Hybrid Autonomous Unmanned Aerial Vehicle with Adaptive Task Allocation and Peer-to-Peer Communication for Surveillance Monitoring System

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Abstract - *In the context of rapidly advancing smart city infrastructure and disaster management systems, autonomous aerial platforms have emerged as pivotal tools for real-time monitoring, anomaly detection, and adaptive decision-making. This study presents a Hybrid Autonomous Unmanned Aerial Vehicle (UAV) Framework that incorporates decentralized multi-UAV coordination, dynamic task allocation, and peer-to-peer communication to achieve resilient and intelligent surveillance operations. Unlike conventional centralized control mechanisms, the proposed system adopts a distributed intelligence model, enhancing fault tolerance, scalability, and energy efficiency under varying environmental conditions. Each UAV in the network is equipped with multimodal sensing units, integrating YOLO-based visual object detection for identifying vehicles, humans, animals, and abnormal events, along with acoustic anomaly recognition to improve environmental perception. The drones collaboratively perform surveillance tasks through an adaptive task allocation mechanism, redistributing workloads according to energy constraints, detection relevance, and spatial coverage requirements. Peer-to-peer communication facilitates real-time information sharing and cooperative path optimization without the need for a central processing node. For navigation and swarm control, the framework combines an Improved Artificial Potential Field (APF) for obstacle avoidance, Bidirectional RRT* for path optimization, and reinforcement learning algorithms to refine coordination strategies through experience-based adaptation. The proposed design would be implemented and validated in simulation environments thereby, it addresses the key challenges in urban surveillance, including coverage gaps, energy-aware coordination, and distributed decision-making. It offers a scalable and modular foundation for traffic monitoring, crowd analysis, and emergency management, contributing to the advancement of intelligent UAV-based surveillance architectures.*

Keywords - anomaly detection, federated learning, path planning, surveillance, task allocation, transformer, uav swarm, yolo

1. Introduction

Unmanned Aerial Vehicles (UAVs) have emerged as a cornerstone technology in contemporary surveillance and monitoring systems, owing to their adaptability, autonomy, and capacity to execute complex tasks in dynamic and hazardous environments. The integration of Artificial Intelligence (AI) and Machine Learning (ML) has significantly enhanced UAV capabilities in real-time anomaly detection, path planning, and adaptive task allocation, rendering them highly effective for both civilian and defence applications. Early research primarily concentrated on establishing secure communication frameworks essential for reliable UAV swarm operations. [19] introduced an enhanced real-time crowd anomaly detection model utilizing YOLOv8, which demonstrated superior accuracy in identifying abnormal behaviours in densely populated environments. Concurrently, [10] addressed the security and privacy challenges inherent in Internet of Drones (IoD) systems, emphasizing the necessity for encrypted communication and secure coordination among drone networks. Subsequent investigations expanded into distributed task allocation and swarm coordination. [18] proposed a networked evolutionary game-theoretic model for dynamic task allocation within UAV swarms, highlighting adaptive behaviour and cooperative decision-making. Similarly, [9] explored the synergy between federated learning and digital twins to enhance energy-efficient task allocation and facilitate seamless service migration, introducing the concept of self-adaptive mission management.

Advancements in path planning have also been significant. [13] developed an improved Continuous Ant Colony Optimization (IACO) algorithm for UAV path planning in complex environments, achieving efficient obstacle avoidance and reduced computational overhead. [15] introduced a 3D path planning methodology that integrates an improved Artificial Potential Field with bidirectional Rapidly-exploring Random Tree Star (RRT*), enhancing real-time obstacle avoidance. [17] proposed the Artificial Fish Swarm Algorithm (AFSA) for 3D path optimization, yielding faster convergence and smoother trajectories.

In the realm of mission coordination and communication, [7] addressed distributed task allocation under limited communication constraints, proposing algorithms that optimize energy and time efficiency. [4] furthered this by implementing ML-based communication models for UAV swarms in search-and-rescue missions, enhancing cooperative behaviour in challenging terrains. [5] contributed a secure communication framework tailored for autonomous drone swarms in surveillance operations, ensuring robust and private inter-UAV data exchange.

Recent developments in real-time visual surveillance have leveraged deep learning architectures. [2] employed Video Swin Transformer models to detect violent behaviours and analyse crowd density with high efficiency. [3] proposed a Transformer-based spatiotemporal attention framework for unsupervised video anomaly detection on large-scale datasets. [21] demonstrated the effectiveness of YOLO-based panoramic surveillance systems in burglary detection, significantly improving situational awareness and visual coverage in expansive areas.

Contemporary research emphasizes Runtime Anomaly Detection (RADD) and Adaptive Swarm Intelligence (ASI). [22] introduced an integrated rule-mining and unsupervised learning approach for real-time drone anomaly detection, enabling self-corrective responses to abnormal flight behaviours. [23] extended this work by implementing adaptive Particle Swarm Optimization (PSO) for autonomous swarm anomaly tracking in dense vegetation, achieving robust detection under occluded conditions. Collectively, these studies underscore the progressive evolution of UAV technologies from foundational communication and path optimization to advanced intelligent perception and cooperative autonomy. The convergence of deep learning-based perception (e.g., YOLO, Transformers), optimization algorithms (e.g., ACO, AFSA), and distributed learning paradigms (e.g., Federated Learning, Game-Theoretic Models) lays the groundwork for the development of Adaptive UAV Surveillance Monitoring Systems with Task Allocation. These systems are poised to deliver autonomous decision-making, efficient communication, and intelligent anomaly response capabilities in real-world surveillance scenarios.

2. Related Works

2.1. Real-Time Visual Surveillance and Anomaly Detection

Recent advancements in deep learning have significantly enhanced UAV-based visual surveillance. [1] proposed Anomaly Detection Network using Transformers (ANDT), a Transformer-based model for detecting anomalies in aerial videos, leveraging long-term temporal dependencies and prediction error analysis. [2] utilized Video Swin Transformers to analyse crowd size and violence levels, integrating optical flow and crowd counting maps for spatial-temporal modelling. [3] introduced a spatiotemporal attention framework using Vision Transformers (ViT) for unsupervised anomaly detection, achieving superior generalization on large-scale datasets. [21] developed a YOLO-based panoramic surveillance system for burglary detection, improving situational awareness in residential environments. [19] enhanced YOLOv8 with Soft-Non-Maximum Suppression (NMS) and multi-scale feature fusion for real-time crowd anomaly detection in dense scenarios. [20] presented a YOLOv11-based framework for airborne vehicle detection under occlusion and altitude variation, demonstrating high precision in complex environments.

2.2. Runtime Anomaly Detection and Adaptive Swarm Intelligence

[22] introduced RADD, a runtime anomaly detection framework integrating rule mining and unsupervised learning, enabling UAVs to self-correct abnormal flight behaviours. [23] developed an autonomous drone swarm system using adaptive particle swarm optimization for anomaly tracking in dense vegetation, achieving robust detection under occluded conditions. [8] addressed chaotic behaviour in drone swarms using CNNs and chaotic attractor models, enabling corrective trajectory generation and maintaining coordinated flight under unstable conditions.

2.3. Distributed Task Allocation and Swarm Coordination

Efficient task allocation is essential for scalable UAV swarm operations. [7] proposed a two-stage distributed auction-based algorithm using Bernoulli communication models to simulate message loss and optimize task assignment. [18] introduced a networked evolutionary game-theoretic framework with time-variant log-linear learning for adaptive decision-making in dynamic environments. [9] combined Federated Learning and Digital Twin technologies to enable energy-aware task allocation and seamless service migration, improving operational efficiency and reliability. [11] applied multi-agent deep deterministic policy gradients (MADDPG) for decentralized UAV swarm coordination, optimizing coverage and obstacle avoidance.

2.4. Path Planning and Environmental Navigation

Path optimization remains a core challenge in UAV autonomy. [13] enhanced continuous Ant Colony Optimization (ACO) with Q-learning for dynamic strategy selection in complex 3D environments. [15] proposed Bi-APF-RRT, a hybrid algorithm combining artificial potential fields with bidirectional RRT for efficient and safe navigation. [17] introduced an Improved Artificial Fish Swarm Algorithm (IAFSA) to overcome local optima and improve convergence speed. Modelled uncertainties in obstacle positions and UAV states, comparing A* and RRT algorithms under dynamic conditions. [14] integrated path planning and task scheduling using hybrid planners and Shortest Processing First (SPF) scheduling, demonstrating improved mission time and energy efficiency.

2.5. Mission Coordination and Communication Efficiency

Robust communication frameworks are vital for coordinated UAV missions. [4] developed a machine learning–based model combining Random Forest regression and clustering for swarm formation prediction in Search and Rescue (SAR) operations. [5] proposed a mesh-based secure communication framework using Delaunay triangulation and encryption to resist cyber threats. A multi-functional Internet of Things (IoT)-enabled UAV system [6] integrated human detection, fire extinguishing, obstacle avoidance, and air-quality monitoring for autonomous disaster response. [12] enhanced drone detection via acoustic signatures and ML-based audio augmentation, improving classification under noisy conditions. [10] provided a comprehensive taxonomy of IoD security challenges, proposing layered defences including cryptography, intrusion detection, and blockchain.

2.6. Swarm Coordination and Multimodal Surveillance

[24] provide a comprehensive review of UAV swarm architectures, emphasizing decentralized coordination, adaptive task allocation, and secure mesh-based communication. [25] present a systematic review of smart surveillance technologies, highlighting the integration of multimodal sensing, real-time anomaly detection, and Docker-based simulation environments. These insights directly support the proposed system's use of YOLOv8 for object detection, acoustic anomaly recognition, and Gazebo-PX4 simulation workflows.

2.7. Existing Challenges

2.7.1 Limitations in Scalable Scene Understanding

Transformer-based models such as ANDT [1], Swin Transformer [2], and ViT-STR [3] have improved anomaly detection in aerial and crowd surveillance. However, they often require high computational resources and struggle with real-time deployment in dynamic environments. YOLO-based systems [4][5] offer faster detection but face limitations in panoramic coverage, occlusion handling, and precision under variable lighting conditions.

2.7.2 Gaps in Autonomous Behavioural Correction

Runtime anomaly detection frameworks like RADD [22] and adaptive swarm tracking systems [23] provide mechanisms for identifying abnormal drone behaviour. Yet, they lack integration with swarm-level coordination and fail to trigger adaptive responses. Chaos mitigation strategies using CNNs and attractor models [8] remain underexplored in multi-agent missions, limiting their practical deployment.

2.7.3 Constraints in Decentralized Task Distribution

Distributed task allocation algorithms [7][18] often assume ideal communication and static environments. Federated Learning and Digital Twin integration [9] offer decentralized learning but are computationally intensive and rarely adapted for real-time UAV swarms. Reinforcement learning-based coordination [11] improves adaptability but lacks modularity for heterogeneous drone roles and dynamic task reassignment.

2.7.4 Inflexibility in Navigation Under Uncertainty

Path planning algorithms such as IACO [13], Bi-APF-RRT* [15], and IAFSA [17] enhance obstacle avoidance and convergence but typically operate under static assumptions. Uncertainty modelling [16] and integrated path-scheduling frameworks [14] are underutilized in swarm contexts, limiting their effectiveness in unpredictable or cluttered environments.

2.7.5 Vulnerabilities in Swarm Communication and Data Integrity

ML-based communication models [4], mesh networks [5], and IoT-enabled systems [21] improve resilience but are often tested only in simulation. Acoustic detection frameworks [12] and IoD security taxonomies [10] offer partial solutions but lack integration with swarm-level coordination and fail to scale securely across large networks.

2.7.6 Traffic Zone Surveillance and Public Transparency

Urban traffic surveillance systems face a range of persistent challenges that hinder their effectiveness in anomaly detection, public accountability, and real-time response. One of the most critical limitations is inadequate coverage caused by static camera infrastructure. Fixed-position CCTV units often suffer from blind spots and limited field-of-view, making it difficult to monitor intersections, pedestrian zones, or areas obscured by vehicles. As a result, dynamic anomalies such as jaywalking, illegal turns, or stray animals frequently go undetected.

3. Proposed Model

This paper outlines the conceptual design of a hybrid autonomous UAV surveillance system that integrates adaptive task allocation, peer-to-peer communication, and multimodal anomaly detection. The proposed architecture is intended for simulation-based validation and serves as a foundation for future real-world deployment.

Fig. 2 illustrates a conceptual framework for a drone-based smart traffic management system for emergency response, the workflow starts when a monitoring drone detects the accident and immediately sends an Alert Notification to the Base and Control Station. Crucially, this monitoring drone then automatically sends a request directly to nearby drones via Peer-to-Peer Communication to coordinate support, bypassing the Control Station for immediate response. The nearest drone with a low-priority task responds to assist, autonomously managing the scene.

Fig. 3 describes a high-traffic urban intersection monitored by a drone using YOLO object detection. It includes bounding boxes for vehicles, pedestrians, motorcycles, buses, and a stray dog all labeled with confidence scores from a top-down aerial perspective.

3.1. Conceptual Overview

The proposed system, titled Hybrid Autonomous Unmanned Aerial Vehicle (UAV) with Adaptive Task Allocation and Peer-to-Peer Communication for Surveillance Monitoring, envisions a decentralized, intelligent UAV swarm capable of performing real-time surveillance and anomaly response. The design eliminates the need for a centralized controller by enabling drones to coordinate autonomously through peer-to-peer (P2P) communication protocols.

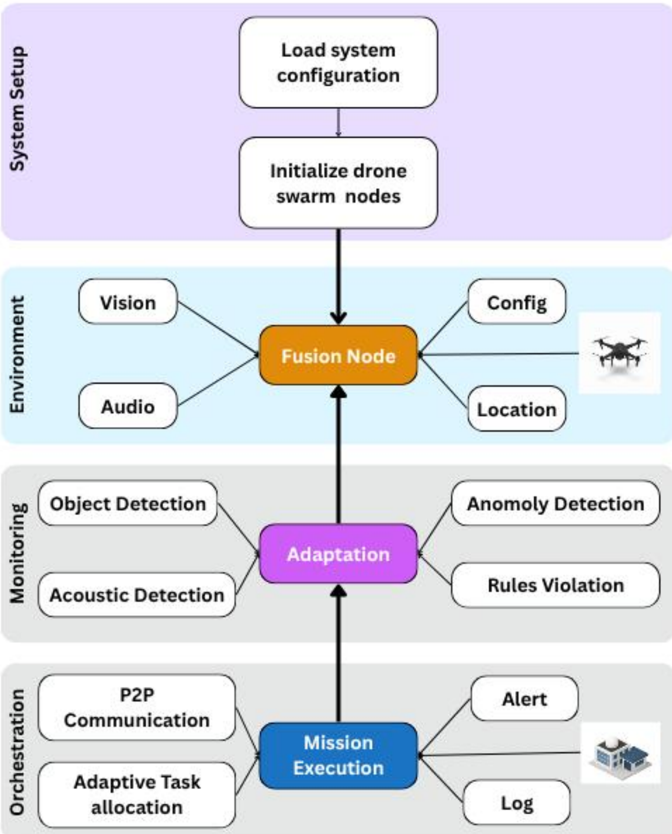

Fig. 1 System Architecture

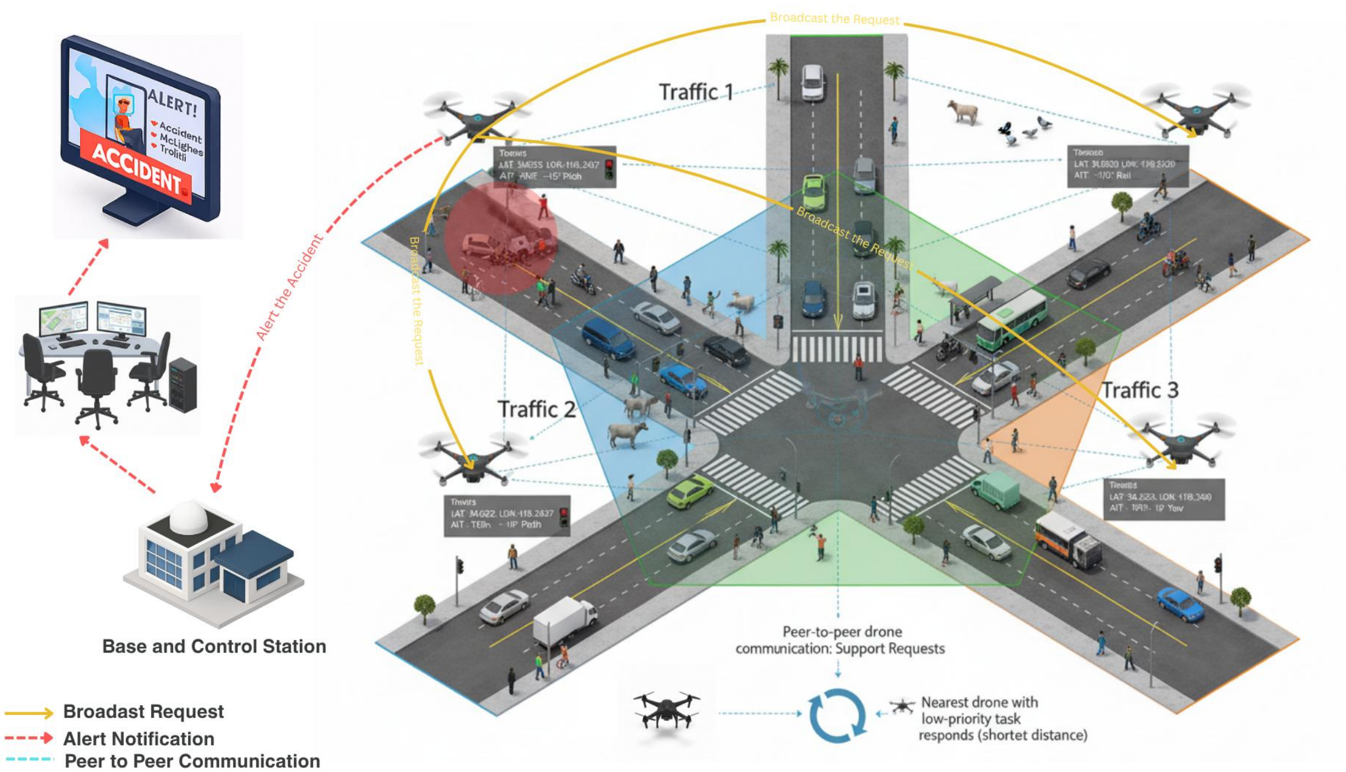

Fig. 2 UAV for Security Surveillance Monitoring System

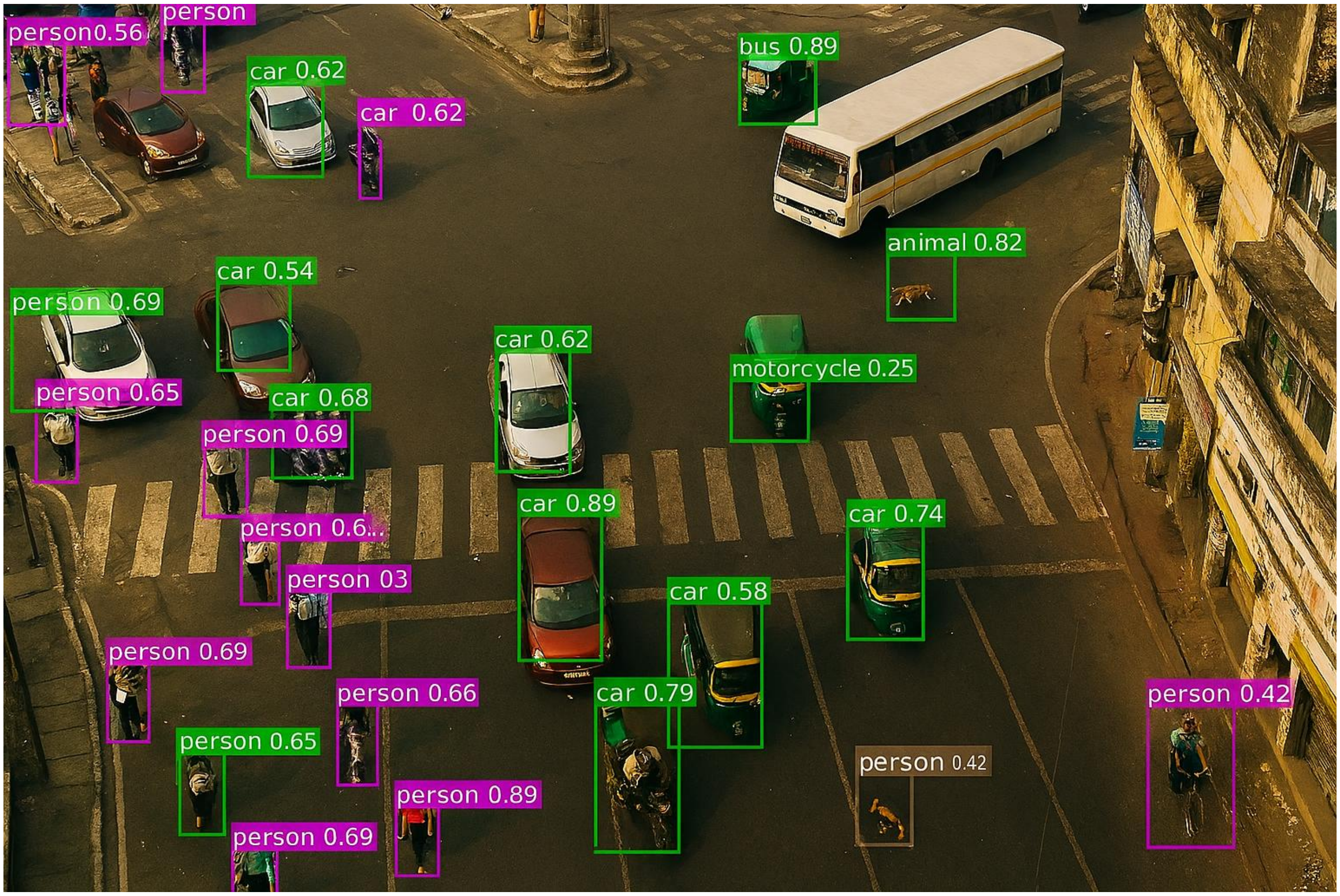

Fig. 3 YOLO based Object Detection model

Fig. 1 describes the system architecture of the autonomous operational cycle of a single drone node within a swarm system, beginning with Load system configuration and Initialize drone swarm nodes. The process moves into an Environment phase where raw sensor inputs like Vision and Audio are fed into a Fusion Node and integrated with the drone's Config and Location data. The resulting fused data enters the Monitoring phase for analysis, using modules like Object Detection and Anomaly Detection to decide on required actions via the Adaptation module. Finally, the Mission Completion phase executes the determined response, which includes sending an Alert to the base station and coordinating with other drones through P2P Communication and Adaptive Task allocation before logging the results and reaching the END of the cycle.

3.2. Multimodal Perception and Anomaly Detection

Each UAV in the swarm is conceptually equipped with visual and acoustic sensors to enhance situational awareness. A YOLOv8-based object detection model [5][19] is proposed for identifying and tracking anomalies such as intrusions or crowd irregularities. Complementary acoustic anomaly detection [12] is envisioned to support detection in occluded or low-visibility environments. These modules are intended to operate in parallel, enabling drones to respond dynamically to visual and auditory cues.

3.3. Adaptive Task Allocation Strategy

The system incorporates a distributed task allocation mechanism inspired by auction-based [7] and game-theoretic models [18]. Each UAV evaluates its suitability for tasks—such as area scanning, anomaly tracking, or perimeter monitoring—based on local context (e.g., battery level, proximity, sensor availability). A negotiation protocol enables autonomous role assignment without centralized oversight, improving resilience and scalability.

3.4. Peer-to-Peer(P2P) Communication Framework

To support decentralized coordination, the architecture proposes a lightweight, encrypted P2P communication layer. Drawing from mesh-based secure networking [5] and swarm communication models [4], this framework is designed to facilitate real-time data exchange, task negotiation, and anomaly broadcasting among UAVs. MQTT or Data Distribution Service (DDS)-based protocols are considered for simulation, with future extensions to secure mesh topologies.

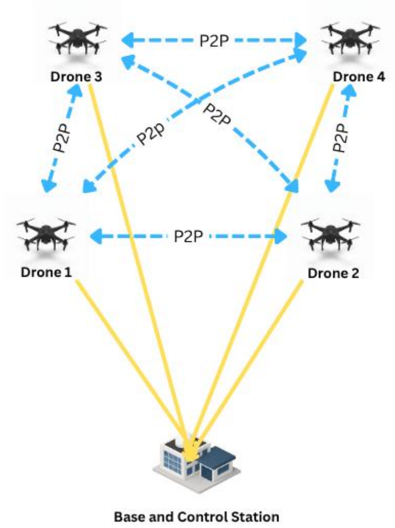

Fig. 4 P2P Communication System

Fig. 4 describes the P2P communication system of a drone swarm system involving four individual drones (Drone 1 through Drone 4) and a Base and Control Station. The primary mode of communication is characterized by a hybrid model, the solid yellow lines show a centralized communication link where all four drones directly report to or receive commands from the Base and Control Station; simultaneously, the dashed blue lines labelled "P2P" (Peer-to-Peer) indicate decentralized communication links allowing the drones to communicate directly with each other to exchange data, coordinate tasks, and manage the swarm autonomously without continuous relay through the central base.

3.5. Path Planning and Navigation Logic

For autonomous navigation, the system conceptually integrates a hybrid path planning module combining Improved Artificial Potential Field (APF) and Bidirectional RRT* algorithms [15]. These planners are selected for their ability to handle 3D obstacle-rich environments and dynamic replanning. The design assumes integration with simulated sensor feedback in Gazebo to validate obstacle avoidance and trajectory optimization [13][16][17].

3.6. Reinforcement Learning for Swarm Behaviour

To enhance coordination efficiency, the system proposes the use of multi-agent reinforcement learning (MARL), particularly Deep Deterministic Policy Gradients (DDPG) [11]. This module is intended to train UAVs in simulated environments to learn cooperative behaviours such as formation flying, adaptive coverage, and collision avoidance. Reward functions will be designed around mission efficiency, energy conservation, and anomaly response time.

3.7. Simulation-Driven Validation

The system is currently under development in a simulated environment using Gazebo and PX4, with Docker-based modularization for reproducibility. Custom world files simulate urban and emergency scenarios, allowing for the evaluation of detection accuracy, task distribution efficiency, communication latency, and navigation robustness. While full implementation may extend beyond the current submission timeline, the conceptual framework is validated through scenario-based simulations and literature-backed design choices.

3.8. Application Scope

The proposed architecture is intended for applications in:

- Urban surveillance and smart-city monitoring.
- Disaster response including search-and-rescue and fire detection.
- Traffic and crowd management using multimodal sensing.

4. Mathematical Formulations of the Proposed System

The proposed conceptual framework integrates multimodal anomaly detection, adaptive task allocation, decentralized communication, and intelligent path planning. The following mathematical models represent the core components of the system.

4.1. Anomaly Detection via Prediction Error

To identify anomalies in video sequences, the system compares predicted and actual frames. Let I_t be the input frame at time t, and $\hat{I}_{t+1}$ be the predicted next frame. The anomaly score A_t is computed as:

$$A_t = \| I_{t+1} - \hat{I}_{t+1} \|_2$$

An anomaly is flagged when:

$$A_t > \theta$$

where θ is a predefined threshold. This approach aligns with Transformer-based anomaly detection models [1][3].

4.2. Adaptive Task Allocation Using Utility-Based Negotiation

Each UAV u_i evaluates its utility $U_{i,j}$ for task T_j based on distance $d_{i,j}$, battery level b_i, and sensor capability s_i:

$$U_{i,j} = \alpha \cdot \frac{1}{d_{i,j}} + \beta \cdot b_i + \gamma \cdot s_i$$

where α, β, γ are weighting coefficients. The task is assigned to the UAV with the highest utility:

$$T_j \rightarrow \arg\max_i U_{i,j}$$

This decentralized allocation reflects auction-based and game-theoretic models [7][18].

4.3. Peer-to-Peer(P2P) Communication Model

Let $G = (V, E)$ be the communication graph, where V is the set of UAVs and E represents active communication links. Each UAV maintains a local state S_i and updates it based on neighbour states:

$$S_i(t+1) = f(S_i(t), \{S_j(t) | j \in \mathcal{N}(i)\})$$

where $\mathcal{N}(i)$ is the set of neighbours of UAV i, and f is a consensus or update function [4][5].

4.4. *Path Planning Using Hybrid APF-RRT**

The Artificial Potential Field (APF) defines attractive and repulsive forces:

$$F_{\text{total}} = F_{\text{att}} + F_{\text{rep}}$$

with:

$$F_{\text{att}} = k_{\text{att}} \cdot (x_{\text{goal}} - x)$$

$$F_{\text{rep}} = \sum_{o \in \mathcal{O}} k_{\text{rep}} \cdot \left(\frac{1}{\| x - x_o \|^2} \right)$$

RRT* refines the path by minimizing cost:

$$C(x) = \min_{x' \in \mathcal{N}(x)} \left[C(x') + \text{Cost}(x', x) \right]$$

This hybrid approach ensures efficient and safe navigation in 3D environments [13][15].

4.5. *Reinforcement Learning for Swarm Coordination*

Each UAV agent u_i learns a policy $\pi_i(a_i|s_i)$ to select action $a_i$given state s_i. The objective is to maximize expected cumulative reward:

$$J(\pi_i) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_i(t) \right]$$

where $r_i(t)$ is the reward at time t, and $\gamma \in [0,1]$ is the discount factor. This supports cooperative behaviors such as formation flying and adaptive coverage [11].

5. Conclusion and Future Work

This paper presents a conceptual framework for a hybrid autonomous UAV system designed for intelligent surveillance monitoring. The proposed architecture integrates adaptive task allocation, peer-to-peer communication, and multimodal anomaly detection to enable decentralized, scalable, and energy-aware aerial monitoring. The system design leverages YOLO-based visual recognition and audio anomaly classification, coordinated through MQTT-based communication and hybrid path planning strategies including Improved APF, Bidirectional RRT*, and adaptive reinforcement learning. The design emphasizes modularity, transparency, and real-world applicability, targeting use cases in smart-city surveillance, disaster response, and security monitoring. This conceptual model lays the groundwork for future simulation, validation, and deployment. The proposed Hybrid Autonomous UAV System currently represents a conceptual framework aimed at addressing the key challenges of decentralized aerial surveillance and adaptive mission control. Future research would focus on transforming this design into a fully functional simulation environment where the mechanisms for multi-drone coordination, adaptive task allocation, and peer-to-peer communication would be systematically validated under dynamic and controlled conditions. Also, planned field trials would focus on evaluating the system's operational performance in traffic surveillance, crowd monitoring, and emergency response applications, thereby bridging the gap between simulation and practical implementation in intelligent aerial monitoring systems.

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