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Swarm-Enabled AI for Smart Mobility and Sustainable Transport

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Abstract

The significant issues facing the modern urban infrastructure are the management of road traffic problems, such as severe traffic congestion, the detection of unsafe driving behavior, and road safety. The traditional ground-based surveillance systems will be helpful, but they will reach their limits in large and dynamic environments. It is because of predetermined perspectives, blindness, and the inability to scale. To designate these problems, the present study proposes a traffic monitoring swarm system utilizing a UAV (unmanned aerial vehicle). This system provides continuous aerial multi-angle surveillance, real-time behavior monitoring, and early identification of anomalies. The swarm applies a decentralized spread-control to maintain an optimal spacing between the swarm members and to avoid overlapping observation space. It identifies and monitors traffic objects such as cars, pedestrians, and two-wheelers on a frame-by-frame basis. They are analyzed based on their movements to do behavioral modeling. This system can detect abnormal driving like sudden braking, driving in the reverse direction, near crashes, and improper lane changes. Verified exceptions are reported to a central traffic control platform, which launches dynamic control actions like timing the signal, regulating localized congestion, and operator alerting. The suggested framework is checked through field experiments and simulations that are carried out in a heterogeneous urban environment. The effectiveness of the suggested method can be observed in the positive outcomes, which present the correct detection, multi-entity tracking, and anomaly classification with significant increases in flow parameters, even in the presence of communication delays, occlusion, and data association difficulties.

Keywords: aerial surveillance, anomaly detection, intelligent transportation systems, road safety, smart mobility, traffic behavior analysis, trajectory tracking, UAV swarm

INTRODUCTION

The high densities of road networks created by rapid urbanization require advanced, flexible, and smart traffic management systems [1, 2]. In particular, for peak times or unexpected disasters, standard designs that use fixed sensors such as CCTV, inductive loops, and fixed roadside units do not adjust to varied traffic conditions. Such systems often lack flexibility, spatial coverage, and predictive capacity [3]. UAVs have attracted attention as a possible alternative to traditional traffic surveillance owing to their versatility, mobility, and ability to record numerous spatiotemporal variations [4, 5]. Compared with ground-based sensors, UAVs have a wider field of view, faster deployment, and real-time data collection in large geographic regions, especially in very overcrowded or geographically insufficient locations [6].

In recent years, methods for UAV coordination have advanced to the extent that multi-angle surveillance is achievable, and reliability is also

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enhanced when compared to the use of single UAVs. This has further enhanced the ability to analyze road behaviors that could be hazardous by incorporating AI-dependent behavior analysis, trajectory analysis, and machine-learning-assisted anomaly detection [7, 8]. Recurrent neural networks and spatiotemporal analysis are AI methods that have proven effective in high-risk event detection, including sudden deviation, near misses, and ghost driving behaviors [9, 10]. This paper introduces an overall UAV swarm system in which coordinated aerial observation, real-time object detection and tracking, and temporal analysis for urban traffic safety control can be effectively accomplished in an urban environment.

RELATED RESEARCH

According to current research, UAVs are becoming increasingly popular as solutions for intelligent transportation and real-time traffic monitoring. A mobile detection system based on YOLOv8+SORT was developed by Zhu et al. (2024) [11], but it lacked multi-UAV coordination. Despite using a small number of datasets, Cao et al. (2023) [12] incorporated environmental elements into the traffic flow prediction. UAV swarms were used for traffic signal optimization through simulations by Alahvirdi et al. (2023) [13], but the results were not verified by actual deployment.

On the other hand, multi-agent reinforcement learning (MARL) techniques enhance the coverage of blind spots, but encounter problems related to the number of UAVs and communication. On the other hand, Bouassida et al. (2024) [14] employed PSO-based models of UAV traffic safety but focused on simulation. Further, the contribution of Ahmed et al. (2024) [15] introduced a multimodal AI system that integrated computer vision and NLP approaches in incident detection. Sarkar et al. (2025) [16] concentrated on the analysis of vehicle collision risks but did not include real-time application logic. Other areas of research include spatiotemporal graph neural networks (GNNs), UAV-assisted vehicle classification models (e.g., VGG16, ResNet, and EfficientNetB3), and YOLOv7 + ByteTrack integration models for lane-level vehicle analysis [17]. Table 1 provides a detailed summary of the key research insights.

Traffic systems based on stationary sensors lack real-time flexibility, have blind spots, and offer slow incident detection with poor predictive capability. Single-UAV aerial surveillance also has poor coverage and strength owing to blind spots and low redundancy. The proposed research will create an intelligent UAV swarm system that will allow coordinated, multi-angle, real-time monitoring of traffic and understanding of behavior. The objectives are to improve the traffic flow and forecast accuracy through autonomous swarm coordination, multiphase anomaly detection, real-time system integration, and performance evaluation.

PROPOSED METHODOLOGY

The suggested approach here incorporates four key elements:

1. UAV swarm coordination,
2. Object detection, tracking, and trajectory generation,
3. Behavioral anomaly detection,
4. Connectivity to traffic management systems.

Table 1. Overview of key studies on traffic monitoring and anomaly detection.

References	Insights	Methods	Limitations	Future work
[11]	Real-time detection on mobile	YOLOv8, SORT	Delay in detection	Efficiency optimization
[12]	Deep learning with environmental factors	Navigation + deep learning	Sparse training data	Improve simulation realism
[13]	UAV swarm traffic optimization	SPSA	Simulation only	Efficiency optimization
[18]	Blind spot coverage	MARL, UAV collaboration	UAV quantity, connectivity	Improve task handling
[15]	UAV-assisted safety	PSO, simulations	CAV perception limits	Real-time testing
[16]	AI for incident detection	CV + NLP	Limited generalization	Real-world deployment

The infrastructure for urban traffic control was connected to these modules to create a closed-loop surveillance system.

UAV Swarm Coordination

The swarm system uses decentralized coordination concepts to cover multilane roadways, roundabouts, and intersections. UAVs dynamically adjust their routes based on visibility, traffic density, and the likelihood of occlusion. Optimal coverage and safe separation were guaranteed using a collision avoidance protocol. Equation (1) provides position updates:

$$\mathrm{P_i}(t+\Delta t) = P_i(t) + v_i(t)\Delta t + a_i(t)\frac{(\Delta t)^2}{2} \tag{1}$$

Object Detection, Tracking, and Trajectory Generation

Each UAV uses a CNN-based pipeline for onboard detection and provides tracked objects with unique IDs. Equation (2) was used to produce trajectories:

$$T_j = \{(x_j^t, y_j^t) \mid t = 1, 2, \ldots, T\} \tag{2}$$

Behavioral Anomaly Detection

A specific sequence model trained to identify patterns, including sudden braking, unpredictable lane deviation, near-collision proximity, and wrong-way travel, was used to segment and process the trajectories.

Integration with Traffic Control Systems

The active UAV swarm sends anomaly alerts and traffic measurements to a centralized traffic control system connected to an urban infrastructure via a real-time communication link. To avoid collisions and reduce congestion, the system constantly modifies signals, reroutes traffic, and notifies operators with low-latency answers based on the incident severity and location. The general UAV swarm-based system architecture for real-time traffic surveillance and behavioral anomaly identification in urban settings is illustrated in Figure 1.

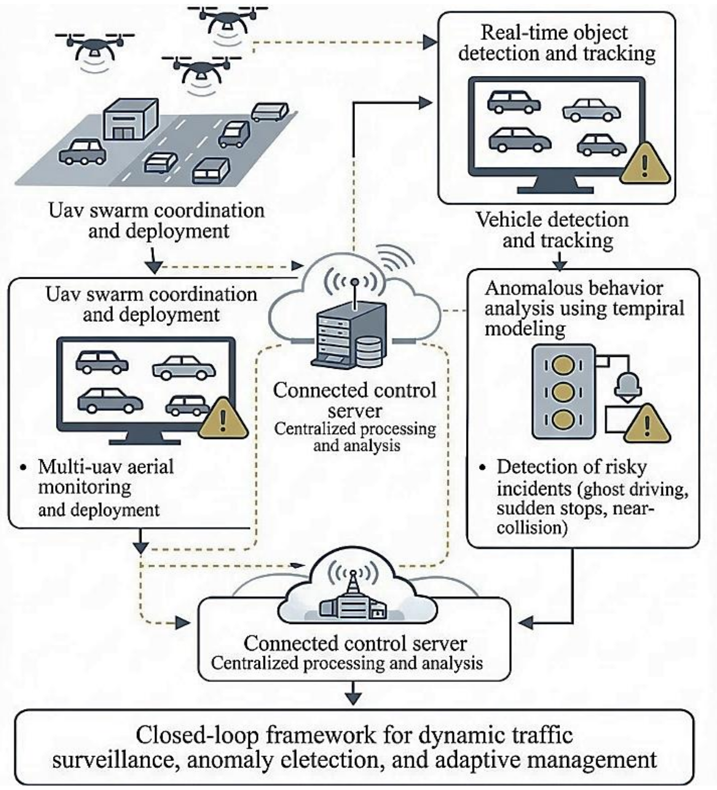

Figure 1. UAV swarm-based architecture for real-time traffic monitoring and anomaly detection.

RESULTS AND DISCUSSION

Through a thorough simulation study and comparison analysis, this section assesses the efficacy of the proposed UAV swarm-based urban traffic monitoring system with a focus on object identification, trajectory tracking, behavioral anomaly categorization, and system responsiveness. The urban traffic data provided by Kaggle were used to record 1,500 vehicle trajectories in 30 traffic scenes with 30 frames per second and a resolution of 1920 × 1080 pixels. The set of scenarios comprises regular driving scenarios and four typologies of abnormal behaviors: ghost driving, abrupt stops, near-miss incidents, and lane deviation. It also captures various lighting situations, traffic jams, and complex traffic dynamics. Table 2 presents the data split.

The object detection and tracking modules, with an average precision of 91.6, a recall of 89.3, and an identification consistency of 93.4, were much better than the state-of-the-art systems with a fixed view and were highly durable in many environmental settings. The entire system may be able to preserve trajectory continuity in the face of extreme congestion, shadows, and cars crossing one another, owing to multiview swarm data. An LSTM-based behavioral anomaly detection model was used to further process the extracted vehicle trajectories. This model maintained a low false positive rate of less than 6% and classified normal and anomalous driving patterns with F1-scores exceeding 0.88 across all anomaly categories, making it appropriate for real-time deployment. The system allows prompt actions to increase road safety, with an average detection-to-response time of less than 2.5 seconds. With a high classification accuracy of 93.6% and significant robustness in complicated and dynamic traffic situations, the LSTM-based model showed great efficacy in traffic behavior analysis. Reliable anomaly detection with fewer false positives and constant real-time performance is enabled by its capacity to learn temporal dependencies. Table 3 shows the results of the final benchmark between a UAV-based model and a conventional fixed camera surveillance configuration (Figure 2).

The significantly higher performance of UAV swarms in dynamic traffic conditions is demonstrated by a comparison benchmark between the UAV-based system and conventional fixed camera surveillance. The UAV system outperformed the fixed cameras in terms of trajectory continuity (93%),

Table 2. UAV traffic dataset summary.

Parameter	Value
Total vehicle trajectories	1,500
Number of traffic scenes	30
Scene duration	10 seconds per scene
Frame rate	30 frames per second (fps)
Spatial resolution	1920 × 1080 pixels
UAV operating altitude	100–150 meters
Normal driving instances	800 samples
Anomalous event—ghost driving	150 samples
Anomalous event—sudden stops	200 samples
Anomalous event—near-miss events	180 samples
Anomalous event—lane deviation	170 samples
Lighting and congestion conditions	Varying (daylight, twilight, dense flow)

Table 3. UAV-based versus fixed camera system performance.

Metric	Fixed camera system	UAV swarm system
Trajectory continuity (%)	76%	93%
Anomaly detection rate (%)	62%	85%
Spatial coverage (%)	60%	95%
Resilience to traffic spikes	Low	High

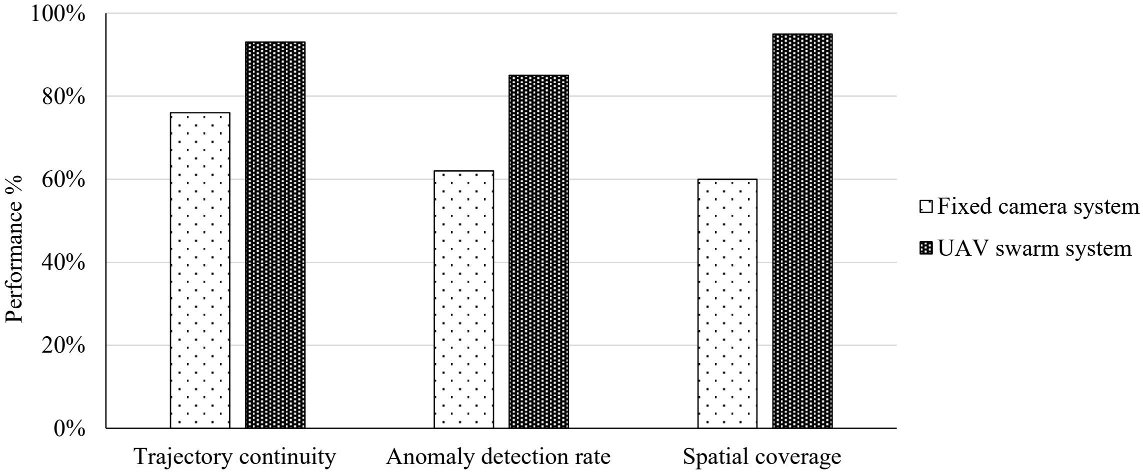

Figure 2. UAV-based versus fixed camera system performance.

anomaly detection rate (85%), and geographical coverage (95%). In addition, fixed camera systems had a low level of adaptability, whereas UAV swarms demonstrated high adaptability and increased tolerance to traffic.

CONCLUSION

The proposed smart urban traffic monitoring system based on a swarm of UAVs is a scalable, responsive, and smart solution to contemporary traffic issues. This is an effective integration of aerial sensing. City-level traffic control, driven behavior analysis, and city-level traffic control. The outcome of the experiment indicated high detection, tracking, and anomaly identification performance, which led to enhanced safety and smoother traffic flow. Inter-UAV communication will be improved in the future, with latency reduction during network load, enhancing the diversity of datasets, and implementing larger swarm setups within more than one district.

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