loops.
0. **Predictive routing:** Estimates future positions based on current motion to choose the next hop. Ideal for high-mobility UAV swarms.

1.5.2 The Classification of Routing Protocols

Early research on UAV swarm communication focused on adapting traditional Ad hoc routing protocols. However, these proved largely unsuitable due to the unique characteristics of UAVs such as high mobility and varying mission requirements. As a result, researchers both enhanced existing protocols and developed new ones specifically for UAV swarms (X. Chen et al., 2020; Koubâ et al., 2017). These routing protocols are now broadly categorized into three main types, each with several subtypes, as shown in 1.13

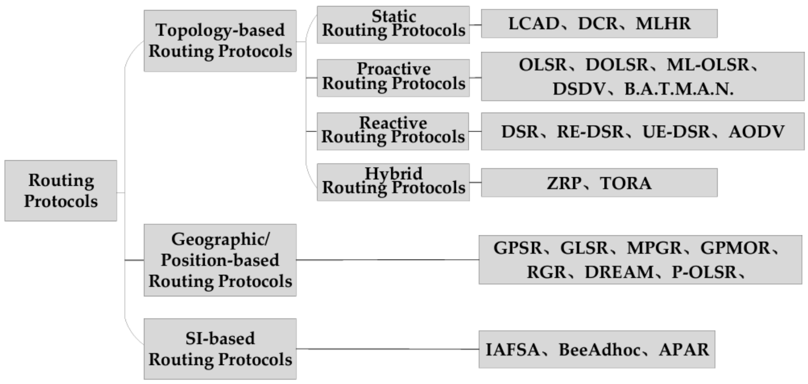

Figure 1.13: Classification of all routing protocols (X. Chen et al., 2020).

1.5.3 Topology-Based Routing Protocols

Topology-based routing protocols rely on IP addresses and known link information to forward packets efficiently. They are typically categorized into static, proactive, reactive, and hybrid protocols.

Static Routing Protocols

Static routing protocols use fixed routing tables and are suitable for stable topologies without task updates. Due to their lack of adaptability, their use in dynamic UAV swarms is limited. Notable examples include:

- **Load Carry and Deliver (LCAD)**: Proposed by Le et al., LCAD uses a centralized system where a UAV carries and delivers data to its destination. It maximizes throughput and reduces hops but suffers from significant delays with increased communication distance.
- **Data Centric Routing (DCR)**: Designed for one-to-many transmission, DCR works well in "single-group swarm Ad hoc networks" with a gateway UAV distributing information. It's ideal for small, planned UAV networks with minimal coordination between nodes.

- **Multilevel Hierarchical Routing (MLHR)**: Derived from vehicular networks, MLHR organizes UAVs into hierarchical layers, with gateway UAVs handling group-to-group communication 1.14. It improves scalability and communication efficiency through geographic clustering.

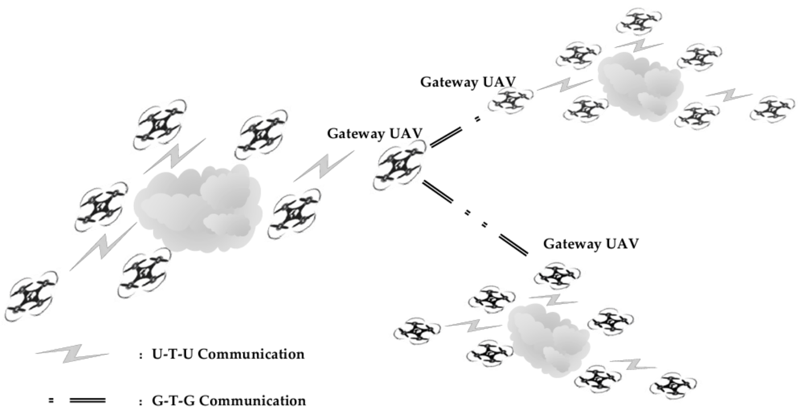

Figure 1.14: Multilevel Hierarchical Routing in a UAV swarm Ad hoc network

Proactive Routing Protocols

Proactive routing protocols (PRPs) periodically update routing tables to reflect network topology, ensuring minimal route delays. While ideal for real-time applications, their frequent updates can be inefficient for fast-moving UAVs, especially in large-scale networks (X. Chen et al., 2020). Popular PRPs include Optimized Link State Routing (OLSR), Destination Sequenced Distance Vector (DSDV), and their variations.

- **Optimized Link State Routing (OLSR)**: OLSR is a link-state protocol optimized for flat topologies (Singh & Verma, 2015). It reduces overhead by selecting multiple point relays (MPR) for forwarding control packets, making it suitable for UAV ad hoc networks with dynamic topologies. Variants like Directional OLSR (DOLSR) and Mobility and Load-aware OLSR (ML-OLSR) further reduce latency and improve delivery rates.

- **Destination Sequenced Distance Vector (DSDV)**: In DSDV, routing tables are periodically updated, with either full or incremental dumps of routing information. While effective in stable networks, DSDV faces challenges in rapidly changing UAV networks, increasing bandwidth usage and overhead. It has been compared with other protocols in UAV networks.

- **B.A.T.M.A.N.**: This protocol proactively identifies the best next hop for each destination and maintains information about all nodes (Sandhu & Sharma, 2012). B.A.T.M.A.N. performs similarly to OLSR in smaller networks but outperforms it in larger, bandwidth-constrained networks (Sandhu & Sharma, 2012).

Reactive Routing Protocols

Reactive Routing Protocols (RRPs), also known as on-demand protocols, initiate route discovery only when needed, resulting in smaller routing information caches (X. Chen et al., 2020). While RRPs generally have lower control overhead compared to PRPs, they suffer from high transmission delays due to the route discovery process. Popular RRPs include Dynamic Source Routing (DSR), Ad hoc On-Demand Distance Vector (AODV), and others.

- **Dynamic Source Routing (DSR)**: DSR is widely used for ad hoc networks, requiring no specific infrastructure. It stores the complete list of routing nodes in each data packet, allowing the network to maintain performance despite topology changes. DSR has been adapted for UAV networks, with variants like Restrict DSR (RE-DSR) to limit hop counts and UAV Energy DSR (UE-DSR) for small UAVs in reconnaissance missions.
- **Ad hoc On-Demand Distance Vector (AODV)**: AODV reduces overhead by maintaining only destination addresses in routing tables. If a path is unavailable, the source node broadcasts Route Request (RREQ) to find a route. Once discovered, the Route Reply (RREP) is sent back to the source. Studies have explored AODV for UAV networks, with improvements aimed at minimizing hops and optimizing route reliability.

Hybrid Routing Protocols

To address the high overhead of control messages in PRPs and the delay in route discovery of RRPs, Hybrid Routing Protocols (HRPs) were introduced. HRPs divide large networks into zones, using PRP within zones and RRP between them (X. Chen et al., 2020). This strategy reduces routing overhead and delays but is challenged by the dynamic nature of UAV networks. Notable HRPs include Zone Routing Protocol (ZRP) and Temporarily Ordered Routing Algorithm (TORA).

- **Zone Routing Protocol (ZRP)**: ZRP utilizes routing zones, applying PRP within zones and RRP for inter-zone communication. This reduces control packet overhead and delays compared to traditional PRPs and RRPs. ZRP's performance remains stable under high network load, but its fixed zone radius limits adaptability. Research focuses on improving ZRP with adaptive zones. Liu et al. proposed a clustering algorithm for UAV networks, while Zang et al. addressed cluster updates with mobility prediction.
- **Temporarily Ordered Routing Algorithm (TORA)**: TORA is a hybrid, distributed protocol designed for high adaptability. It minimizes control message spread by limiting updates to neighboring nodes and using longer routes to recover from link failures. TORA constructs a directed acyclic routing structure with "height" values to forward traffic effectively.

1.5.4 Geographic/Position-Based Routing Protocols

Due to the high mobility in UAV ad hoc networks, maintaining routing tables becomes challenging, and traditional protocols introduce significant overhead. To address this, researchers have proposed position-based routing protocols that use location services, such as Reactive Location Services (RLS), Grid Location Services (GLS), and Hierarchical Location Services (HLS), which are well-suited for dynamic UAV networks (X. Chen et al., 2020).

- **Greedy Perimeter Stateless Routing (GPSR)**: A position-based protocol that outperforms proactive and reactive protocols in UAV networks. It is especially effective in dense UAV deployments but requires further reliability improvements.
- **Geographic Load Share Routing (GLSR)**: An extension of GPSR, GLSR selects the next hop based on the "distance of advance" to improve path reliability.
- **Mobility Prediction-based Geographic Routing (MPGR)**: This protocol uses Gaussian motion prediction to evaluate node connectivity and select a reliable next hop.
- **Geographic Position Mobility Oriented Routing (GPMOR)**: Uses GPS and the Gaussian-Markov mobility model to predict UAV movement and improve routing decisions.
- **Reactive-Greedy-Reactive (RGR)**: Combines AODV with Greedy Geographic Forwarding (GGF), switching between AODV and GGF based on connectivity. It improves packet delivery but can suffer from packet loss if position information isn't updated.
- **DREAM**: A location-based protocol using a location table to store node coordinates, consuming less bandwidth but being more complex than flooding strategies.
- **Prediction-OLSR**: A protocol that uses GPS to assist routing decisions, adjusting based on node speed and expected transmission count.

1.5.5 Swarm Intelligence-Based Routing Protocols

Swarm intelligence (SI) is a multi-agent system inspired by the behavior of animals like fish, birds, and insects. It is applied to mobile robots and enhances collaborative task optimization. In UAV swarm systems, SI is used to improve routing protocols (Zungerua et al., 2012).

For example, the **Improved Artificial Fish-Swarm Algorithm (IAFSA)** adjusts group topology to address communication range expansion and information leakage, ensuring secure communication in large swarms. Other SI-based routing protocols include the **Bee colony algorithm-based Ad hoc network (BeeAdhoc)** and the **Ant Colony Optimization-based Polymorphism-Aware Routing (APAR)**.

1.5.6 Discussion

Static routing protocols are unsuitable for UAV swarm Ad hoc networks due to fixed routing tables and limited scalability. Proactive protocols incur high overhead for maintaining up-to-date tables and react slowly to topology changes. Reactive protocols suffer from high latency in route discovery. Source routing does not scale well due to large network overhead and header size. Hybrid protocols combine proactive and reactive methods to address these issues, but dynamic nodes and link behaviors in UAV networks complicate information maintenance. Topology-based protocols are not ideal for highly dynamic networks with many nodes. Geographic/position-based routing protocols, by incorporating node location data, excel in handling high mobility and frequent topology changes in UAV networks.

1.6 Conclusion

This chapter has presented the main elements that define the structure and functionality of UAV systems. It has covered the various UAV types including multirotors, fixed-wing, and hybrid designs, as well as performance-related characteristics such as weight, endurance, and propulsion methods. These classification frameworks help in selecting the right UAVs for different use cases and also support a better understanding of how these systems connect and communicate. As UAV technologies continue to advance and expand into more complex applications, it becomes increasingly important to understand their technical foundations and communication protocols. The content of this chapter lays the groundwork for further study into communication systems, interoperability issues, and the integration of UAVs within intelligent and collaborative environments.

Chapter 2

AI-Driven Optimization and Secure Autonomy in UAV Systems

Introduction

Unmanned Aerial Vehicles (UAVs) have become indispensable in fields such as agriculture, surveillance, and disaster response, thanks to their agility and advanced sensing capabilities. A key driver of their success is the integration of Artificial Intelligence (AI) and optimization techniques, which improve trajectory planning, mission efficiency, and real-time decision-making. This chapter examines how machine learning including supervised, unsupervised, and reinforcement learning enhances UAV operations, from energy-efficient navigation to dynamic feature extraction. It also addresses critical security risks in UAV networks, such as jamming, spoofing, and malicious attacks, while discussing countermeasures. By reviewing advancements in AI-driven optimization and cybersecurity, this chapter establishes a foundation for understanding the current state of UAV technology and its future directions.

2.1 Machine learning optimization for UAVs

2.1.1 ML for UAV trajectory planning and mission scheduling

In recent years, machine learning (ML) has played a significant role in enhancing flight control strategies to improve the overall quality of UAV services. By strategically planning trajectories, UAVs are able to collect data from target nodes while ensuring that the information remains up to date. Supervised learning methods are commonly employed to reduce training errors, which contributes to more efficient trajectory design. In addition, reinforcement learning techniques such as Deep Q-Networks (DQN) and Deep Deterministic Policy Gradient (DDPG) offer strong predictive and classification capabilities, making them suitable for both discrete and continuous action space environments. These reinforcement learning approaches are widely used in UAV trajectory optimization and mission scheduling.

Supervised Learning-based UAV Communications

The prediction of UAV flight paths has been explored in the context of communication services within smart cities. In such scenarios, having precise information about the UAV's position is essential, since it directly affects the beamforming process conducted by the connected base station. A method based on recurrent neural networks (RNNs) for predicting the angle of arrival, supported by a set of data preprocessing steps, has shown promising results. Simulation outcomes demonstrate that this method can successfully learn and adapt angle data, making it suitable for UAVs operating at high speeds.

A related application is presented in (Annepu & Rajesh, 2020), where a UAV functions as a dynamic aerial anchor to assist in locating ground-based sensors. It estimates the sensor positions by measuring the received signal strength (RSS) from them. Compared to traditional fixed ground anchors, the use of UAVs enhances localization accuracy due to the dominance of line-of-sight (LOS) paths. As illustrated in Fig. 2.1, a multilayer perceptron (MLP) model is constructed to predict sensor locations using RSS values as input features. The MLP is trained using the backpropagation algorithm, with training samples consisting of randomly distributed node positions within a sensor field. Thanks to its nonlinear activation functions, the MLP can effectively model the log-normal shadow fading, achieving up to 35% better localization precision than non-ML-based techniques. This approach is further improved through the use of radial basis function models, as proposed in (Annepu et al., 2021).

Unsupervised Learning for Trajectory Planning and Communications

Unsupervised learning techniques, such as autoencoders, GANs, and GMMs, have been applied to UAV trajectory planning and communications. Autoencoders generate waypoints through a three-step process: extracting potential waypoints from historical trajectories, creating trajectory-based images, and identifying waypoints via repeating pixel patterns. This approach reduces waypoints by 84.21% compared to K-means, enhancing energy efficiency. Autoencoders also predict movement in dynamic environments by reconstructing action-conditioned video frames for trajectory planning. For attitude control, deep autoencoders with multiple hidden layers fuse data from gyroscopes, accelerometers, and magnetometers, outperforming single-layer architectures in attitude estimation through restricted Boltzmann machine-based networks.

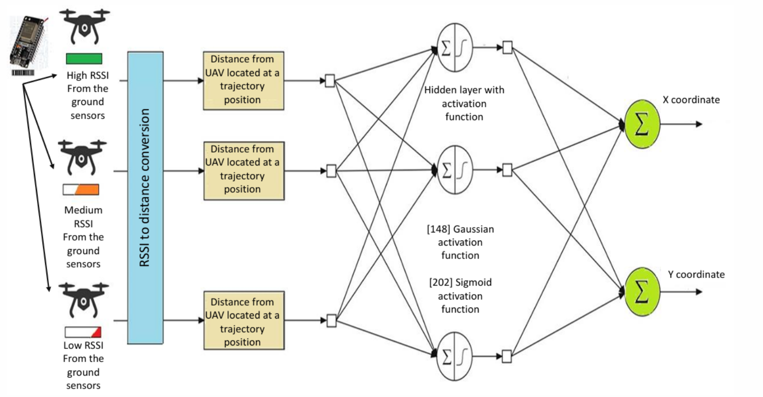

Figure 2.1: The MLP for UAV-based localization of a WSN node using the Gaussian activation function (Annepu & Rajesh, 2020) and the RBF model using the Sigmoid activation function (Annepu et al., 2021)

In UAV-aided image analysis, challenges like camera pose variations, shadows, and illumination changes often stem from noise or acquisition issues. Autoencoders address these by clustering image features based on similarity, with the encoder network learning to distinguish dynamic changes through training and reduces the required number of training images.

Semi-supervised Learning for UAV Trajectory Opti mization

A Generative Adversarial LSTM (GA-LSTM) network can be used to optimize resource allocation in UAV-assisted machine-to-machine wireless communications. This architecture combines the capabilities of Generative Adversarial Networks (GANs) and Long Short-Term Memory (LSTM) networks to jointly optimize transmit power, communication mode, frequency channel selection, and UAV selection and trajectory within a partially observable multi-agent environment. The LSTM component enables the tracking of UAV movements and supports reward evaluation. Numerical evaluations show that this integrated model achieves higher sum rates compared to standalone LSTM or Deep Q-Network (DQN) methods.

In cellular networks that include both UAV-based aerial base stations (BSs) and ground BSs, a Gaussian Mixture Model (GMM) with weighted expectation-maximization can be employed to represent the spatial traffic distribution and guide base station deployment, including UAV positioning. This technique allows for traffic congestion prediction and determines the optimal placement of UAVs to reduce energy costs related to both communication and relocation. Simulation results highlight energy savings of up to 20% for communication and 80% for relocation when compared to heuristic approaches.

Reinforcement Learning for Joint Trajectory Plan ning and Mission Scheduling

Deep Reinforcement Learning (DRL) techniques offer innovative approaches for planning UAV trajectories in dynamic environments.

Deep Q-Network with Trajectory Discretization In UAV-assisted communications, reinforcement learning approaches like Q-learning face challenges with large state/action spaces, prompting the use of Deep Q-Networks (DQNs) which leverage neural networks to handle extended spaces. DQNs have been particularly effective for Age of Information optimization, where they balance energy efficiency with data freshness while using autoencoders with LSTM to manage large state spaces through spatiotemporal feature extraction (Abedin et al., 2020; Ferdowsi et al., 2021).

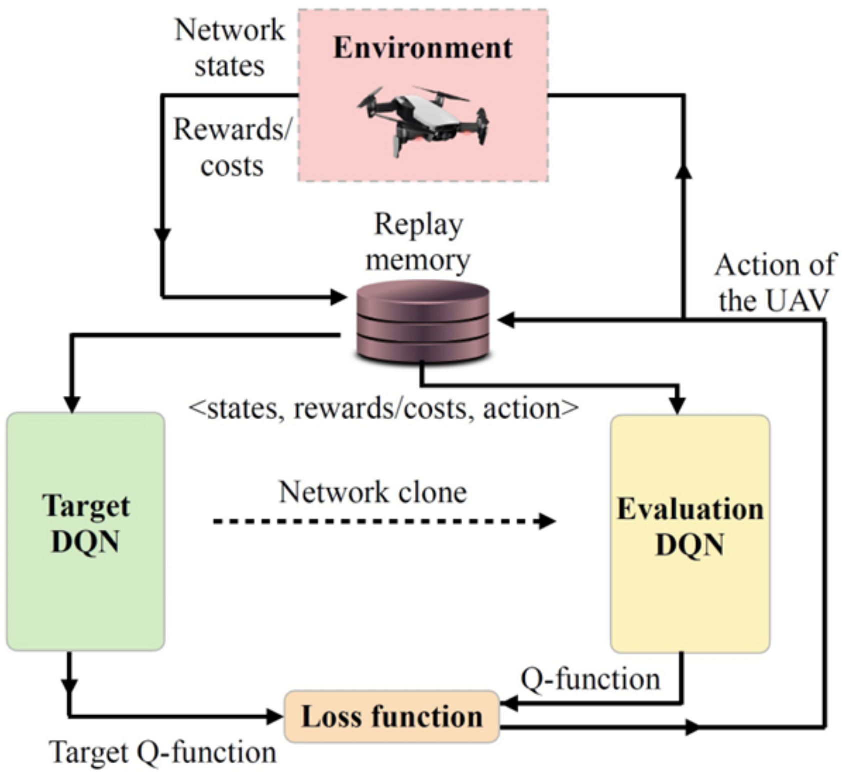

Figure 2.2: Schematic overview of a DQN-based framework for UAV trajectory and mission planning. The model is deployed onboard the UAV and trained to generate optimal policies for both path planning and radio resource allocation. (Kurunathan et al., 2022)

For throughput and energy optimization, deep Q-networks (DQNs) are used to jointly optimize UAV trajectories and bandwidth allocation. These methods take into account node states and data volume to enhance overall network performance. Packet loss issues are mitigated by adjusting UAV velocity and scheduling communications based on real-time data, including battery levels, queue statuses, and channel conditions.

In coverage-oriented applications, DQNs are applied to maintain robust network connectivity. They dynamically adapt to changes in topology and optimize UAV paths to balance coverage fairness and energy consumption. Advanced versions such as dueling DQNs are employed for scenarios requiring optimized flight paths for uplink throughput. These approaches also integrate obstacle avoidance and prioritize data with latency sensitivity.

In UAV-assisted Mobile Edge Computing (MEC) systems, double DQNs support effective task offloading decisions. This improves throughput while managing energy limitations and addressing data security challenges like eavesdropping. Wireless power transfer systems benefit from DQN-based optimization techniques as well, especially for planning UAV trajectories and selecting energy-harvesting nodes. These strategies are sometimes enhanced using probabilistic algorithms such as Naive Bayes for estimating node locations.

Although these techniques have broad applicability, their reliance on discrete action spaces poses a limitation. This constraint reduces their suitability for continuous control problems, such as fine-tuned UAV cruise control, highlighting the need for alternative or hybrid approaches in such contexts.

Online Trajectory Planning With Deep Deterministic Policy Gradient The Deep Deterministic Policy Gradient (DDPG) algorithm effectively combines value iteration and policy iteration approaches, offering a robust framework for deep reinforcement learning in continuous state and action spaces. Unlike Deep Q-Networks (DQN), which predict Q-values for discrete state-action pairs, DDPG employs a dual-network structure: a critic network that estimates Q-values and an actor network that determines optimal actions. This architecture allows DDPG to manage continuous control problems more efficiently than traditional DQN methods.

0. **Cruise Control:** DDPG demonstrates strong capabilities in UAV cruise control by learning optimal headings and velocities to minimize network costs in continuous action spaces. Its experience replay mechanism improves training stability by reusing past learning samples. Applications include autonomous landing on dynamic platforms, air combat maneuvering through precise trajectory control, and urban navigation that integrates obstacle avoidance with energy-efficient route planning.

0. **Age of Information (AoI):** DDPG is effective in minimizing the Age of Information by adapting to dynamic traffic and environmental conditions. Advanced variants like twin delayed DDPG (TD3) improve energy efficiency while maintaining low AoI in IoT networks. Multi-agent extensions enhance trajectory learning, and policy-based enhancements enable optimization of flight altitude and transmission scheduling.

0. **UAV-assisted MEC:** In Mobile Edge Computing scenarios, DDPG handles complex action spaces, making it suitable for joint optimization of content caching, delivery, and power control. It plays a key role in vehicular networks, managing spectrum and computing resource allocation and addressing the multifaceted challenges of UAV-assisted MEC environments.

0. **Other Applications:**

- Deep reinforcement learning-based frameworks have achieved improved fairness and energy efficiency in coverage and resource allocation.
- Game-theoretic approaches combined with DDPG enable optimal UAV deployment and trajectory planning while ensuring obstacle avoidance.
- Hybrid systems integrating DDPG with LSTM networks facilitate dynamic spectrum sharing through intelligent timeslot allocation.
- Enhanced Q-network variants have been applied to outage minimization and integrated navigation with radio environment mapping.

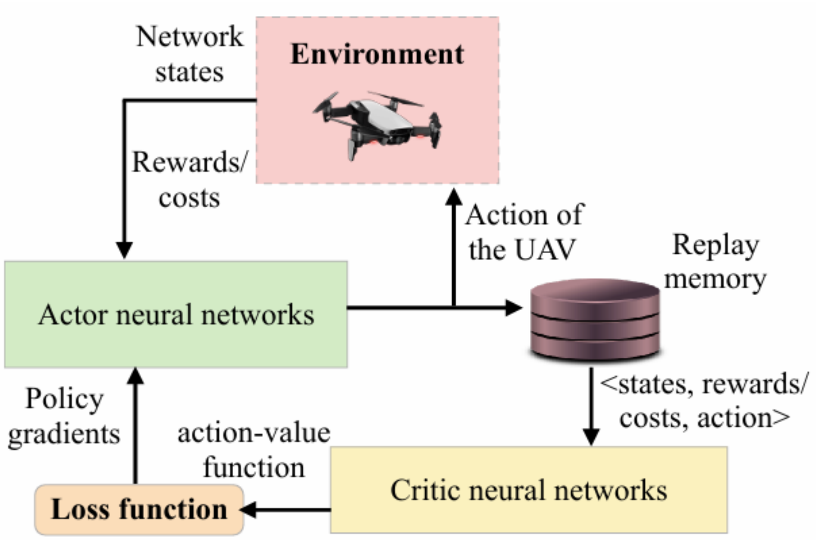

Figure 2.3: DDPG Architecture Overview with Actor-Critic Networks and Experience Replay for UAV Control (Kurunathan et al., 2022)

Multi-agent DRL for Multi-UAV Cooperation The multi-agent DQN framework has been successfully implemented for cooperative UAV systems, where the network state incorporates ground nodes' battery levels, data queue statuses, and all UAV waypoints (**dqn_multi_115**). This approach enables intelligent scheduling of ground node transmissions while dynamically adapting to changing data and energy arrival patterns.

Building upon this foundation, researchers have enhanced the multi-agent DQN framework to incorporate velocity adjustment capabilities at waypoints, while maintaining optimal ground node selection for data transmission. This extension provides more refined control over UAV movements during mission execution.

For cellular network applications, multi-agent DQN can effectively address the complex joint optimization of UAV trajectories and communication scheduling. The solution coordinates data transmissions from cellular tower ground nodes based on relative positions between UAVs and ground stations.

In energy conservation scenarios, a non-cooperative game formulation with periodic UAV beaconing establishes optimal beaconing equilibrium durations without requiring knowledge of other UAVs' transmission schedules.

Security applications have leveraged multi-agent DDPG approaches, where UAV jammers are coordinated to enhance secure channel capacity. The framework simultaneously optimizes jammer trajectories, jamming power levels, and legitimate UAV transmission power.

For MEC systems, a multi-agent DDPG model improves resource allocation fairness while optimizing UAV trajectories and computation offloading decisions to boost MEC device energy efficiency.

Further advancing MEC applications, a comprehensive multi-agent DDPG framework for vehicular networks treats the MEC server as an intelligent agent coordinating UAV and ground vehicle scheduling, along with computational resource allocation. Integration with federated learning significantly improves task offloading performance from vehicles to UAVs.

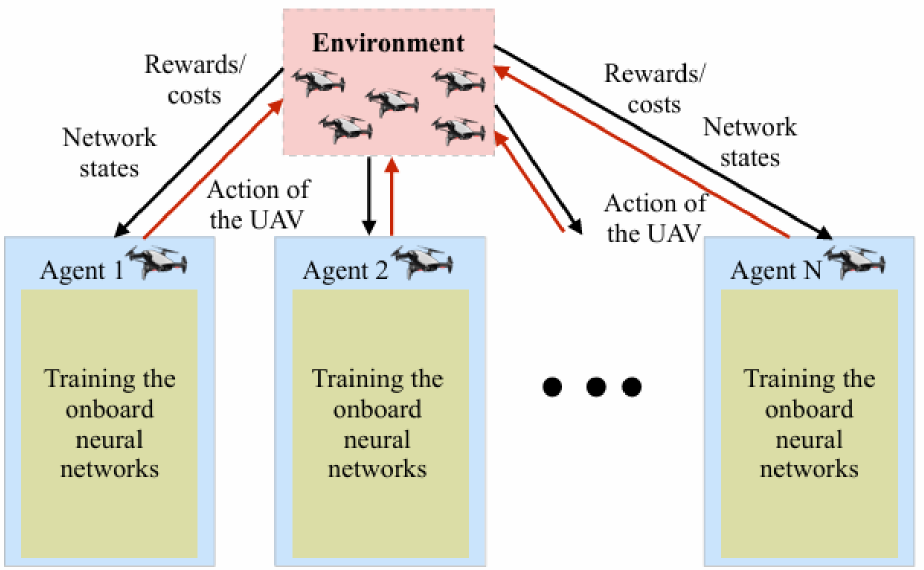

Figure 2.4: A multi-agent DRL structure where each UAV trains an onboard neural network to determine the optimal joint actions (Kurunathan et al., 2022)

Note: The selection between multi-agent DQN and DDPG implementations depends on the action space characteristics of the target application. DQN is preferred for discrete decision spaces (e.g., UAV clustering), while DDPG excels in continuous control scenarios (e.g., precise trajectory planning). Complementary techniques like autoencoding further enhance these frameworks through efficient feature extraction and supervised learning components.

2.1.2 Machine Learning for UAV Perception and Feature Extraction

Feature extraction is a technique for reducing dimensionality. It typically begins with a set of real-time data collected through the UAV's camera, followed by the creation of derived values (such as edges, shapes, and object recognition) that carry meaningful information. This derived learning is non-redundant and supports subsequent learning to enhance feature extraction. Unlike traditional imaging platforms, UAVs offer a unique vantage point, providing an expansive view of the area of interest. Additionally, the mobility of UAVs allows them to cover a larger geographical area compared to stationary imaging systems. In the following sections, we explore key machine learning techniques applied to UAV-assisted imaging.

Supervised Learning-based UAV Operations

Supervised machine learning techniques, like MLP, are capable of processing information through multiple layers, assisting in the interpretation of images captured by the UAV. Approaches such as CNN can segment and link the layers of an image, facilitating feature extraction.

0. **Multilayer Perceptron for Image Processing**

   UAVs have gained significant traction in precision agriculture, particularly in crop disease analysis and vegetation management, where MLP models demonstrate notable effectiveness. In (**Abdulridha2020**), a UAV equipped with hyperspectral cameras captures hyperspectral images of a tomato field to facilitate early disease detection caused by fungus and bacteria. An MLP neural network classifies the images, achieving an impressive accuracy rate of 99%. In an other approach a quadcopter UAV, outfitted with a Raspberry Pi single-board computer and an onboard camera module, is employed for vegetation mapping in tomato crops. MLP is used to segment the crop images, outperforming the support vector machine (SVM) alternative in terms of precision and recall.

   The utility of MLP in aerial image analysis extends beyond agriculture to environmental management, such as weed eradication (**Tamouridou2017**). In this study, a multi-spectral camera is mounted on an eBee fixed-wing UAV to capture high-resolution images of a field. An MLP with automatic relevance detection (MLP-ARD) is used to detect the weed species *Silybum marianum* among various types of vegetation. The MLP, featuring one hidden layer and one output unit, is regulated through Bayesian regularization to prevent overfitting and is trained on spectral and textural input data to classify the weed effectively. MLP has also been applied to flood management, with UAVs capturing aerial images of flooded areas in Houston, Texas. In this case, an MLP is used for semantic analysis following the use of a densely connected CNN and RNN to process the images.

   Furthermore, MLP models have proven useful in UAV route planning and agricultural harvesting. In (Annepu & Rajesh, 2020), UAVs assist in route planning and harvest volume estimation for unmanned agricultural harvesting systems, addressing the challenge of harvest losses due to untimely collection. The UAV, equipped with multi-spectral cameras, captures images that are analyzed using various neural networks, including MLP. The MLP, with three neurons in the hidden layer, provides optimal performance compared to other tested models, such as generalized regression networks and radial basis function networks.

0. **Convolutional Neural Network for Image Processing**

CNN is widely utilized for classifying and segmenting remotely sensed imagery due to its ability to extract detailed features. In UAV forest imagery, CNN can effectively identify features such as vegetation and dry areas. It is also employed in multi-object tracking for real-time applications, where it associates objects efficiently. Challenges arise from poor radio connections between the UAV and the base, which can degrade the quality of transmitted images, leading to packet loss and bandwidth wastage. A solution for this issue involves an Optimal Strategy Library (OSL) for video encoding, which adapts to the packet loss rate and bandwidth, ensuring improved video sequence encoding and recovery of partially corrupted videos (Kurunathan et al., 2022).

CNN-based approaches have shown high precision and accuracy (around 90%) in detecting slope failures from UAV remote sensing imagery. Similar performance is observed in several other image classification applications, where CNN achieves over 90% accuracy. In high-throughput phenotyping using high-resolution multispectral imaging, CNN classification and segmentation techniques provide nearly 99% accuracy. For search and rescue operations, UAVs with video cameras can analyze avalanche debris, and CNN can identify features indicative of survivors. Additionally, a linear Support Vector Machine (SVM) can be used in conjunction with CNN to enhance object detection.

CNN excels in imaging applications such as localization, object detection, and segmentation. Despite its strengths, one limitation is the time, energy, and resources required for segmentation tasks. To address this, techniques like recurrent CNN (R-CNN) have been developed to streamline the processing. In certain UAV imagery applications, R-CNN improves detection accuracy and resolves issues related to image resolution. Lightweight CNN architectures have also been proposed for efficient execution on embedded processors, providing a balance between performance and resource consumption. Energy-aware designs have been suggested to minimize power consumption in UAV tracking and landing tasks, with CNN's Quality of Service (QoS) level adjusting to save energy.

Although CNN is highly effective, it does not encode object position and orientation, and its detailed segmentation process can be resource-intensive. The layers closer to the CNN input focus on simple features such as edges, corners, and endpoints, but deeper layers, which offer more complex feature extraction, require longer training times. To mitigate this, lightweight CNN models have been introduced to reduce the need for powerful GPUs. Additionally, integrating Recurrent Neural Networks (RNN) with CNNs has shown promise in improving image processing, where dense connections enhance information flow and gradient propagation, thus improving training efficiency and reducing overfitting. This integration has achieved impressive results, with reported accuracy rates of 96% on real-world datasets.

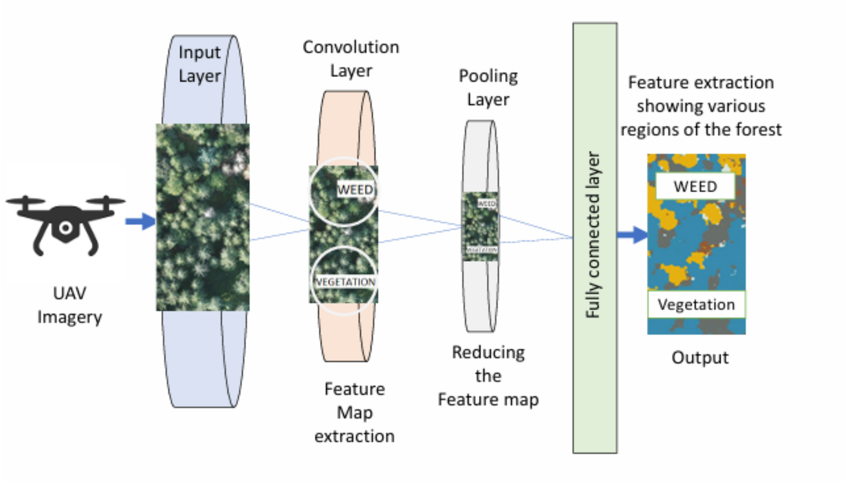

Figure 2.5: Convolutional Neural Networks in Image Processing (Kurunathan et al., 2022)

Unsupervised Learning-based Approaches

Novel unsupervised learning techniques, such as spiking neural networks (SNN), have energy-efficient and high-processing capabilities, making them suitable for faster and more energy-efficient control decisions in UAV operations. Neuromorphic SNNs utilize temporal difference learning to predict both rewards and temporal sequences in physical time. Temporal difference learning can be achieved by analyzing the temporal distance between neighboring events that vary in decay time constant. Neuromorphic SNNs replicate the functionality of a central nervous system, and typically operate at orders of magnitude lower power than traditional computing systems. This low-power capability is due to the event-driven, massively parallel nature of SNNs, where only a small portion of the system is active at any given time while the rest remains idle. This makes them suitable for applications such as edge computing, where strict energy constraints exist (Kurunathan et al., 2022).

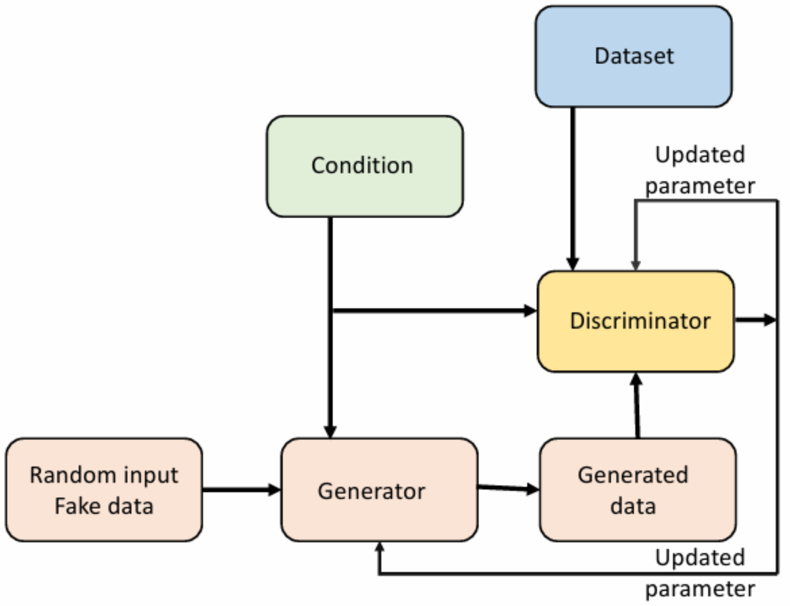

Figure 2.6: Generative Adversarial Network Framework for UAVs (Kurunathan et al., 2022)

To leverage the ultra-low-power capabilities of neuromorphic processors (on the order of several milliwatts), a neuromorphic SNN model has been studied for onboard deployment in UAVs to control their movements for obstacle avoidance. Differential evolution and Bayesian optimization are used to obtain the optimal configuration for the SNN. An SNN-based proportional-integral-derivative (PID) controller has been integrated with UAV motor control to ensure ultra-low power consumption while maintaining a high processing rate. In this architecture, each spiking neuron carries sensor measurements and control information, firing a spike when thresholds or biases are reached.

SNNs are also studied to control a hexacopter UAV in six degrees of freedom: yaw, roll, pitch, height, position, and angular velocity. A recurrent spiking controller is proposed to solve nonlinear control problems in continuous domains using a topology evolution algorithm as the learning mechanism. The results suggest that SNNs can solve ongoing control problems by maintaining sufficient spike activities and decoding from weighted spike frequencies. Additionally, an unsupervised Spike Time Dependent Plasticity (STDP) approach has been developed to detect UAVs in images. This asynchronous system, utilizing event-based camera features, is both low in power consumption and computational overhead.

A decision-making model for UAV flight control uses an SNN to simulate brain zone functions, determining control actions based on the relative positions of obstacles and the UAV. A system has been developed where spiking neurons detect and locate obstacles by partitioning the onboard camera image and mapping it for navigation. One SNN model, the liquid state machine, can track network states over time and predict data feature distributions. Liquid state machines have also been applied to resource allocation in cache-enabled UAVs, learning the data request distribution from ground nodes and determining data caching policies for the UAV.

2.1.3 Machine Learning for Feature Interpretation and Regeneration

Feature extraction is a form of dimensionality reduction. Feature extraction, pattern recognition, and image processing usually start from an actual set of measured data (taken through the camera of the UAV). It builds derived values (features such as edges, shapes, object recognition) that are informative. This derived learning is non-redundant and facilitates subsequent learning to obtain better feature extraction. UAVs can provide an eagle-eyed view of the region of interest compared to their counterparts, i.e., the non-UAV imaging platforms. The mobility of UAVs can also provide the capability to cover a larger geographical area than their stationary counterparts (**244**). In what follows, we discuss important ML techniques used in UAV-assisted imaging.

Feature interpretation by Linear Regression

The use of UAVs for environmental observation and agricultural monitoring has been growing steadily. These aerial platforms collect various types of sensory data through onboard instruments like cameras and infrared sensors. One of the most widely adopted techniques for analyzing such data is linear regression (LR), along with its different extensions.

Linear regression, a core technique in supervised machine learning, is employed to model the relationship between a set of input features and a continuous target output. This approach provides numerical insight into how features influence the target variable, offering a way to explain and quantify feature importance.

In one application, LR was used to evaluate how the spatial placement of sensors affects air pollution measurements in a UAV-based system (Villa et al., 2016). This study also proposed design guidelines for UAV systems tasked with locating emission sources.

In the field of precision agriculture, LR helped establish a correlation between the crop coefficient and the normalized difference vegetation index to estimate evapotranspiration (Niu et al., 2020). A deep stochastic configuration network was also utilized to complement the LR model and enhance predictive performance.

Other research combined plant height and vegetation indices derived from UAV imagery to estimate biomass using a multiple LR model. Additionally, structure-from-motion (SfM) techniques were applied to generate 3D point clouds from overlapping aerial images. These were used to evaluate the health of wetland vegetation by linking them to vegetation indices through LR models.

In bathymetric mapping, LR's limitations were addressed by introducing a geographically weighted regression (GWR) model, which improved accuracy and reduced the spatial biases often present in standard multiple regression approaches .

For soil salinity mapping, advanced regression techniques such as random forest models were applied on data collected from electromagnetic induction sensors and hyperspectral cameras.

Although LR is easy to implement and interpret, it assumes a linear relationship between inputs and outputs. This assumption can lead to poor model performance when the actual relationship is more complex. Furthermore, LR is sensitive to noise and prone to overfitting, especially when the number of input features exceeds the number of available observations.

Classification by K-Means Clustering

K-means clustering has been effectively applied in path planning for multi-UAV systems, particularly when coordinating multiple tasks within a designated area. Given the geographic distribution of tasks, K-means is used to group them into several clusters. Each cluster can then be assigned to a UAV, and route optimization techniques such as simulated annealing or genetic algorithms are employed to determine efficient paths within those clusters.

In addition to task allocation, K-means plays a role in guiding UAV movement for coverage-related objectives. For instance, in scenarios where UAVs are deployed to deliver cellular connectivity, the approach dynamically groups users based on their spatial positions. UAVs are then directed to the centroids of these groups to ensure adequate coverage and maintain service quality. This method has demonstrated convergence toward locally optimal deployments. Similar strategies have also been implemented in aerial surveillance tasks to ensure efficient area monitoring using multiple UAVs.

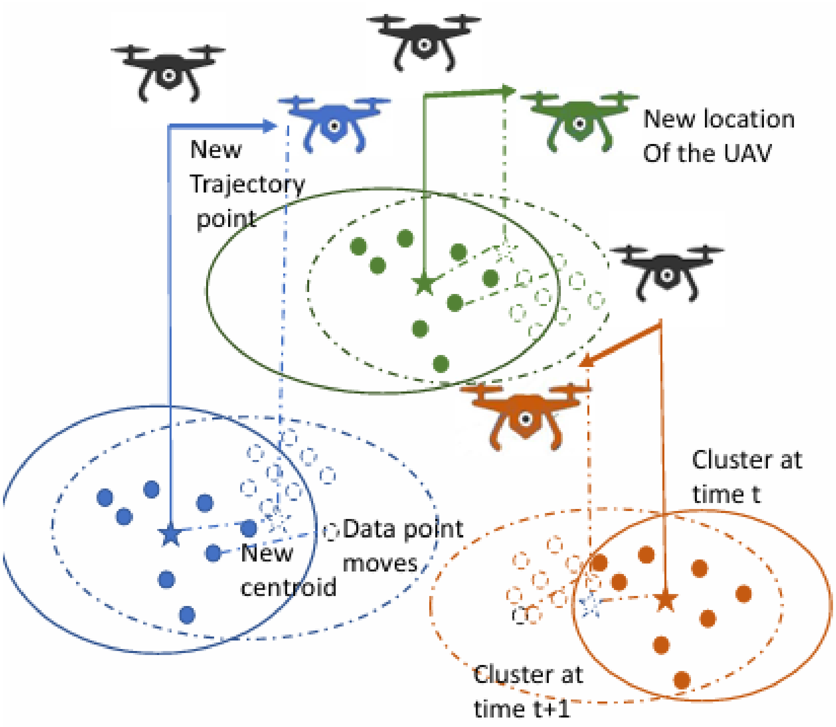

Figure 2.7: Centroid-Based Coordination in Multi-UAV Surveillance Using K-Means Clustering (Huang & Savkin, 2021)

Environment Modeling Using Gaussian Mixture Models

GMM (Gaussian Mixture Model) is applied to model static, complex-shaped, two-dimensional obstacles, aiding in the prevention of UAV collisions. Given prior probabilistic knowledge about obstacles, GMM is generated to form the potential field of the target area. The parameters of the GMM are iteratively estimated using the Expectation-Maximization (EM) method, allowing the model to approach the true distribution of the obstacles. By taking derivatives over the GMM, the potential field is created, and UAV flight paths are determined by following the field directions. A trajectory prediction model based on GMM clusters trajectory data into distinct components and applies Gaussian process regression to predict possible future trajectories. Additionally, GMM is utilized to create heatmaps of object detection probabilities in a designated area. For instance, a UAV can be used to maximize the probability of locating a specific object by planning an efficient flight path, taking into account environmental factors like foliage coverage, shadowing, and illumination. The spatial distribution of detection probabilities is modeled using GMM, which aids in creating a hierarchical search plan for a mission.

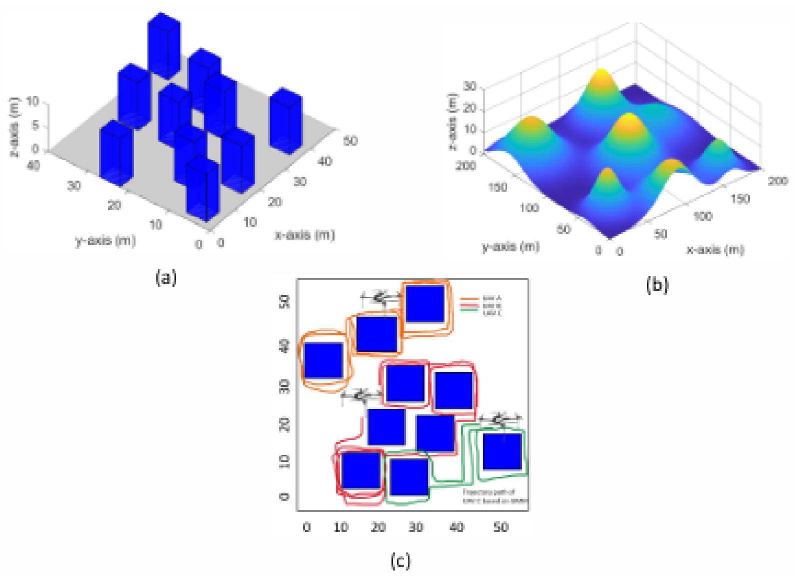

Figure 2.8: Trajectory Planning for UAVs Using GMM-Based Environment Modeling (Huang & Savkin, 2021)

Furthermore, GMM is integrated with horizon control techniques to optimize the trajectories of multiple UAVs tasked with searching a complex environment. In these setups, receding horizon control (model predictive control, MPC) is used for dynamic path planning to optimize search efforts, avoid collisions, and ensure simultaneous arrival at a target. Cooperation among UAVs is facilitated by regular flight path broadcast messages. GMM is also used to model the distribution of radio traffic in cellular networks involving UAV-based base stations (BSs), which helps in optimizing UAV placement. By utilizing a weighted EM algorithm, GMM can predict traffic congestion and reduce UAVs' energy consumption for communication and mobility. Simulations indicate a reduction of 20% in communication energy use and 80% in mobility energy compared to heuristic methods.

In conclusion, techniques such as K-means clustering and linear regression are effective in feature interpretation and environmental data analysis, while probabilistic models like GMM excel at spatial distribution modeling and feature classification. These methods prove highly accurate when sufficient prior data is available, enabling complex applications like UAV control.

2.2 Conclusion

AI and optimization techniques have revolutionized UAV applications, enabling smarter path planning, resource management, and autonomous decision-making. Reinforcement learning methods like DQN and DDPG have proven particularly effective in handling both discrete and continuous control tasks. However, as UAV networks expand, security threats such as data tampering and denial-of-service attacks demand stronger defenses, including protocols like SAODV and collision-free MAC layers. Future research should focus on lightweight AI models for real-time processing and resilient encryption methods to safeguard UAV communications. This chapter highlights the synergy between AI advancements and security measures, emphasizing both the progress made and the challenges that remain in UAV technology.

Chapter 3

Traffic monitoring methods

Introduction

Traffic monitoring is a critical component of modern urban infrastructure, enabling efficient traffic management, accident prevention, and emergency response. With the rapid growth of urbanization and the increasing complexity of road networks, traditional traffic monitoring systems often struggle to provide real-time, scalable, and cost-effective solutions. In recent years, advancements in Unmanned Aerial Vehicle (UAV) technology and wireless communication systems have opened new possibilities for innovative traffic monitoring approaches. These methods leverage the flexibility, mobility, and adaptability of UAVs to address the limitations of ground-based systems, such as fixed cameras and sensors.

This chapter explores six distinct methods for UAV-based traffic monitoring, each offering unique solutions to specific challenges in traffic surveillance. From real-time video relay systems to collaborative hotspot selection frameworks, these methods demonstrate the potential of UAVs to enhance traffic monitoring capabilities. The chapter begins with an overview of early systems like the Airborne Traffic Surveillance System (ATSS) and progresses to more advanced approaches, such as 5G-integrated UAV systems and cooperative traffic monitoring using multiple UAVs. Each method is analyzed in terms of its architecture, operational workflow, performance, and limitations, providing a comprehensive understanding of the current state of UAV-based traffic monitoring technologies.

By examining these methods, this chapter highlights the transformative potential of UAVs in traffic management while also addressing the technical, regulatory, and environmental challenges that must be overcome for widespread adoption. The following sections delve into the details of each method, offering insights into their design, implementation, and real-world applicability.

3.1 Method 1: Airborne Traffic Surveillance System (ATSS)

In (Srinivasan et al., 2004), the University of Florida (UFL) research team, in collaboration with the Florida Department of Transportation (FDOT), developed the **Airborne Traffic Surveillance System (ATSS)**. This innovative system leverages **Unmanned Aerial Vehicles (UAVs)** and **microwave IP networks** to transmit highway surveillance data to a **Base Station (BS)**. The UAV captures video footage of traffic and transmits it in real-time. Two computers located in towers function as video encoders, while another computer at the State Emergency Operations Center receives and displays the strongest video signal. Figure 3.1 illustrates the system framework.

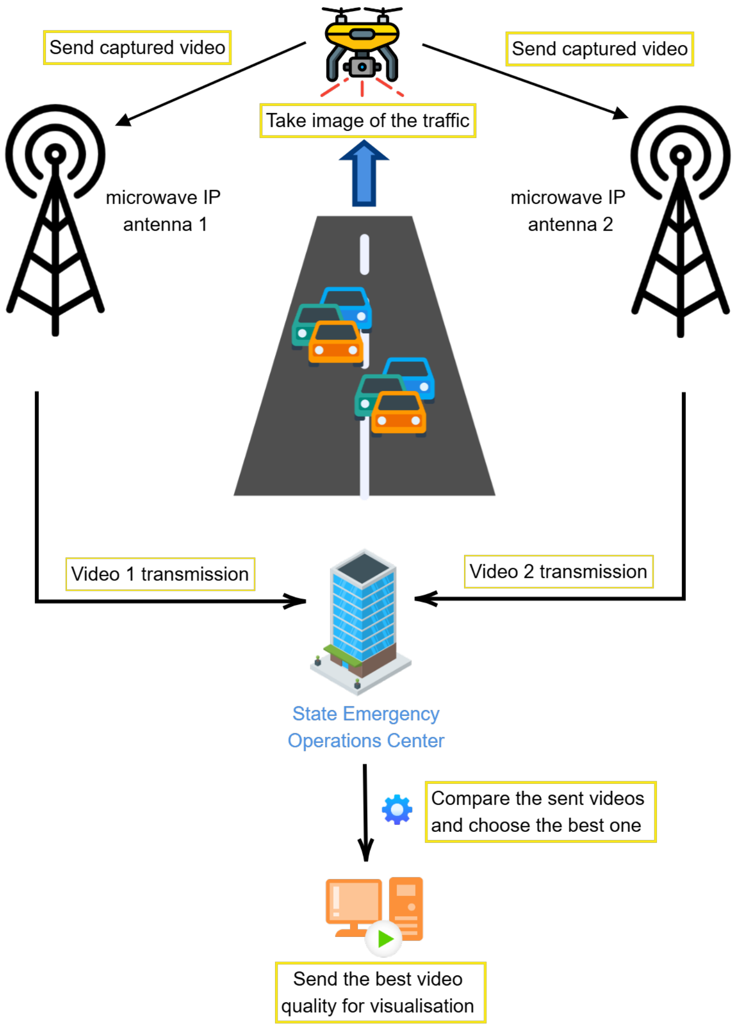

Figure 3.1: Airborne Traffic Surveillance System (ATSS) Architecture

3.1.1 Key Features of ATSS

The ATSS represents a significant advancement in traffic monitoring, offering the following capabilities:

- Real-time video capture and transmission of traffic conditions.
- Utilization of UAVs for flexible and scalable surveillance.
- Integration with microwave IP networks for data transmission.
- Centralized monitoring at the State Emergency Operations Center.

3.1.2 Limitations of ATSS

Despite its innovative approach, the ATSS faces several challenges that impact its effectiveness and scalability:

- **Regulatory Constraints:** Federal Aviation Administration (FAA) restrictions limit UAV operations, requiring specific approvals and slowing deployment.
- **Communication Challenges:** Bandwidth limitations, signal reliability issues, and potential interference, especially in adverse weather conditions.
- **Energy and Flight Duration:** Limited battery life necessitates frequent landings and recharging, reducing operational efficiency.
- **Environmental Factors:** Strong winds, rain, and fog degrade video quality and affect UAV stability.
- **Real-Time Video Transmission:** Requires efficient data compression and robust network infrastructure to minimize delays and ensure reliability.
- **Operational Costs:** While more cost-effective than manned aircraft, UAV deployment involves expenses for equipment, trained personnel, and maintenance.
- **Privacy and Security Concerns:** Raises ethical and legal issues, necessitating strict regulations for data collection and surveillance.

3.1.3 Future Potential

Despite these limitations, UAV-based traffic monitoring holds significant promise. Future advancements, such as **AI-driven analysis**, **improved communication technologies (e.g., 5G)**, and **autonomous UAV operations**, could enhance its feasibility for large-scale implementation. These developments may address current challenges and unlock new possibilities for real-time traffic management.

3.1.4 Conclusion

The Airborne Traffic Surveillance System (ATSS) represents a pioneering approach to UAV-based traffic monitoring, offering real-time video capture and transmission through microwave IP networks. Despite its innovative design, the system faces challenges such as regulatory constraints, communication limitations, energy inefficiencies, and environmental sensitivities. However, future advancements in AI-driven analytics, 5G communication, and autonomous UAV operations hold the potential to address these limitations, making the ATSS a promising foundation for scalable and efficient traffic surveillance systems.

3.2 Method 2: Video Relay Model Using Public Networks

A comparable surveillance method was proposed in (Y. M. Chen et al., 2007), where researchers developed a **video relay model** using existing public networks. This approach addresses the limitations of traditional traffic surveillance systems, such as the high cost and time-consuming installation of cameras on microwave towers along highways (Srinivasan et al., 2004). Instead, this method leverages **mobile broadband connections** to transmit video footage directly to a ground base station (BS) located near the UAV. The efficiency of this method depends on the proximity of ground stations and the availability of a stable broadband network.

3.2.1 Ground Control Station and Network Setup

A distinctive aspect of this project is the strategic placement of the ground control station near the highway, allowing seamless access to a roadside communication tower. This setup enables the use of the existing mobile broadband network to transmit surveillance video efficiently. The primary goal of video relaying is to send video signals from the UAV ground station in the field to control office computers. Since most of these computers are connected to the Internet, using the public Internet as the main network for video transmission simplifies the setup and reduces system requirements for end-user computers. Figure 3.2 illustrates the proposed architecture.

3.2.2 Operational Workflow

The ground station, which consists of a laptop equipped with an antenna, is placed in the field to ensure that the UAV has a suitable flying range covering a section of the Interstate Highway. The best location for the ground station may not always have a wired Internet connection. However, since it is usually set up near the highway, it can take advantage

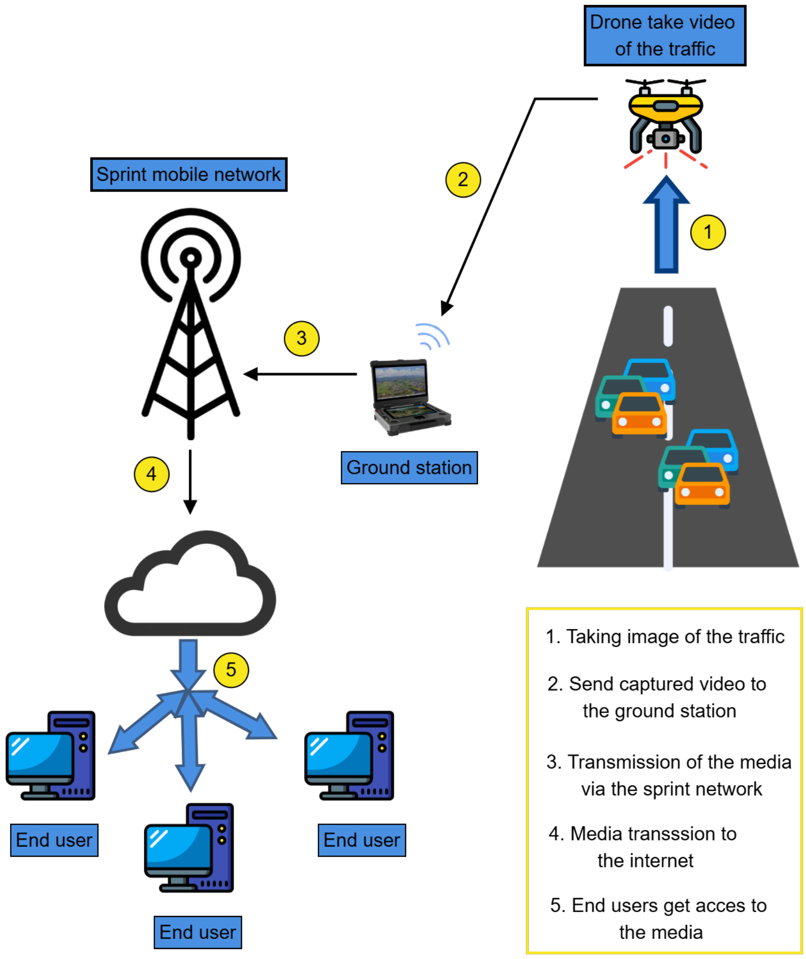

Figure 3.2: Proposed Architecture of the Video Relay Model

of nearby cellular towers for communication. To send video over the Internet, the UAV ground station uses the nationwide **Sprint mobile broadband network**. The laptop at the ground station connects to this network using a wireless PC card, which acts as a bridge to the Internet. Once online, the transmitted video is received by the mobile base station through the Internet.

One drawback of this approach is that the wireless connection in the Sprint mobile broadband network can slow down data transmission. In other words, the system's performance is limited by the available bandwidth in the wireless network. To address this limitation, researchers developed two methods for transmitting the video over the Internet.

3.2.3 Direct IP Address Sharing

In the first method (see Figure 3.2), the UAV ground control laptop shares its IP address with end users, who can then use a media player to stream the video from that address.

However, the Sprint mobile broadband service assigns a new IP address each time a connection is established. As a result, the IP address changes every time the ground control laptop reconnects to the Sprint network. This requires the ground crew to update and inform end users of the new IP address for each session, creating operational inefficiencies.

3.2.4 Server-Based Video Relay

An improvement to the system involves using an additional server to manage the data connection. This server has a **fixed IP address**, which is known in advance by both the UAV ground control laptop and the end-user computers. The UAV ground control laptop streams the video to the server using this fixed IP address, and end users access the video from the same server. Besides real-time streaming, the server can also save the received video for later analysis. Additionally, it hosts the project website, which includes a page displaying the live video feed from the UAV camera. To handle both website hosting and incoming video streams, the server has multiple open network ports. However, using a server may introduce some delays in processing and could be affected by firewall restrictions.

In this second method, the UAV ground control laptop transmits the video to the server through the mobile broadband network. The server then forwards the video to end-user computers using a wired Internet connection. The number of users who can watch the video at the same time depends on the server's wired connection speed, which is significantly higher than that of the wireless network. As a result, more users can access the video stream simultaneously with a stable data rate. This approach overcomes the limitations of the wireless connection, which is the main bottleneck for video transmission.

3.2.5 Limitations of the Method

Despite its innovative approach, the video relay model using public networks has several limitations that need to be addressed for practical deployment:

- **Bandwidth Constraints**: The system's performance is heavily dependent on the available bandwidth of the mobile broadband network. In areas with poor network coverage or high congestion, video transmission may suffer from delays or interruptions.
- **Operational Inefficiencies**: The direct IP address sharing method requires manual updates to inform end users of new IP addresses, leading to operational inefficiencies and potential delays in accessing video feeds.
- **Server Dependency**: The server-based relay method introduces additional complexity and cost. Delays in processing and potential firewall restrictions can impact the system's real-time performance.

- **Energy Consumption**: UAVs and ground stations rely on battery power, which limits their operational duration. Frequent recharging or battery replacement may be required, especially in large-scale deployments.
- **Environmental Factors**: Adverse weather conditions, such as heavy rain or strong winds, can affect UAV stability and the quality of video footage, reducing the system's reliability.
- **Scalability Issues**: While the system performs well in small-scale deployments, scaling it to cover larger areas or higher traffic volumes may introduce challenges in network organization and resource allocation.

3.2.6 Conclusion

In conclusion, the video relay model using public networks represents a **cost-effective and scalable solution** for UAV-based traffic monitoring. While challenges such as bandwidth limitations and operational inefficiencies persist, the integration of server-based relay systems significantly enhances the method's feasibility and performance.

3.3 Method 3: UAV-Based Traffic Surveillance with 5G Integration

In (Khan et al., 2024), researchers proposed a novel solution to address the weaknesses of SAHER, an automated traffic enforcement system used in Saudi Arabia. SAHER relies on cameras and radar technology to detect traffic violations such as speeding, running red lights, and lane violations. While effective, the system has several limitations:

- Drivers often hide their license plates to avoid detection.
- Drivers warn others when they spot a speed camera.
- Drivers adhere to speed limits only in areas monitored by SAHER cameras.
- Drivers slow down near speed cameras but speed up afterward.

To overcome these challenges, the researchers proposed an **airborne traffic surveillance system** using drones (UAVs) and 5G technology. This system is structured into three layers, each serving a distinct purpose.

3.3.1 System Architecture

The proposed system consists of three layers:

- **Layer 1**: UAVs fly over highways, capturing video footage and GPS data, which are transmitted to a mobile police base station.
- **Layer 2**: 5G technology ensures a fast and stable connection between the UAVs and the police station.
- **Layer 3**: The system facilitates efficient highway traffic management.

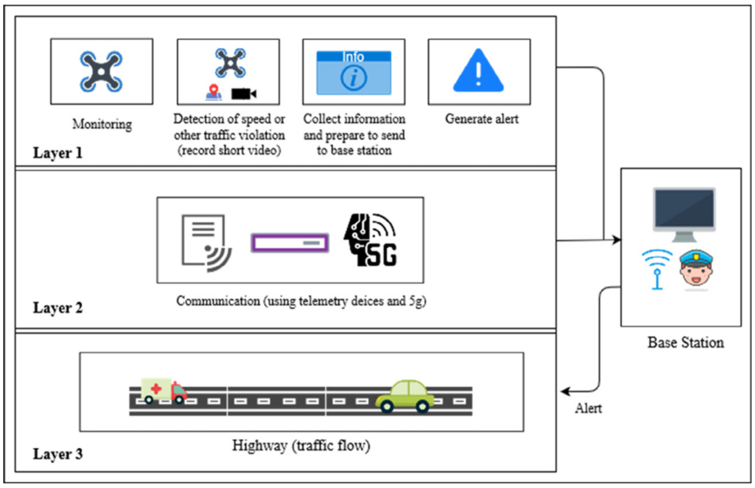

Fig. 7. Architecture design for the proposed model.

Figure 3.3: Proposed Architecture of the UAV-Based Traffic Surveillance System (Source: (Khan et al., 2024))

3.3.2 Traffic Monitoring and Violation Detection

The UAV monitors highway traffic, detects violations, and ensures road safety. When a violation occurs, the system follows a two-step enforcement approach:

- **First Violation**: The UAV issues a warning to the driver through an integrated communication system.
- **Repeated Violation**: If the driver commits the same offense again, the UAV records the details, issues a ticket using License Plate Recognition (LPR), and sends the information to the nearest base station for legal action.

3.3.3 Layer 1: UAV-Based Traffic Monitoring

A UAV is deployed to monitor highways, equipped with an advanced camera and GPS tracking system. It continuously scans traffic for speeding and other infractions, recording real-time violations. When a violation is detected, the UAV captures a short video and logs the GPS coordinates. If it's the driver's first offense, the system issues a warning via an integrated module in the vehicle. The collected data is transmitted to the base station for further action. To counteract license plate tampering (e.g., covering plates with tape to evade detection), the base station maintains vehicle records and can take legal action when the vehicle reaches a designated checkpoint.

3.3.4 Layer 2: Communication Network

This layer facilitates data transmission between the UAV and the base station using telemetry or modern communication technologies. With advancements in communication, **5G** is the preferred choice due to its high speed, broad coverage, and low latency. The system relies on 5G for seamless and real-time data exchange, ensuring efficient monitoring and response.

3.3.5 Layer 3: Highway Traffic Management

This layer focuses on optimizing vehicle flow in the monitored areas. By integrating the UAV's data with traffic control systems, authorities can make informed decisions to improve road safety and efficiency.

3.3.6 Algorithm for Traffic Monitoring

The following algorithm, adapted from (Khan et al., 2024), outlines the process of traffic monitoring and violation detection:

Algorithm 1 Traffic Monitoring and Rule Violation Detection (Source: (Khan et al., 2024))

Step 1: Initialize
Step 2: Start monitoring traffic
Step 3: Detect speed and other traffic rule violations
Step 4: **if** *Rule violation found and first time* **then**
  4.1 Generate warning and alert the driver **4.2** Record a short video and GPS coordinates **4.3** Send video and associated data to ground control station
end
Step 5: **else if** *Rule violation found* **then**
  5.1 Record a short video and GPS coordinates **5.2** Send video and associated data to ground control station **5.3** Ground control station will process data and send to authorities **5.4** Go to Step 3
end
Step 6: **if** *Flight time ended* **then**
  6.1 Go to Step 8
end
else
  7.1 Go to Step 2
end
Step 8: Go to ground control station
Step 9: Exit

3.3.7 Limitations of the Proposed System

Despite its innovative approach, the proposed UAV-based system faces several challenges:

- **Higher Mobility**: The movement of UAVs can cause instability in the communication link, as the network must continuously adjust to their changing positions.
- **Line-of-Sight Interference**: UAVs rely on clear line-of-sight communication, and obstacles like buildings or terrain can block or degrade the signal.
- **Energy Constraints**: The limited battery life of UAVs restricts their ability to operate over long periods, especially in large or remote areas where frequent recharging or battery swaps are required.

These factors contribute to the complexity of cellular network planning and make the implementation of this system challenging.

3.3.8 Conclusion

The proposed UAV-based traffic surveillance system with 5G integration represents a significant advancement in traffic monitoring and enforcement. While challenges such as mobility, line-of-sight interference, and energy constraints persist, the system's potential for real-time monitoring and efficient traffic management makes it a promising solution for future implementation.

3.4 Method 4: Cooperative Traffic Monitoring Using Multiple UAVs

In (Elloumi et al., 2018), researchers introduced a cooperative traffic monitoring system using multiple UAVs. This system incorporates two distinct approaches: one focused on maximizing vehicle coverage and the other on detecting various traffic events, such as vehicle positions and speeds. While the first approach dynamically adjusts UAV trajectories based on the movement of targeted vehicle groups, the second relies on predefined vehicle mobility models to determine UAV paths. However, this multi-UAV system lacks real-time capabilities for identifying and reporting speed violations to the mobile police base station.

3.4.1 Key Components of the System

The system is constracted through three main steps:

Collecting Information About Vehicles

Various parameters can be monitored and measured based on the devices deployed over the coverage area, including:

- Vehicle position, speed, and direction.
- The number of vehicles in an area.
- The number of vehicles passing through specific points, such as intersections or crossings.

Specific events, such as speeding or traffic jams, are identified by changes in these parameters. For example:

- Speeding is detected when a vehicle exceeds a set speed limit.

- Traffic jams are identified when the speed of multiple vehicles drops below a certain threshold.

In this research, (Elloumi et al., 2018) consider multiple UAVs equipped with image-processing capabilities that enable them to accurately measure these parameters. The UAVs are assumed to:

- Always detect targets within their field of view, with no obstacles obstructing their line of sight.
- Temporarily adjust their altitude to avoid collisions.
- Exchange information about the vehicles they are tracking, including identifiers and positions.

Deploying UAVs Over Coverage Areas

The key challenge is determining the number of UAVs required to effectively cover a city area. Since deploying an unlimited number of UAVs is impractical, each UAV must monitor multiple targets. To minimize the required number of UAVs, targets are grouped into clusters, with each UAV assigned to a specific cluster. The clustering process considers factors such as:

- Distance between targets.
- Velocities of targets.
- Movement directions of targets.

An off-line algorithm (Algorithm 1) is proposed for this clustering, allowing system operators to estimate the UAV count. The algorithm inputs are shown in Table 3.1. Three criteria are used for clustering:

- Distance between the central target and potential group members (mandatory).
- Speed difference between targets (optional).
- Direction of movement (optional).

Abbreviation	Description
Tnb	Targets numbers
G	Groups members
D	Max distance value
V	Max speed difference
Pt	Target position
Mt	Target direction
Vt	Target velocity
compt	Covered targets
Ttag	Target tag
Tid	Target id
Cid	Central target id
Pc	Central target position
Mc	Central target direction
Ctag	Central target tag
Vc	Central target speed

Table 3.1: Input Parameters for Clustering Algorithm (Source: (Elloumi et al., 2018))

Algorithm 2 Clustering Algorithm

Step 1: Initialize $j \leftarrow 1$, compt $\leftarrow 0$
Step 2: **while** $compt < T_{nb}$ **do**
  2.1 while $C_{tag}(j) = 1$ **do**
    2.1.1 Sample $P_c(j) \sim \text{Uniform}(P_t)$
    2.1.2 Set $C_{\text{tag}}(j) \leftarrow 1$
    2.1.3 Set $G(j, j) \leftarrow C_{\text{id}}(j)$
    2.1.4 Increment compt $\leftarrow$ compt $+ 1$
    2.1.5 for $i = 1$ **to** T_{nb} **do**
      2.1.5.1 if $(T_{tag}(i) = 0) \wedge (i \neq j)$ **then**
        2.1.5.1.1 if $M_t(i) = M_c(j)$ **then**
          2.1.5.1.1.1 if $|V_t(i) - V_c(j)| < V$ **then**
            2.1.5.1.1.1.1 if $|P_t(i) - P_c(j)| < D$ **then**
              2.1.5.1.1.1.1.1 Set $G(j, i) \leftarrow T_{\text{id}}(i)$
              2.1.5.1.1.1.1.2 Increment compt $\leftarrow$ compt $+ 1$
              2.1.5.1.1.1.1.3 Set $T_{\text{tag}}(i) \leftarrow 1$
            end
          end
        end
      end
    end
    2.1.6 Increment $j \leftarrow j + 1$
  end
end
Step 3: End

Designing UAV Trajectories

Once the number of UAVs is estimated, the next step is to design their trajectories. Three different approaches are explored:

- **Fixed Trajectory Approach** This method relies on predetermined UAV paths guided by fixed Points of Interest (POIs), such as busy intersections or high-traffic zones. A single UAV is used to monitor these areas.
- **Mobile POI Approach** This method incorporates multiple cooperative UAVs. Each UAV detects targets within its field of view (FoV), estimates their positions and speeds, and shares this data with other UAVs and a central system. Unlike the fixed trajectory approach, both UAV trajectories and POIs are dynamic. The objective is to maximize the number of targets in a UAV's FoV for the longest possible duration.
- **Vehicular Mobility-Based Approach** This method leverages vehicular mobility models to determine UAV trajectories. Multiple UAVs are deployed, following the Shortest Path Map-Based Movement model, which aligns their paths with road networks to enhance observation opportunities. UAV speeds are adjusted to match those of the observed vehicles.

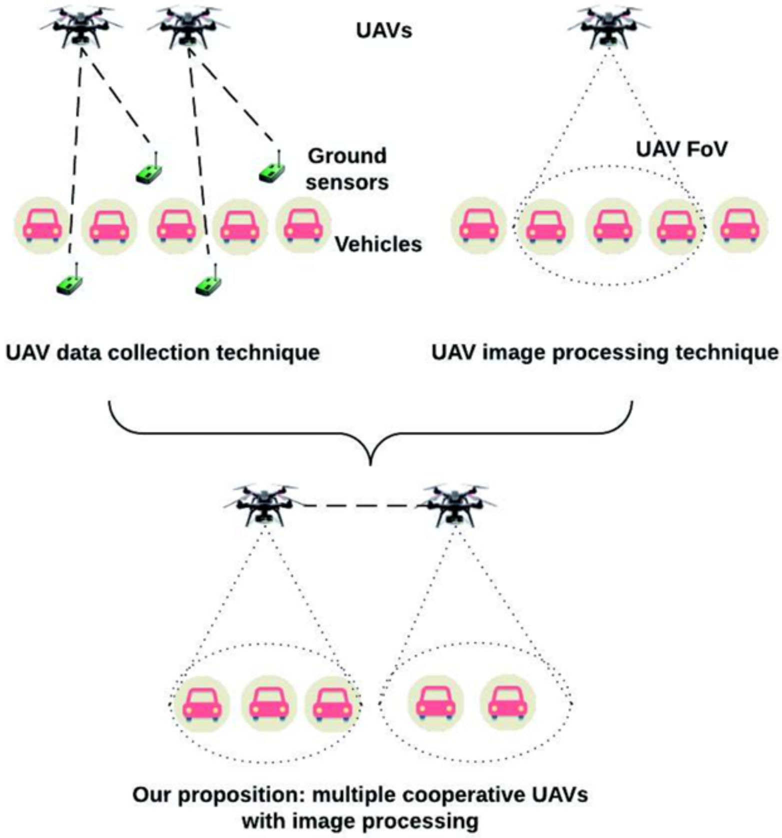

Fig. 1: Traffic monitoring techniques

Figure 3.4: Traffic monitoring techniques (Source: (Elloumi et al., 2018))

3.4.2 Simulation and Results

The study evaluates UAV-based road traffic monitoring (RTM) through simulations. Real-world taxi mobility datasets from Rome and San Francisco were initially considered but deemed unsuitable due to sparse vehicle distribution. Instead, the Opportunistic Network Environment (ONE) simulator was used to generate vehicle movement patterns based on real maps, applying Dijkstra's shortest path algorithm. The research tested different UAV clustering methods based on distance, velocity, and direction to optimize monitoring. Simulations examined UAV coverage efficiency, event detection (speeding, congestion), and tracking methods.

Key Findings

- **Fixed POI Method with Random UAV Movement**: The detection rate of speeding vehicles increases from 32% (5 POIs) to 80.87% (50 POIs). However, as the number of POIs increases, the time UAVs spend over a given area decreases, leading to shorter detected event durations.

- **Mobile Trajectory Methods**: These methods perform better, achieving up to 28.62% coverage (Mobile POI with 50 UAVs) and a 30.09% speeding violation detection rate (Vehicular Mobility-Based Method with 50 UAVs). Since UAVs follow mobile trajectories rather than fixed points, they can track events more accurately over time.
- **Impact of UAV Numbers**: For a small number of UAVs, all methods perform similarly. However, from 25 UAVs onward, the proposed methods show significant improvement. The initial estimate was that 25 UAVs would cover 10% of targets, but with the proposed methods, the coverage rate reaches 17%.

This table compares three UAV trajectory methods: the **Fixed Trajectory Approach**, the **Mobile POI Method**, and the **Vehicular Mobility-Based Method**. It highlights key differences in target tracking, adaptation, application domains, and UAV speed, showcasing how each approach is suited for specific monitoring tasks such as traffic surveillance, crowd tracking, or animal monitoring.

Criterion	**Fixed Trajectory Approach**	**Mobile POI Method**	**Vehicular Mobility Based Method**
Target Tracking	Fixed Points of Interest (POIs)	Center of gravity of target groups	Pre-calculated trajectories on roads
Adaptation	Static, predefined paths	Dynamic, based on target movements	Static, follows pre-generated points
Application Domain	High-traffic zones (e.g., intersections)	Crowd monitoring, animal tracking, etc.	Traffic monitoring
UAV Speed	Fixed	Variable, depending on group movements	Adjusted to match vehicle speeds

Table 3.2: Comparison of Fixed Trajectory, Mobile POI, and Vehicular Mobility Based Methods

3.4.3 Limitations of the Method

Despite its innovative approach, the proposed cooperative traffic monitoring system using multiple UAVs has several limitations:

- **Real-Time Reporting**: The system lacks real-time capabilities for identifying and reporting speed violations to the mobile police base station. This limits its effectiveness in enforcing traffic regulations promptly.

- **Energy Constraints**: UAVs have limited battery life, which restricts their operational duration and requires frequent recharging or battery swaps, especially in large or remote areas.
- **Communication Challenges**: Maintaining stable communication links between UAVs and the ground station can be difficult, particularly in urban environments with obstacles that block or degrade signals.
- **Scalability Issues**: While the system performs well with a moderate number of UAVs, scaling it up to cover larger areas or more targets may require significant computational and logistical resources.
- **Environmental Factors**: Adverse weather conditions, such as strong winds or heavy rain, can affect UAV stability and the quality of video footage, reducing the system's reliability.

3.4.4 Conclusion

The proposed cooperative traffic monitoring system using multiple UAVs demonstrates significant potential for urban traffic management. While challenges such as real-time speed violation reporting, energy constraints, and scalability persist, the integration of dynamic trajectory planning and clustering techniques enhances the system's effectiveness. Future work could focus on improving real-time capabilities, extending UAV battery life, and addressing communication challenges to enable large-scale implementation.

3.5 Method 5: UAV-Assisted Emergency Vehicle Routing

In a distinct approach, (Oubbati et al., 2019) proposed a UAV-based system specifically designed to assist emergency vehicles, such as ambulances, in identifying the optimal route through traffic to reach incident sites. The system is structured into four primary components:

- **Weighting of Road Segments**: Based on traffic fluidity.
- **Network Organization**: Establishing a robust and energy-efficient backbone among UAVs.
- **Reactive Routing**: Deploying communication between the Area of Interest (AoI) and relevant services.
- **Path Calculation**: Determining the near-optimal path in terms of travel time to the AoI.

3.5.1 System Overview

The proposed system enables UAVs to analyze nearby road segments and track changes in traffic conditions. UAVs communicate and collaborate by:

- Exchanging messages to organize their network.
- Overseeing road activity to detect incidents.
- Promptly notifying appropriate services to support intervention.

3.5.2 System Composition

The system is composed of n UAVs distributed across a three-dimensional (3D) space, moving randomly above various road segments. Key features of the UAVs include:

- **Initial State**: Each UAV starts with a fully charged battery.
- **Movement Parameters**: UAVs have access to their position, speed, direction, and information about nearby UAVs.

3.5.3 UAV States and Communication

UAVs operate in one of two states:

- **Normal UAV**: Performs standard monitoring tasks.
- **Backbone UAV**: Acts as a communication relay for the network.

Communication between UAVs and ground vehicles is facilitated using the **IEEE 802.11p** wireless standard. To address energy constraints, the authors define three distinct levels of remaining battery capacity:

- **High**: 66–100% remaining energy.
- **Medium**: 33–66% remaining energy.
- **Low**: 0–33% remaining energy.

3.5.4 Operational Constraints

Each UAV has the following operational constraints:

- **Line-of-Sight (LoS) Range**: Up to 300 meters.
- **Altitude**: Operates at low altitudes, remaining below 300 meters.
- **Incident Detection**: Under clear weather conditions, UAVs can detect road incidents using image processing techniques. However, the specifics of image analysis fall outside the scope of this work.

3.5.5 Weight Calculation

To determine the weight of a road segment, the hovering UAV collects Hello packets that are periodically exchanged between vehicles. Each intercepted Hello packet contains movement information, including the vehicle's position and speed. Regardless of its energy level or state, the UAV maintains a monitoring table to track traffic density, updating it as it receives Hello packets from vehicles traveling on a given road segment.

As illustrated in Table 3.3, four UAVs (u_1, u_2, u_3, u_4) monitor Hello packet exchanges from vehicles on four distinct road segments, each divided into three fixed zones. For instance, the monitoring table of UAV u_3 (Table 3.3) is used to compute key parameters required to determine the weight of the road segment between intersections I_X and I_Z.

Table 3.3: Monitoring table of UAV u_3 (adapted from (Oubbati et al., 2019))

Zone	Vehicle (Position (x,y))	Speed (m/s)
Zone 1	v_1 (100.00, 5.00)	10
Zone 2	v_2 (90.00, 305.00)	8
	v_3 (90.00, 405.00)	8
Zone 3	v_4 (90.00, 505.00)	8
	v_5 (100.00, 610.00)	14

The total number of vehicles on segment $S_{I_X I_Z}$ is given by:

$$T_{S_{I_X I_Z}} = 5, \quad SP_{av} = 96 \text{ m/s} \tag{3.1}$$

The traffic density regulation is assessed by computing the standard deviation, which reflects how vehicles are distributed across a given road segment:

$$\sigma_{S_{I_i I_j}} = \sqrt{\frac{1}{S_{I_i I_j}} \sum_{i=1}^{S_{I_i I_j}} T^2_{Zone_i}} \tag{3.2}$$

where:

- $T_{S_{I_iI_j}}$ is the total number of vehicles in the road segment $S_{I_iI_j}$ between intersections I_i and I_j.
- $\overline{T_{Zone}}$ is the average number of vehicles per zone.
- T_{Zone_i} is the number of vehicles in zone $Zone_i$.
- $S_{I_iI_j}$ is the number of fixed zones in the road segment $S_{I_iI_j}$.

If $\sigma = 0$, vehicles are evenly distributed, implying free traffic flow. Otherwise, if $\sigma > 0$, vehicles tend to cluster, often due to traffic lights or congestion.

The weight of a segment $S_{I_iI_j}$ is calculated as:

$$\text{Weight} = \frac{T_{S_{I_iI_j}} + 1}{d_{I_iI_j}} \times \frac{1}{SP_{av} + 1} \tag{3.3}$$

where $d_{I_iI_j}$ is the segment length. The weight is directly proportional to $T_{S_{I_iI_j}}$ and $d_{I_iI_j}$. The computed weight is always non-negative and provides an indicator of traffic conditions: lower weight values correspond to better road segments.

Table 3.4 presents the computed weight values for different segments.

Table 3.4: Weight Calculation Scenario (adapted from (Oubbati et al., 2019))

Segment	$d_{I_iI_j}$ (m)	$T_{S_{I_iI_j}}$	SP_{av} (m/s)	**Weight**
$S_{I_XI_Z}$	1500	5	10	463.82
$S_{I_ZI_Y}$	1500	0	0	0.00
$S_{I_YI_W}$	1500	2	14	136.05
$S_{I_WI_X}$	1500	12	0	7468.87

The segment $S_{I_ZI_Y}$ has the lowest weight and is thus the most suitable for emergency vehicle traversal.

3.5.6 Organization and Data Routing

To address the complexity of making a stable and reliable data transmission for alert messages, a stable backbone network is established by considering both UAV connectivity and their remaining energy levels. Graph-based modeling simplifies backbone construction by leveraging established graph theory algorithms. In this approach, UAVs and target services are represented as an undirected graph $G(V, E)$, where V denotes vertices (UAVs and services), and E represents bidirectional links between them at a given time t.

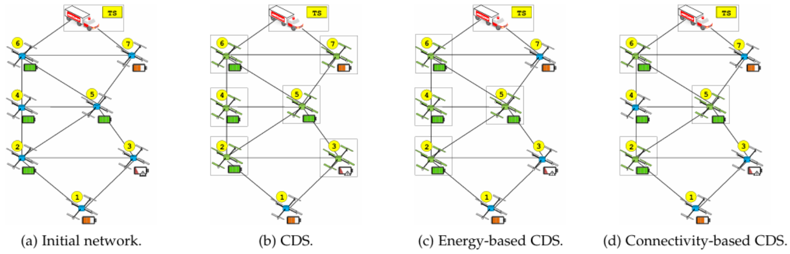

Figure 3.5: Connected dominating set (CDS) formation (Source: (Oubbati et al., 2019))

3.5.7 Connected Dominating Set (CDS) Formation

A Connected Dominating Set (CDS) is a subset D of vertices where each non-member is connected to at least one node in D, and all members of D are interconnected. Figure 3.5 illustrates this process. UAVs periodically exchange Hello packets (Fig. 3.7), which contain their ID, remaining energy (RE), mobility data (position, speed, velocity), and neighboring nodes. These details help calculate link connectivity lifetime and define network segments. A flag in the packet indicates whether a UAV belongs to the backbone (1) or not (0).

To construct the CDS, a marking process is applied:

- All UAVs are initially unmarked, except the Target Service (TS), which is permanently marked.
- Each UAV shares its neighbor list.
- UAVs with two unconnected neighbors are marked.

This results in a subgraph M, where $M = G[D]$, ensuring two key properties:

- **Property 1**: D forms a dominating set in G.
- **Property 2**: M remains a connected subgraph.

Since minimizing a CDS is NP-complete, we refine D using two rules:

- **Rule 1**: If a UAV u_i has a subset of its neighbors covered by another UAV u_j and $RE_{u_i} < RE_{u_j}$, then u_i is removed from M.
- **Rule 2**: If u_i has a lower average connectivity lifetime (ACL) than u_j, it is removed. ACL is calculated using the estimated connectivity duration between UAVs.

Applying these rules optimizes the CDS, ensuring long-term connectivity while maintaining a stable backbone. The CDS updates continuously through Hello packet exchanges, providing robust network reliability.

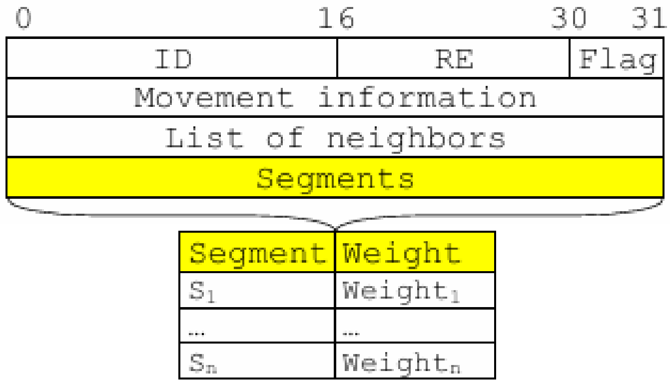

Figure 3.6: Hello packet format (Source: (Oubbati et al., 2019))

3.5.8 Routing

Once the CDS is defined, an innovative routing strategy is implemented to ensure communication between the UAVs and the relevant services. This reactive approach considers two essential aspects:

- Excluding UAVs with low energy levels to preserve their autonomy.
- Selecting routes based on link stability.

Packet Format

The RREQ (Route Request) packet contains several fields:

- Transmission ID: identifier of the discovery process.
- NS: number of segments traversed.
- DelayP: transmission delay to the target service (TS).
- Source / TS: identifiers of the communicating nodes.
- Movement information: used to estimate the connection duration between UAVs.
- CLP (connectivity lifetime path): minimum connection duration between the UAVs in the path.
- REP (residual energy path): minimum energy level of the UAVs in the path.
- Distance: total number of UAVs traversed.

The RREP (Route Reply) packet includes these fields to inform the source about the status of the selected path. Once the RREP is received, alert transmission can begin.

Routing Process

Consider the example of an accident detected on a road. The nearest UAV immediately sends an alert to a backbone UAV, u_1. This alert contains a unique identifier, location (AoI), and the nature of the incident. Initially, only the road segments detected by the source UAV are recorded.

The UAV u_1 then broadcasts an RREQ packet to find a path to TS (hospital). At each step, information about link stability and residual UAV energy is collected. To avoid redundancies, an RREQ that has already been received with the same Transmission ID is ignored.

As soon as the first RREQ reaches TS, a short delay allows the accumulation of all available responses before selecting the optimal route. The path is chosen based on a multi-criteria score considering available energy (REP), connection duration (CLP), and number of segments traversed (NS), according to the following equation:

$$Score = \frac{REP \times NS}{Distance} \times \frac{CLP}{DelayP}$$

A high score indicates a reliable and stable route. Path1 ($u_1 \rightarrow u_2 \rightarrow u_4 \rightarrow u_5 \rightarrow TS$) is selected as it offers the best performance.

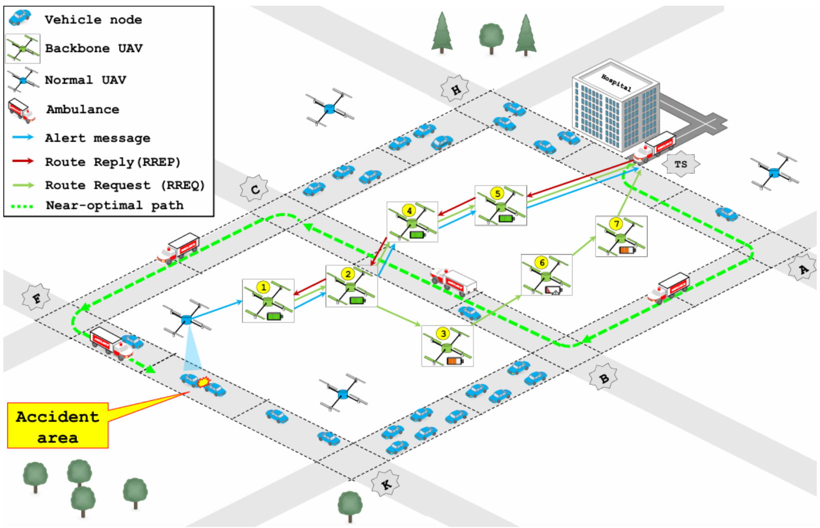

Figure 3.7: alert model functioning (Source: (Oubbati et al., 2019))

Optimal Path Calculation to the Incident

Once the alert is transmitted to TS, it has precise information about the incident and surrounding traffic density. Based on the weights assigned to road segments, TS calculates the best ground route to reach the AoI, ensuring a rapid emergency response.

3.5.9 Performance Evaluation

The performance of the proposed application is evaluated through a series of experiments using NS-2, SUMO, and MobiSim for mobility generation. A test urban area of $3 \times 3\,\mathrm{km}^2$ is imported from OpenStreetMap, with relevant road segments and intersections marked for simulation. Key simulation parameters are summarized in Table 3.5.

Table 3.5: Simulation Parameters

Parameter	Value
Frequency Band	5.9 GHz
Transmit Power	21.5 dBm
Sensitivity	-81.5 dBm
MAC Layer	IEEE 802.11p
Data Rate	1 Mbit/s
Area Size	$3 \times 3\,\mathrm{km}^2$
Simulation Time	300 s
Number of UAVs	[10, 100]
Number of Vehicles	100
UAV Altitude	300 m
Communication Range	300 m
Hello Interval	0.1 s
Initial Energy of UAVs	2000 J

Routing Performance

Three metrics are evaluated: Packet Delivery Ratio (PDR), End-to-End Delay (EED), and Overhead (OH). The proposed routing protocol is compared with LAROD and MPGR. Results show that:

- **PDR**: The proposed protocol outperforms others, increasing PDR by more than 20% due to efficient backbone utilization.
- **EED**: The average delay is minimized as UAV density increases, thanks to energy-rich and well-connected routing paths.
- **OH**: Control overhead decreases with higher UAV density, as fewer route discoveries are needed.

Energy Consumption Performance

The remaining energy levels of 50 UAVs are analyzed. The proposed protocol demonstrates well-regulated energy consumption, as it relies on backbone UAVs with high energy levels. In contrast, LAROD and MPGR show unbalanced energy consumption, with some UAVs consuming up to 60% more energy.

Application Performance

Experiments focus on road segment coverage, backbone UAVs, and ambulance travel time:

- **Coverage**: Full road segment coverage is achieved with approximately 70 UAVs.
- **Backbone UAVs**: The number of backbone UAVs increases uniformly with UAV density.
- **Travel Time**: The proposed application provides less crowded paths, significantly reducing ambulance travel time compared to the shortest path.

3.5.10 Limitations of the Method

Despite its innovative approach and promising results, the proposed method has several limitations that need to be addressed for practical deployment:

- **Energy Constraints**: UAVs have limited battery life, which restricts their operational duration. Frequent recharging or battery replacement is required, especially in large-scale deployments.
- **Communication Reliability**: The system relies on IEEE 802.11p for communication, which is susceptible to interference and signal degradation in urban environments with obstacles like buildings and trees.
- **Line-of-Sight Dependency**: UAVs require a clear line of sight for effective communication and monitoring. This limits their effectiveness in densely built urban areas or during adverse weather conditions.
- **Scalability Issues**: While the system performs well with up to 100 UAVs, scaling to larger areas or higher UAV densities may introduce challenges in network organization and backbone maintenance.
- **Real-Time Processing**: The system assumes real-time processing of traffic data and incident detection. However, delays in data transmission or processing could impact the timeliness of emergency responses.
- **Regulatory Restrictions**: UAV operations are subject to strict regulations, including altitude limits, no-fly zones, and licensing requirements. These constraints could hinder widespread adoption.
- **Environmental Sensitivity**: The system's performance may degrade in extreme weather conditions, such as heavy rain, fog, or strong winds, which can affect UAV stability and communication.

3.5.11 Conclusion

The proposed UAV-assisted emergency vehicle routing system demonstrates significant potential for improving emergency response times in urban environments. By leveraging UAVs for real-time traffic monitoring and dynamic route optimization, the system provides a robust solution for navigating congested road networks. However, addressing the limitations related to energy, communication, scalability, and regulatory compliance will be critical for its successful deployment and adoption.

3.6 Method 6: Collaborative Hotspot Selection (CHS) for UAV-Based Traffic Surveillance

In (Bashir et al., 2022), the authors proposed a Collaborative Hotspot Selection (CHS) framework, which leverages a closed-loop control system to dynamically adjust UAV operations based on feedback from a Wireless Sensor Network (WSN). Unlike traditional open-loop systems, where UAVs follow fixed paths or remain stationary, the CHS system adapts to real-time traffic conditions, optimizing the detection of overspeeding incidents. This section provides an overview of the CHS architecture, its probabilistic model for UAV trajectory control, and its performance evaluation through simulations.

3.6.1 System Overview

The CHS framework integrates UAVs and a WSN to monitor traffic violations, particularly overspeeding, in real-time. The system operates as follows:

- **Wireless Sensor Network (WSN):** The WSN consists of Reporting Nodes (RNs) equipped with speed sensors and Helping Nodes (HNs) that facilitate communication. RNs detect overspeeding vehicles by analyzing disturbances in the Earth's magnetic field, while HNs ensure seamless data transmission between RNs, UAVs, and the Mobile Base Station (MBS).
- **UAV Trajectory Control:** The UAV dynamically adjusts its position based on overspeeding data collected by RNs. A probabilistic model determines the optimal hotspot for the UAV to monitor, ensuring maximum detection efficiency.
- **Closed-Loop Feedback:** The system continuously compares actual overspeeding incidents detected by the UAV with expected incidents reported by the WSN, enabling real-time adjustments to UAV operations.

Figure 4.1 illustrates the overall architecture of the CHS system.

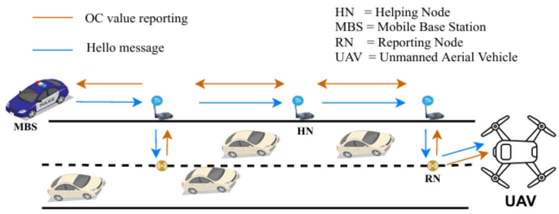

Figure 3: The architecture of CHS

Figure 3.8: CHS System Architecture (Source: (Bashir et al., 2022))

3.6.2 Probabilistic Model for UAV Trajectory Control

The CHS system employs a probabilistic approach to manage the UAV's flight trajectory. Overspeeding incidents are modeled as a Poisson process, where the Overspeeding Count (OC) represents the average rate of violations over a given time period. The Poisson distribution function for a random variable Y is given by:

$$P(Y = y) = \frac{\lambda^y e^{-\lambda}}{y!} \tag{3.4}$$

where:

- λ is the mean success rate (average OC value).
- e is Euler's number.
- y is the actual number of overspeeding incidents in a defined time frame.

The UAV calculates the probability of detecting overspeeding incidents at each RN using the following steps:

0. **Probability of Fewer Incidents:** The probability of an RN detecting fewer than OC_{max} overspeeding vehicles is calculated as:

$$Pr(Y < OC_{max}) = \sum_{y=0}^{OC_{max}-1} \frac{(OC_{rtn-1})^y e^{-OC_{rtn-1}}}{y!} \tag{3.5}$$

0. **Probability of More Incidents:** The probability of an RN detecting at least OC_{max} overspeeding vehicles is:

$$Pr(Y \geq OC_{max}) = 1 - Pr(Y < OC_{max}) \tag{3.6}$$

0. **Travel Time Adjustment:** The UAV adjusts its trajectory based on the travel time between RNs, calculated as:

$$t_{r,x} = \frac{d_{r,x}}{v} \tag{3.7}$$

where $d_{r,x}$ is the distance between RNs r and x, and v is the UAV's speed.

The UAV uses these probabilities to determine its next position, prioritizing RNs with the highest likelihood of overspeeding incidents. Figure 3.9 illustrates the UAV's movement based on probabilistic calculations.

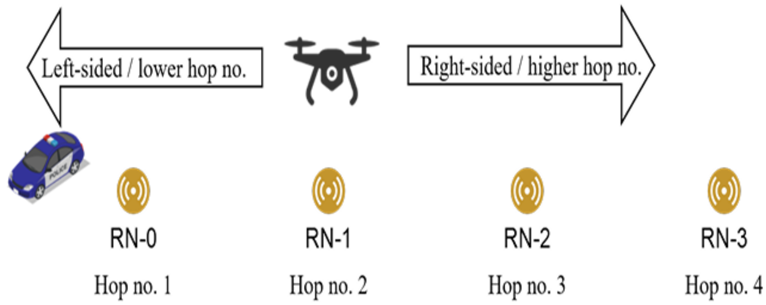

Figure 3.9: Movement Control Algorithm and Hop Count Assignment (Source: (Bashir et al., 2022))

3.6.3 Hop Number Allocation and Instant Reporting

The Mobile Base Station (MBS) broadcasts hello messages to assign hop numbers to UAVs and wireless nodes. This process ensures efficient data routing and communication within the network. Key features include:

- **Hop Number Assignment:** Each node updates its hop number based on the received hello message and rebroadcasts it with an incremented hop count.
- **Instant Reporting:** Severe speed violations are reported immediately to the MBS, while less critical violations are transmitted when the UAV is near the MBS.

Figure 3.9 illustrates the hop number assignment procedure.

3.6.4 Performance Evaluation

The performance of the CHS system was evaluated through simulations using Network Simulator-2 (NS-2). Four traffic scenarios were tested to assess the system's ability to minimize UAV movements while maximizing overspeeding detection. The results were compared with two existing methods:

- **Static:** The UAV remains stationary at a fixed hotspot.
- **Stepwise:** The UAV follows a predefined trajectory without adapting to real-time data.

Key Metrics

The evaluation focused on three metrics:

0. **Detection Rate:** The number of overspeeding incidents detected by the UAV.
0. **Response Time:** The delay in reporting critical violations to the MBS.
0. **Energy Efficiency:** The UAV's energy consumption during surveillance.

Simulation Results

- **Simulation-I:** When RN-2.0 was the dominant hotspot, the Static-2.0 scheme detected the most violations. However, the CHS system performed similarly by dynamically adjusting to the hotspot.
- **Simulation-II:** When RN-3.9 became the dominant hotspot, Static-3.9 outperformed other static schemes, while CHS adapted effectively by relocating the UAV to RN-3.9.
- **Simulation-III:** With RN-5.3 as the dominant hotspot, Static-5.3 detected the most violations, while CHS maintained high detection rates by balancing movement and monitoring.
- **Simulation-IV:** In a dynamic scenario with shifting hotspots, CHS outperformed all static and stepwise schemes by continuously adapting to real-time data.

Table 3.6: Simulation Parameters

Parameter	**Value**
Network size	10 m x 10000 m
UAV speed	15 m/s
Transmission range	100 m
Number of wireless nodes	78
Number of vehicles	200–300
Vehicle speed range	13–27 m/s
OC reporting interval	100 s
Simulation time	0–2500 s

3.6.5 Limitations and Challenges

While the CHS system demonstrates significant potential, it faces several limitations:

- **Energy Constraints:** UAVs have limited battery life, which restricts their operational duration. Frequent recharging or battery replacement is required, especially in large-scale deployments.

- **Communication Reliability:** The system relies on IEEE 802.11p for communication, which is susceptible to interference and signal degradation in urban environments.
- **Environmental Sensitivity:** Adverse weather conditions, such as heavy rain or strong winds, can affect UAV stability and communication.
- **Real-Time Processing:** The system assumes real-time processing of traffic data, but delays in data transmission or processing could impact its responsiveness.
- **Regulatory Restrictions:** UAV operations are subject to strict regulations, including altitude limits and no-fly zones, which could hinder widespread adoption.

3.7 Conclusion

The six methods discussed in this chapter illustrate the diverse and innovative approaches to UAV-based traffic monitoring, each addressing specific challenges in traffic surveillance and management. From early systems like the Airborne Traffic Surveillance System (ATSS) to advanced frameworks such as Collaborative Hotspot Selection (CHS), these methods demonstrate the potential of UAVs to revolutionize traffic monitoring by providing real-time, adaptive, and scalable solutions. Key advancements include the integration of 5G technology for high-speed communication, probabilistic models for dynamic UAV trajectory control, and cooperative systems that leverage multiple UAVs for comprehensive coverage.

Despite their promise, these methods face several challenges that must be addressed for practical deployment. Energy constraints, communication reliability, and regulatory restrictions remain significant barriers to the widespread adoption of UAV-based traffic monitoring systems. Additionally, environmental factors such as adverse weather conditions and line-of-sight limitations can impact system performance. However, ongoing advancements in UAV technology, artificial intelligence, and wireless communication networks offer promising avenues for overcoming these challenges.

In conclusion, UAV-based traffic monitoring systems represent a significant leap forward in traffic management, offering unparalleled flexibility, efficiency, and adaptability. By addressing the limitations of traditional systems and leveraging the unique capabilities of UAVs, these methods pave the way for smarter, safer, and more efficient urban transportation networks. As research and development in this field continue, the integration of UAVs into traffic monitoring systems is expected to play a pivotal role in shaping the future of intelligent transportation systems.

Syntheses

The rapid evolution of UAV technology presents unprecedented opportunities for transforming traffic surveillance and management systems. Across the three chapters, we observe how foundational advancements in UAV architectures and communication protocols enable increasingly sophisticated applications. The development of specialized communication standards and decentralized network architectures has addressed critical challenges in reliability and scalability for UAV operations. These technical foundations support the integration of AI-driven optimization techniques that enhance autonomous decision-making while maintaining robust security against emerging cyber threats.

Practical implementations demonstrate the versatility of UAV systems in traffic monitoring applications, from basic surveillance to complex cooperative frameworks. The successful deployment of 5G-enabled systems and probabilistic control models shows particular promise for real-time traffic management. However, these technological achievements must be balanced against persistent limitations in operational endurance, communication stability, and regulatory frameworks. Addressing these constraints through continued innovation in energy systems, network protocols, and policy development will determine the pace of UAV adoption in transportation infrastructure.

Looking ahead, the convergence of these technical domains - communication systems, artificial intelligence, and practical applications - points toward a future where UAV networks become integral components of smart city ecosystems. The research presented in these chapters establishes both the current state of the art and critical pathways for future development in this dynamic field. As these technologies mature, they will enable more responsive, efficient, and intelligent transportation networks capable of meeting the growing demands of urban mobility.

Part II

Contribution

Chapter 4

Conception

Introduction

This chapter presents the design choices and reasoning behind the development of our Collaborative Highway Surveillance (CHS) system for detecting and responding to speeding violations in real time. It introduces the hybrid architecture combining UAVs and ground speed sensors, outlines the challenges related to communication latency, energy constraints, and coverage optimization, and explains the strategies applied to ensure reliable data exchange between all components.

We then describe the control logic of the system, which integrates a distributed drone selection algorithm based on residual energy and proximity, as well as a routing mechanism leveraging a hierarchical network of ground nodes to guide UAVs towards high-infraction zones. While this architecture ensures adaptability and responsiveness, the integration of prediction capabilities using machine learning introduces additional computational requirements that may challenge onboard resources.

To address this, we design a lightweight communication and decision-making protocol using MAVLink and UDP, enabling drones to exchange essential operational data efficiently while offloading heavy processing to ground stations when possible. Various simplification techniques and modular implementations are applied to balance decision accuracy with real-time performance and system scalability.

By combining robust communication, an adaptive control algorithm, and predictive analytics, the goal is to build a surveillance system that is both effective and deployable in real-world highway monitoring scenarios.

4.1 Problematic and Objectives

Problematic

Road safety remains a major public concern worldwide, with excessive speed being one of the leading causes of serious and fatal accidents. Conventional speed enforcement methods, such as fixed roadside radars, have shown limited effectiveness over time. Their locations are often publicly known and reported in real-time via mobile applications, allowing some drivers to slow down momentarily before the control point and accelerate again immediately afterwards.

To address this limitation, certain high-risk road segments are occasionally monitored using helicopters. While effective in terms of detection, this method is costly in terms of human resources, fuel, and operational logistics, and it cannot ensure continuous large-scale coverage. As a result, many high-speed violation hotspots remain unmonitored, leaving a significant gap in traffic law enforcement.

Recent advances in Unmanned Aerial Vehicles (UAVs) have opened new perspectives for intelligent, mobile, and cost-effective traffic surveillance. UAVs can be rapidly deployed, repositioned in real time, and equipped with various sensors to monitor vehicle behavior. However, existing UAV-based solutions often rely on probabilistic flight plans without precise knowledge of the real-time distribution of traffic violations. Additionally, many approaches use UAVs in isolation, without integration into a larger, coordinated sensor network. This leads to inefficient coverage, redundant deployments, and higher energy consumption, ultimately reducing the operational lifespan of the system.

The core challenge, therefore, lies in designing a surveillance architecture that combines the mobility and flexibility of UAVs with the persistent monitoring capability of ground-based sensors. Such a system must intelligently detect high-risk zones, allocate UAV resources efficiently, and adapt dynamically to traffic conditions, all while operating within constraints of energy, communication range, and cost.

Objectives

The main objective of this work is to design and validate a collaborative hybrid architecture for highway speed surveillance that significantly improves detection efficiency compared to existing fixed or isolated UAV systems.

The specific objectives are as follows:

- **Develop a closed-loop collaborative surveillance system** (Collaborative Highway Surveillance – CHS) combining UAVs and wireless ground speed sensors for real-time detection and tracking of speeding vehicles.
- **Implement an efficient communication protocol** enabling UAV-to-UAV and UAV-to-ground data exchange, allowing the sharing of key information such as vehicle speed, UAV position, and residual energy levels.

- **Design a distributed decision-making algorithm** to select the most suitable UAV for deployment to detected infraction hotspots, based on criteria such as energy availability and distance.
- **Integrate an onboard computer vision module** to enable UAVs to autonomously identify and classify vehicles, providing visual confirmation of detected violations.
- **Introduce predictive surveillance capabilities** through Machine Learning algorithms trained on historical and real-time speed data, enabling early UAV deployment to anticipated violation zones.
- **Maximize coverage and operational lifespan** of the surveillance network through optimal task allocation, hierarchical sensor deployment, and adaptive routing strategies.

4.2 Overview of the Proposed Solution

The proposed **Collaborative Highway Surveillance (CHS)** system aims to overcome the limitations of traditional speed enforcement methods by combining the adaptability of Unmanned Aerial Vehicles (UAVs) with the persistent monitoring capabilities of a ground-based sensor network. The system operates in a closed-loop fashion: speeding events are detected by ground sensors, which trigger the deployment of UAVs to the corresponding high-risk areas.

Once on site, UAVs equipped with onboard cameras and computer vision modules can confirm violations in real time and transmit evidence to Mobile Base Stations (MBS) for enforcement. This hybrid approach ensures optimal coverage of the monitored road network, reduces redundant drone deployments, and improves energy efficiency. Furthermore, predictive analytics are incorporated to anticipate high-risk zones, enabling proactive rather than reactive surveillance.

This section presents the conceptual operation of CHS, while the following *System Architecture* subsection details the physical and logical organization of its components and their interactions.

4.2.1 System Architecture

The **CHS architecture** is designed as a multi-layered, hybrid network integrating aerial and ground-based elements to ensure continuous, adaptive, and efficient traffic surveillance. It is composed of the following main components:

- **UAVs (Unmanned Aerial Vehicles)**: serve as the mobile aerial units of the system, capable of being dynamically deployed to specific locations as soon as a speeding event is detected. They are equipped with high-resolution cameras for capturing real-time video footage of vehicles, and onboard computing platforms such as Raspberry Pi or NVIDIA Jetson for running computer vision algorithms. These algorithms enable vehicle detection, tracking, and speed estimation directly on the UAV, reducing the need for constant ground-based processing. UAVs are also fitted with wireless communication modules to exchange data with ground nodes and Mobile Base Stations (MBS), and they can operate autonomously or semi-autonomously with automated path planning and obstacle avoidance.

- **RN (Reporting Nodes)**: are fixed ground-based units positioned along monitored highways at regular intervals. Each RN is equipped with speed detection sensors such as radar, LIDAR, or magnetic sensors to monitor passing vehicles. When a vehicle exceeds the legal speed limit, the RN generates a violation alert that includes contextual data such as the timestamp, GPS position, and detected speed. This information is then transmitted to the nearest UAV or Helping Node (NH). Designed for continuous operation, RNs consume minimal energy to support long-term deployment in remote or infrastructure-limited locations.

- **NH (Helping Nodes)**: function as intermediate communication relays between RNs, UAVs, and MBS. Their primary role is to enable multi-hop wireless connectivity, extending the operational coverage area and maintaining communication in environments where direct line-of-sight is not possible. NH nodes also contribute to redundancy and fault tolerance by providing alternative data transmission paths in case of node failure or poor connectivity. These nodes can be mounted on existing roadside infrastructure such as lamp posts or integrated into mobile platforms for flexible placement.

- **MBS (Mobile Base Stations)**: are ground-based enforcement units, typically operated by traffic police or highway patrol officers. They receive validated infraction reports from UAVs, which include photographic evidence, GPS coordinates, and measured vehicle speed. Based on this information, MBS operators can initiate immediate enforcement actions such as dispatching officers, issuing electronic tickets, or recording violations in a centralized database. In addition to their enforcement role, MBS act as control hubs for UAV operations, managing mission assignments, receiving live video feeds, and storing collected evidence for later review.

The CHS system follows a closed-loop control process:

1. **Detection Layer:** RN sensors monitor vehicle speeds and detect violations in real time.

2. **Communication Layer:** NH nodes relay detection data to UAVs using a multi-hop wireless protocol.

3. **Decision Layer:** UAVs exchange data and execute a distributed selection algorithm to assign the most suitable drone to each hotspot.

4. **Action Layer:** The selected UAV navigates to the target area, visually confirms violations using onboard computer vision, and transmits evidence to the nearest MBS.

Figure 4.1 illustrates the overall architecture of the CHS system, showing the main components, data flows, and interactions between layers.

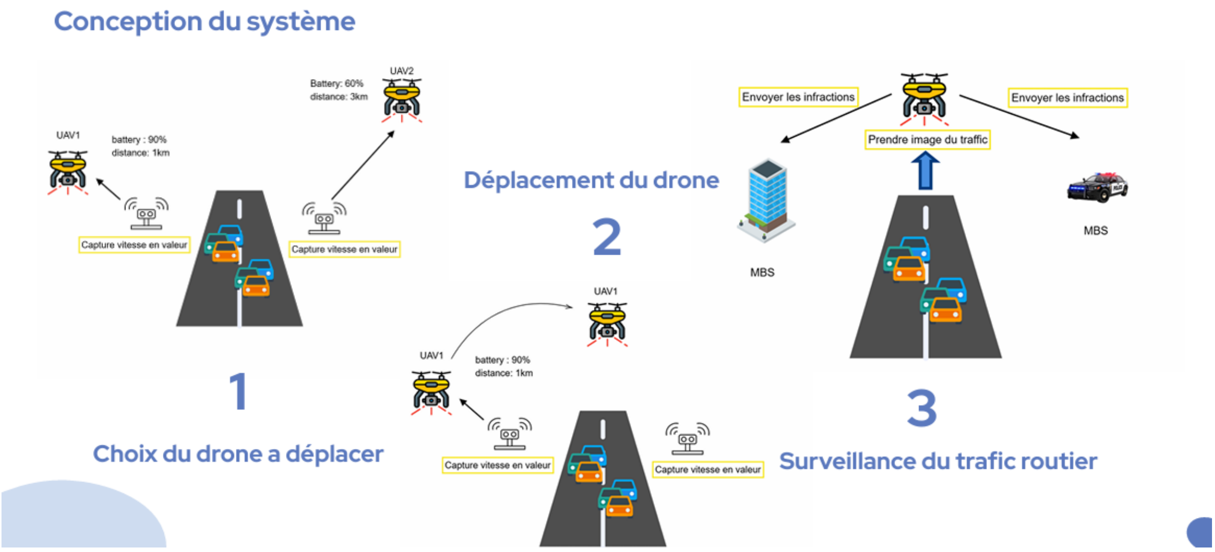

Figure 4.1: Proposed CHS system architecture.

4.2.2 Communication Framework

The efficiency of the CHS system relies heavily on a robust communication framework that ensures seamless data exchange between UAVs, ground sensors, and Mobile Base Stations (MBS). The framework is designed to be both real-time and resilient, adapting to dynamic traffic conditions and UAV movements.

- **UAV-to-UAV Communication:** UAVs exchange information about their current positions, battery levels, assigned patrol zones, and ongoing tasks to maintain a shared operational picture of the monitored highway network. This exchange supports the distributed decision-making algorithm, which selects the most suitable UAV to address new incidents or respond to emerging high-risk areas. To ensure interoperability and reliability, the MAVLink protocol is adopted, enabling standardized message formats and robust data delivery even under variable signal conditions. This communication channel is particularly important in multi-drone deployments, where coordination prevents redundant coverage and optimizes flight paths for energy efficiency.
- **UAV-to-Ground Sensors (RNs and NHs):** Ground-based Reporting Nodes (RNs) act as the initial source of infraction data, detecting speeding vehicles and transmitting alerts that include speed measurements, timestamps, and GPS coordinates. These alerts are relayed to UAVs either directly or via intermediate Helping Nodes (NHs), which extend communication range through multi-hop routing. This mechanism ensures that UAVs maintain situational awareness even in areas with limited direct sensor coverage, allowing them to dynamically adjust their trajectories to intercept and verify violations in real time. By integrating both fixed and

mobile communication elements, the system guarantees that UAVs receive timely and reliable updates regardless of terrain or infrastructure limitations.

- **UAV-to-Mobile Base Stations (MBS):** Once a UAV has visually confirmed a traffic violation using its onboard computer vision system, it compiles a comprehensive evidence package that includes vehicle imagery or video, positional data, measured speed, and time of detection. This evidence is transmitted to the nearest MBS, where ground officers can initiate enforcement procedures such as issuing fines or intercepting the offending vehicle. Beyond enforcement, MBS units also serve as operational control points, providing UAVs with updated mission priorities, relaying new hotspot predictions, and adjusting patrol schedules based on the evolving traffic situation.

- **Data Management:** To maintain operational integrity, all transmitted data is timestamped and geotagged, ensuring that every detected violation can be precisely traced to its origin. The framework prioritizes low-latency communication through the use of the UDP protocol, while incorporating error-checking mechanisms to mitigate packet loss or corruption. Collected datasets are stored in a structured format compatible with downstream processing by machine learning modules, enabling predictive analytics that identify recurring patterns, optimize UAV patrol strategies, and anticipate future violations. This approach ensures that communication not only supports immediate operational needs but also contributes to long-term system intelligence.

This communication framework enables collaborative, adaptive, and efficient surveillance, ensuring that each component of the CHS system can contribute effectively to reducing speeding violations across the monitored highway network.

4.2.3 Decision-Making and Control Logic

The decision-making and control logic of the CHS system governs how UAVs respond to real-time traffic conditions and coordinate among themselves for optimal surveillance. This logic ensures that resources are efficiently allocated to high-risk zones while avoiding redundant coverage.

- **Initial Patrol Planning:** Before any mission is declared, each UAV follows a predefined initial patrol route designed to provide baseline coverage of the monitored highway network. These patrol paths are assigned to maximize spatial distribution and reduce the likelihood of coverage gaps. During this phase, UAVs operate autonomously, collecting environmental and traffic data while conserving energy through efficient path planning. This proactive patrolling ensures that the system maintains situational awareness even in the absence of active violations, and it positions UAVs strategically so that they can respond more rapidly when an infraction is detected.

- **Dynamic Zone Assignment:** When a Reporting Node (RN) detects a speeding event, it sends a mission declaration to the network, specifying the location of the violation — which directly corresponds to the sensor's geographic position. At this moment, UAVs begin exchanging state information, including their current position, remaining battery level, and ongoing assignments. The distributed decision-making algorithm then evaluates which UAV is best suited to address the new mission based on proximity to the hotspot, energy reserves, and current workload. This ensures a quick and efficient allocation of resources, minimizing response time to high-risk areas.

- **Energy-Aware Routing:** To maintain operational longevity, UAVs continually share battery status updates with nearby drones. The selection algorithm incorporates this information to ensure that only UAVs with sufficient energy are assigned to missions, avoiding situations where a drone might fail to complete its task due to battery depletion. This approach balances workload across the fleet, preventing overuse of individual UAVs and extending the system's sustained surveillance capabilities.
- **Conflict Resolution:** In scenarios where multiple UAVs are equally capable of responding to a mission, the system employs a conflict resolution strategy that prioritizes the UAV closest to the target zone while factoring in available energy. This prevents multiple UAVs from converging on the same hotspot unnecessarily, which reduces overlapping coverage and frees up other drones to remain on standby for future missions.
- **Adaptive Control Loops:** The CHS operates in a continuous feedback loop, with UAVs, ground sensors, and Mobile Base Stations (MBS) exchanging operational data in real time. Insights from confirmed infractions, evolving traffic conditions, and predictive analytics allow the system to dynamically reassign UAVs, adjust flight paths, and update surveillance priorities. This adaptability ensures that UAV deployment is not only reactive to detected violations but also anticipates and prevents future incidents by focusing on areas with a high predicted risk.

This decision-making framework enables the CHS system to operate collaboratively, beginning with independent patrol patterns and transitioning into coordinated, data-driven missions when violations occur. As a result, the system maintains both proactive coverage and rapid, targeted responses to emerging threats.

4.2.4 Onboard Computer Vision Module for Vehicle Detection

The CHS system integrates a computer vision module on each UAV to detect and track vehicles in real-time. This module enhances the surveillance capabilities by providing automated identification of speeding vehicles and supporting dynamic hotspot monitoring.

- **Camera Integration:**
  - Each UAV is equipped with a high-resolution camera capable of capturing video streams in real-time.

  - The camera is stabilized and gimbal-mounted to maintain clear visuals even during UAV movement.

- **Vehicle Detection Algorithm:**
  - The module employs machine learning-based object detection models (e.g., YOLO or SSD) to identify vehicles in the captured frames.
  - Detection includes localization (bounding boxes) and classification of vehicles (cars, trucks, motorcycles) to assist in traffic analysis.

- **Speed Estimation:**
  - By tracking the position of vehicles across consecutive frames and combining it with UAV telemetry (altitude and camera angle), the module estimates the speed of each detected vehicle.
  - Vehicles exceeding predefined speed thresholds are flagged as violations.

- **Data Transmission:**
  - Detected violations, including vehicle type, position, speed, and associated images, are transmitted to the Mobile Base Stations (MBS) through the communication framework.
  - This ensures immediate reporting and enables timely enforcement actions.

- **Integration with Decision-Making:**
  - Detection results feed into the UAV's decision-making module, influencing real-time adjustments in flight paths and targeting of new hotspots.
  - The system can prioritize zones with the highest number of violations detected by the vision module, improving the overall effectiveness of highway surveillance.

The onboard computer vision module provides autonomous, real-time monitoring capabilities, significantly enhancing the CHS system's efficiency in detecting speeding vehicles and dynamically allocating UAV resources.

4.2.5 Predictive Surveillance Module

The Predictive Surveillance Module enhances the CHS system by forecasting potential traffic infractions and enabling proactive UAV deployment. This module uses historical and real-time data to predict hotspots, improving coverage and reducing response time.

- **Data Sources:**

    - Historical traffic data from ground sensors (Reporting Nodes) and past UAV missions.
    - Real-time speed measurements and incident reports transmitted by UAVs and Mobile Base Stations (MBS).

- **Machine Learning Algorithms:**
    - Supervised learning models (e.g., Random Forest, Gradient Boosting, or Neural Networks) are trained to identify patterns leading to speeding or risky driving behavior.
    - The models output probabilities for potential infractions across different road segments.

- **Hotspot Prediction:**
    - Predicted high-risk zones are continuously updated as new data arrives.
    - UAVs receive prioritized task assignments based on these predictions, allowing for early monitoring of likely violation points.

- **Integration with UAV Decision-Making:**
    - Predicted hotspots feed directly into the decision-making and control logic, guiding UAV routing and scheduling.
    - This proactive approach complements reactive monitoring from the onboard vision module, ensuring comprehensive surveillance.

- **Performance Feedback:**
    - The system compares predicted infractions with actual detections, refining the prediction models over time.
    - Continuous learning ensures improved accuracy and efficiency in UAV deployment.

By predicting potential infractions, the Predictive Surveillance Module enables the CHS system to anticipate traffic violations, optimize UAV deployment, and maximize overall surveillance effectiveness.

4.3 Conclusion

In this chapter, we have presented the design of the Collaborative Highway Surveillance (CHS) system, detailing its architecture, components, and functional modules. The system combines UAVs, ground sensors, and mobile base stations to achieve real-time, adaptive monitoring of highway traffic. Key aspects include:

- A **modular architecture** that ensures scalability, fault tolerance, and efficient integration of UAVs and ground sensors.
- A **communication framework** enabling reliable data exchange between UAVs, ground nodes, and mobile base stations.
- A **decision-making and control logic** that dynamically allocates UAVs to high-risk zones based on energy levels, distance, and real-time traffic conditions.
- An **onboard computer vision module** that detects and tracks vehicles in real-time, supporting automatic identification of traffic violations.
- A **predictive surveillance module** that leverages machine learning to anticipate infractions, guiding UAVs proactively to potential hotspots.

Overall, the proposed solution provides a comprehensive and intelligent approach to highway surveillance, enhancing the efficiency of traffic monitoring while reducing the reliance on costly human-operated interventions. This chapter lays the foundation for the next chapter, which focuses on the implementation and experimental evaluation of the CHS system.

Chapter 5

Implementation

Introduction

This chapter describes the implementation details of the Collaborative Highway Surveillance (CHS) system developed for real-time detection of speeding violations. It presents the tools, libraries, and development environments used to build, integrate, and test the communication modules, routing logic, and prediction components. Special attention is given to the configuration and synchronization of UAVs and ground nodes, ensuring stable data exchange and minimal latency across the network.

Next, we detail the development of the communication protocol, combining MAVLink for drone-to-drone and drone-to-ground communication with UDP for lightweight sensor data transmission. The distributed drone selection algorithm is implemented to account for residual energy, proximity to target zones, and avoidance of redundant coverage.

We then describe the integration of the machine learning prediction module, trained on historical and simulated speeding data to anticipate infraction hotspots. The implementation ensures that computationally heavy operations are executed on ground stations when possible, preserving UAV autonomy.

The final section focuses on system optimization, including strategies for reducing energy consumption, improving communication reliability, and achieving a balance between real-time responsiveness, processing requirements, and operational scalability.

Chapter 6

Tests and Evaluation

Introduction

This chapter is dedicated to evaluating the performance of our proposed Collaborative Highway Surveillance (CHS) system for real-time detection of speeding violations. It begins with a presentation of the evaluation metrics used to assess detection accuracy, communication reliability, coverage rate, and energy efficiency—factors that are crucial for real-world deployment on UAV-based platforms.

We then detail the experiments conducted to compare the effectiveness of the distributed drone selection algorithm, the communication protocol, and the machine learning prediction module. Multiple system configurations were tested under different operational scenarios, including real-time hotspot detection, predictive deployment, and mixed reactive–predictive strategies. Their performance was analyzed using metrics such as average detection latency, prediction accuracy, coverage ratio, and network lifetime.

The results presented in this chapter provide insight into the trade-offs between system complexity, operational performance, and deployment feasibility, validating the benefits of combining real-time sensor data with predictive analytics in creating an adaptive and efficient highway monitoring solution.

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