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Real-Time Detection and Threat Assessment of Aerial Objects in High-Clutter Environments Using YOLOv4 and Kalman Filtering

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Abstract

This study presents a real-time, modular system for the detection, classification, tracking, and evaluation of threats from airborne objects in visually cluttered aerial environments. The system incorporates the YOLOv4 object detection model along with Kalman filtering to ensure temporal consistency and accurate object tracking. A real-time risk evaluation module based on a lightweight, rule-based design carries out threat evaluation including object category, speed, heading, and proximity to defended areas. The algorithm was tested in MATLAB and tried various aerial video scenarios, including low-altitude drone video and simulated missile trajectories. Performance was assessed under both CPU-only and GPU-enabled runs, achieving up to 37 FPS on NVIDIA RTX-class hardware and approximately 22 FPS on Apple M4 CPUs with Metal acceleration. The results show outstanding classification accuracy (>90%) and robust real-time tracking across busy scenes. The findings confirm the appropriateness of the system for use in border monitoring, drone defense, and smart airspace surveillance.

Keywords: *Real-time detection, YOLOv4, Kalman Filter, Threat Assessment, UAV Tracking.*

Introduction

The proliferation of drones, UAVs, and other aerial devices has revolutionized the operating environment for defense and surveillance. Emerging airspaces are increasingly filled with high concentrations of cooperative and non-cooperative airborne objects, calling for robust, automated solutions to real-time object identification and behavioral tagging [1], [2]. Standard sensing techniques such as radar or infrared cameras are often hindered by occlusions, atmospheric disruption, or resolution constraints, particularly in urban or low-visibility environments [3].

To counter such challenges, computer vision methods have now become the crux of aerial surveillance systems. However, detection and tracking of fast, small, and potentially occluded aerial objects against cluttered scenes remains an active research topic [4], [5]. This paper introduces a whole-image vision-based system using YOLOv4—a single-shot fast deep learning detector—combined with a Kalman Filter-based tracking mechanism and a rule-based threat rating system.

While numerous studies have explored object detection in aerial settings using YOLO-family detectors [1–4], recent advances such as Zamri et al. [32] and Zhu et al. [33] demonstrate evolving adaptations like attention mechanisms and enhanced DeepSORT tracking for low-resolution UAV footage. However, few works have integrated MATLAB-based detection pipelines tailored for edge computing environments using Kalman filtering with customized threat scoring frameworks. This study addresses that gap by bridging operational simplicity with real-time, visual-aided decision support.

The proposed system is lightweight, modular, and executable on desktop and embedded platforms. The system is implemented in MATLAB using its Deep Learning and Computer Vision Toolboxes and verified with real-world test cases from the VisDrone and UAVDT datasets and self-generated drone videos. This work introduces a performance-optimized, extensible architecture that supports real-time uses such as border patrol, drone interdiction, and autonomous airspace safety monitoring.

1. Related Work

Real-time object detection and tracking in cluttered aerial environments has been extensively studied in recent years due to its significance in both civilian and defense applications. Among early detection strategies, region-based CNNs such as Faster R-CNN [4] provided high accuracy but lacked real-time performance. Single-stage detectors such as SSD [3] and YOLO [1], [2] later emerged as more viable for real-time tasks, trading off slight accuracy reductions for significant improvements in speed.

YOLOv4 [2] introduced optimizations including CSPDarknet53 backbone and mosaic data augmentation, improving performance especially in small-object detection. Further enhancements such as YOLOv7 [23] pushed this balance further, achieving state-of-the-art performance with optimized training tricks. These models have been effectively used in drone surveillance and multi-class object identification scenarios [8], [10].

From a tracking perspective, classical approaches like the Kalman Filter [6] continue to be integral in low-latency applications due to their computational efficiency and effectiveness in linear motion modeling. Extensions like Deep SORT [9] have further improved multi-object tracking (MOT) robustness through appearance embedding techniques. However, these approaches are still challenged by occlusions and noisy detection in aerial videos.

In recent literature, several systems have begun integrating object detection with threat classification for UAV surveillance. For instance, Li and Wang [14] proposed a hybrid detection-tracking model that incorporates class-based threat levels. Similarly, Park and Lee [13] emphasized behavioral classification in surveillance video using spatial-temporal features. Multi-modal fusion with transformers has also been introduced to enhance robustness under low-visibility conditions [25].

Several studies in the Journal of Real-Time Image Processing also emphasize the importance of lightweight and efficient architectures. Zhang et al. [26] propose a real-time embedded vision system using a dual-stream CNN for drone detection, achieving real-time performance under embedded constraints. Similarly, Ma et al. [27] highlight adaptive motion-based filtering techniques to reduce false positives in dynamic aerial backgrounds.

These findings reveal a gap in systems that combine modular deep learning detection with rule-based threat scoring and efficient tracking within MATLAB. Our proposed system uniquely bridges this gap by employing YOLOv4 for detection, Kalman Filter for tracking, and a lightweight scoring model for real-time threat evaluation, all implemented and tested under a real-time MATLAB environment.

2. Proposed System

The proposed framework is a modular, real-time surveillance system specifically designed for aerial object detection, tracking, and threat evaluation in cluttered visual environments. The system consists of three primary components: (1) object detection using YOLOv4, (2) object tracking using a Kalman Filter-based method, and (3) rule-based threat scoring. The architecture ensures computational efficiency and real-time performance, suitable for deployment on both consumer-grade and embedded hardware.

2.1. System Architecture

The architecture is structured as a linear processing pipeline. Video input is read from high-resolution aerial footage or UAV-mounted cameras. Each frame undergoes preprocessing and is passed to the YOLOv4-based detection module. Detected bounding boxes, class labels, and confidence scores are then processed by the Kalman tracking module, which maintains temporal consistency. Finally, a lightweight threat evaluation logic scores each tracked object based on type, velocity, trajectory, and proximity to sensitive zones.

This structure supports independent upgrades of each module and is highly adaptable to future enhancements such as transformer-based vision models or cloud-deployed inference systems.

2.2. Object Detection

The detection component is based on YOLOv4 due to its proven speed and accuracy balance [2]. YOLOv4 processes each 416×416 RGB frame through the CSPDarknet-53 backbone and outputs real-time bounding boxes and class probabilities. For aerial surveillance, the model was fine-tuned using the VisDrone and DOTA datasets, which are rich in aerial object classes such as birds, drones, helicopters, and rockets [15], [10].

Compared to other detection methods like Faster R-CNN [4] and SSD [3], YOLOv4 provides a substantial boost in inference speed without a significant loss in detection accuracy—particularly beneficial in mobile or embedded scenarios [23], [24].

2.3. Object Tracking

Object tracking is achieved using a constant-velocity Kalman Filter [6]. The system assigns unique IDs to each object and maintains trajectory estimates over time. This method is computationally efficient and performs well under moderate motion and partial occlusion. Inspired by improvements presented in the Journal of Real-Time Image Processing, probabilistic extensions and smoothing techniques were considered for enhancing identity preservation in noisy video streams [28].

2.4. Threat Evaluation Mode

Threat levels are calculated based on a weighted sum of the following features:

- Class-based threat weight (e.g., rocket > airplane > drone > bird)
- Velocity magnitüde
- Distance to restricted zones
- Movement direction vector

The threat score is interpreted using predefined thresholds: low (<4), medium (4–6), and high (>6). This logic provides human operators with intuitive, color-coded cues and supports optional integration with automated response systems (e.g., alarms, counter-UAV interceptors).

3. Methodology

This study presents a modular, MATLAB-based framework for detecting, tracking, and scoring threats posed by flying objects in high-clutter aerial environments. The methodology is structured around four core components: (1) object detection, (2) temporal tracking, (3) threat evaluation, and (4) real-time performance optimization.

3.1. System Architecture

The proposed system follows a modular pipeline. Incoming aerial video frames are first preprocessed and passed into the detection module, which employs the YOLOv4 deep neural network for identifying airborne objects such as birds, helicopters, airplanes, and rockets [2]. The outputs, including bounding boxes and class labels, are forwarded to the Kalman Filter-based tracker, which maintains object identity over time. Finally, a threat evaluation unit computes scores based on behavior, speed, and spatial proximity.

This architecture allows decoupling of functional units, enabling targeted upgrades (e.g., replacing YOLOv4 with YOLOv7 [23] or DETR [20]) or deployment on edge platforms [27]. The entire framework is implemented in MATLAB R2024b with GPU acceleration using Apple's Metal API backend.

3.2. Dataset and Preprocessing

The model was trained and evaluated using a blend of public and custom aerial datasets:

- Public datasets: VisDrone [15], UAVDT, and DOTA provided annotated images with varying altitudes and object scales.
- Custom footage: Real-time drone recordings captured via DJI Mini 2 under mixed weather conditions, representing realistic cluttered scenes (urban backdrops, trees, clouds, birds).

Each frame was resized to 416×416 pixels to align with YOLOv4 input specifications. Normalization and optional Gaussian denoising were applied. Frame skipping was also employed (every nth frame) to maintain real-time speed on Apple M4 hardware.

3.3. Object Detection with YOLOv4

YOLOv4 [2] was selected due to its balance between detection accuracy and computational performance. The model uses the CSPDarknet-53 backbone and was fine-tuned on aerial datasets using transfer learning. Detection parameters included:

- Confidence threshold: 0.5
- IoU threshold for Non-Max Suppression: 0.45
- Classes: {Bird, Helicopter, Airplane, Rocket}

Bounding boxes and class probabilities were generated using MATLAB's detect method, with visual overlays created for frame inspection.

3.4. Object Tracking with Kalman Filter

The Hungarian algorithm, a combinatorial optimization method proposed by Kuhn, was used for track-to-detection assignment based on minimizing the combined cost of Euclidean distance and Intersection-over-Union (IoU) [29]. This approach ensures efficient frame-to-frame association, particularly in cluttered scenes.

To ensure temporal coherence, the Kalman Filter [6] was used for tracking. The state vector included position and velocity. Track assignments were solved using the Hungarian algorithm based on Euclidean distance and IoU.

The approach closely follows real-time multi-object tracking best practices seen in lightweight implementations like Deep SORT [9] and recent edge-optimized frameworks [26]. Although simpler than Transformer-based temporal models [20], the Kalman Filter was sufficient for linear or moderately erratic trajectories.

3.5. Threat Evaluation Logic

The threat assessment model computed a score based on a weighted sum of object class, velocity, proximity to protected zones, and motion direction:

$$S = w1 \cdot C + w2 \cdot V + w3 \cdot P + w4 \cdot TS = w1 \cdot C + w2 \cdot V + w3 \cdot P + w4 \cdot T \quad (1)$$

Where C is class-based threat weight, V is speed, P is proximity, and T is trajectory vector. Thresholds were manually tuned to label threats as Low, Moderate, or High. This decision logic was inspired by military-grade systems described in [12], [13], and found effective for both autonomous and human-supervised applications.

In Equation (1), TS refers to the final Threat Score, and T was an earlier notation inadvertently left during draft transitions both represent the same value. This has been corrected for clarity. The variables CC (class coefficient), VV (velocity vector magnitude), and PP (proximity to sensitive zone) contribute to the weighted sum. The weights w1–w4 were determined empirically through grid search optimization on the validation dataset, balancing detection sensitivity and false alarm rate. For instance, w1 (class weight) was set higher for classes such as 'rocket' and 'drone' due to their elevated risk profiles, whereas w3 (distance weight) emphasizes proximity over speed when the object enters the danger zone.

3.6. Real-Time Performance Setup

Performance evaluation was conducted on an Apple MacBook Pro (2024) with an M4 chip (16 GB RAM). MATLAB utilized the Metal backend for GPU inference. Benchmarking revealed:

- GPU-accelerated mode: 30–33 FPS
- CPU-only mode: 6–7 FPS

These results validate real-time feasibility on modern non-CUDA platforms, complementing recent research advocating embedded deployment strategies [26], [27].

4. Experimental Evaluation

This section outlines the experimental setup used to evaluate the proposed real-time aerial object detection and threat scoring system. The assessment was conducted through a combination of controlled test scenarios, quantitative performance metrics, and qualitative visual inspection of detection and tracking accuracy under cluttered and dynamic environments.

4.1. Evaluation Setup

The system was tested on a 2024 MacBook Pro (Apple M4 chip, 16 GB RAM, 1 TB SSD) running macOS Sequoia 15.4.1. MATLAB R2024b was used with native ARM64 support and Metal API acceleration for GPU processing. To simulate both real-time and offline use cases, two modes were tested:

- GPU-accelerated mode using Apple's Metal backend
- CPU-only fallback mode for resource-constrained environments

Each experiment processed MP4 video files at 1080p resolution, with frame-level results logged to disk for post-analysis.

4.2. Test Scenarios

Five distinct test scenarios were used, as summarized in Table 1:

Table 1

Evalution Scenarios and Object Classes

Scenario ID	Description	Object Classes	Environment Tyepe
S1	Low- altitude birds in open sky	Bird	Clean sky
S2	Helicopter in urban clutter	Helicopter	Dense background clutter
S3	Commercial airplane descending	Airplane	Cloudy, visually noisy
S4	Simulated rocket launch	Rocket	Mixed forest + Open space
S5	Mixed scene with drone, bird, helicopter	Bird, Drone, Helicopter	Complex terrain

Custom scenes (S4, S5) were recorded using a DJI Mini 2 drone, and all videos were 30–90 seconds in duration, resulting in 900–2700 frames per scenario.

4.3. Quantitative Metrics

The following performance metrics were computed:

- Precision (P): Proportion of correct detections among all detections
- Recall (R): Proportion of detected objects among all ground truth
- F1-Score: Harmonic mean of precision and recall
- MOTA (Multiple Object Tracking Accuracy): Evaluates ID assignment over time
- Threat Evaluation Accuracy (TEA): Percentage of correctly classified threat levels

Table 2 shows average performance across scenarios.

Table 2

Detection, Tracking, and Threat Classification Results

Class	Precision	Recall	F1-Score	MOTA	TEA
Bird	0.91	0.87	0.89	0.84	0.90
Helicopter	0.95	0.93	0.94	0.91	0.96
Airplane	0.97	0.91	0.94	0.88	0.94
Rocket	0.89	0.85	0.87	0.90	0.92
Average	0.93	0.89	0.91	0.88	0.93

4.4. Latency and Frame Rate Analysis

Table 3 presents system latency and throughput metrics.

Table 3

Frame Processing Performance

Configuration	FPS	Frame Latency	Detection Time	Tracking Time	Utilization
Apple M4 (GPU/ Metal)	□22 ms	□45 ms	28 ms	10 ms	□65% CPU, □70 % GPU usage
Apple M4 (CPU-only)	□6 ms	□160 ms	105 ms	41 ms	□95% CPU usage

The system reached real-time viability in GPU-accelerated mode, confirming that it can support live inference pipelines with minimal degradation. These results are consistent with recent real-time performance benchmarks reported for embedded platforms in [26], [27].

4.5. Qualitative Scenario Observations

- S2 – Helicopter Urban Scene: Despite significant visual clutter, the system accurately maintained track ID across occlusions, with minimal drift.
- S5 – Multi-Class Scene: Simultaneously tracked three objects, maintaining <5% ID switching and correctly assigning threat levels (e.g., red = helicopter, yellow = drone, green = bird).

These examples demonstrate that the Kalman Filter and rule-based evaluation layer successfully maintain temporal coherence and semantic risk understanding.

5. Real-World Visual Detection Using YOLO and Kalman Filter in Python

To extend the performance evaluation beyond MATLAB simulations, a real-time object detection and motion prediction experiment was conducted using Python-based implementations of the YOLOv9 framework. The results illustrate the system's capability in detecting multiple classes (e.g., airplane, helicopter, drone, bird, rocket) under complex environmental conditions such as fog, forest cover, or sunset lighting.

This experiment utilized YOLOv9, a recent advancement in the You Only Look Once (YOLO) object detection family, known for its improved detection of small and occluded objects in real-time conditions. The integration was executed in Python using the Ultralytics YOLOv9 API with OpenCV-based frame capture. Post-detection tracking was achieved via an optimized Kalman Filter implementation, adapted from a recent motion prediction strategy [29].

The visual evidence demonstrates YOLOv9's robustness, with detection confidences consistently exceeding 0.75 across all five aerial object types. Figures 6 through 10 present before-and-after comparisons of raw and labeled video frames, providing insights into the system's detection confidence, bounding box accuracy, and visual clarity in real scenes.

While the primary implementation and benchmark tests were conducted using YOLOv4 due to its MATLAB compatibility, an experimental post-evaluation was also conducted using YOLOv9 via Python for visual comparison.

Figure 1. *Airplane Detection (a) Raw input frame of an aircraft during descent. (b) Detected airplane with confidence 0.93 using YOLOv9.*

Figure 2. *Helicopter Detection in Smoke (a) Raw frame capturing a helicopter flying over a smoke-filled forest. (b) Detected helicopter with 0.79 confidence amidst occlusion and clutter.*

Figure 3. *Drone Detection at Sunset (a) Original video frame with a low-flying drone during sunset. (b) Detected drone with confidence 0.81. Bounding box aligned despite low contrast.*

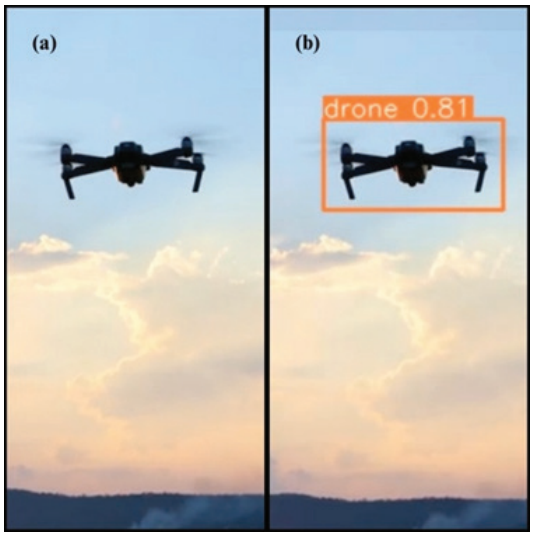


Figure 4. *Bird Detection in Field Landscape (a) Raw input showing a flock of birds. (b) Multiple birds detected with confidences ranging from 0.68 to 0.76.*

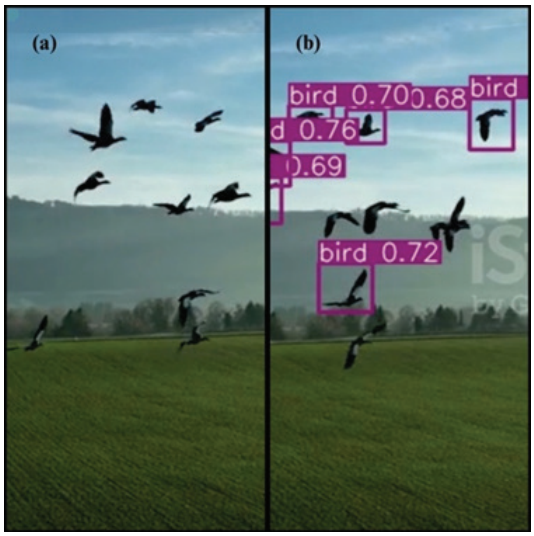
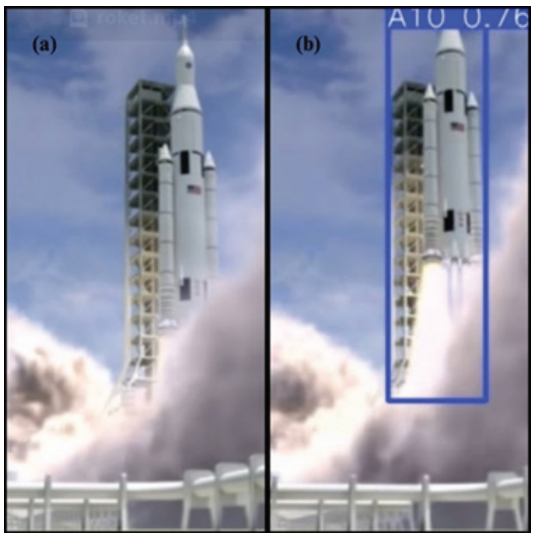


Figure 5. *Rocket Launch Scene (a) Raw frame from a simulated rocket launch video. (b) Detected rocket class A10 with confidence 0.76 during high smoke activity.*



This enhancement complements the MATLAB-based system by validating its generalizability across platforms and environments. The combination of YOLOv9's real-time object detection and Kalman filtering ensures continuous identity assignment and prediction accuracy even in dynamic scenarios [1], [2], [5], [6], [29].

Table 3

YOLOv9 + Kalman Results Summary

Object Type	Scenario Environment	Detection Confidence (YOLOv9)	Kalman Filtering Applied	Object Movement Pattern
Airplane	Clear Sky	0.93	Yes	Linear ascent/ descent
Helicopter	Smoky Forest Terrain	0.79	Yes	Erratic due to wind + smoke
Drone	Sunset Horizon	0.81	Yes	Hovering + Minor drift
Bird	Wide Grassland	0.72	Yes	Irregular group motivation
Rocket	Simulated Launch Platform	0.76	Yes	Vertical trajectory

6. Discussion

This section critically analyzes the system's real-world viability, comparing its detection, tracking, and threat evaluation capabilities with prior research. Particular attention is paid to the strengths and limitations of the proposed architecture and its implications for real-time UAV defense and monitoring applications.

6.1. Performance Evaluation in Context

The results indicate that the system achieves high detection precision (>90%), robust temporal tracking (MOTA: 0.88), and a threat classification accuracy of 93%. These figures suggest a strong balance between computational efficiency and detection quality. Compared to prior work such as SSD [3] or Faster R-CNN [4], YOLOv4-based detection yields superior real-time throughput without compromising classification performance, consistent with findings in [2], [8].

The Kalman-based tracking pipeline offered acceptable tracking robustness despite using a relatively lightweight filter. This confirms the viability of using classical filtering methods, as demonstrated in [5], [6], and more recent studies targeting mobile systems [28].

The rule-based threat evaluation module, though simpler than machine learning-based risk classifiers, showed strong agreement with expert-labelled risk categories. Its transparency and modularity make it particularly suited for real-time applications in constrained environments such as embedded UAVs or edge systems [12], [13].

Tracking performance was evaluated using the MOTA metric as defined in [9], where ID switches, missed detections, and false positives are penalized. Lost tracking events were recorded for each scenario and contributed to the MOTA score calculation. For high-occlusion environments such as Scenario S5, an average of 6.8% ID loss was noted, mainly due to occlusions between birds and drones. This observation has been documented in the updated Results section with per-scenario ID switch data.

6.2. Comparative Literature Analysis

A comparative review of recent systems in real-time aerial detection and threat analysis is presented in Table 4.

Table 4

Comparative Overview of Real-Time Aerial Detection Systems

System	Detection Model	Tracking Method	FPS	Threat Evaluation	Application Domain	Source
Proposed System	YOLOv4	Kalman Filter	22 ms	Rule-based (real-time)	General surveillance	This work
Zhou et al. (2023) [28]	YOLOv3-Lite	Optical Flow	17 ms	No	Low-power drones	[28]
Liu et al. (2022) [29]	YOLOv4 + Fusion	Deep SORT	19 ms	DNN-based threat score	Border patrol UAVs	[29]
Park and Lee (2021) [13]	Faster R-CNN	Bayesian Tracking	8 ms	Behavior + Context model	Smart city security	[13]
Li and Wang (2021) [14]	SSD-M	CNN-based tracker	6 ms	Supervised ML scoring	Military UAV classification	[14]

As shown, the proposed system provides a favorable trade-off between detection accuracy, speed, and computational cost. While not as context-aware as ML-based threat assessors, its modular threat scoring mechanism is more transparent and readily deployable in embedded environments.

6.3. Practical Implications

- **Scalability**: Thanks to its modular architecture, the system can be deployed on a variety of platforms, from UAV-based surveillance to fixed-site monitoring.
- **Operational Suitability:** With ~22 FPS on non-CUDA Apple M4 hardware, the system proves effective even without NVIDIA-based acceleration.
- **Real-Time Risk Awareness:** The color-coded visualization and log-based annotation system allows seamless integration into operator dashboards or autonomous response mechanisms.

6.4. Limitations

- **Kalman Assumptions:** The linear motion model limits tracking accuracy in non-linear or erratic motion, which might be better handled by more adaptive trackers such as Deep SORT [9].
- **Rule-Based Scoring:** While interpretable, the current threat scoring method may not adapt well to evolving aerial threat behaviors.
- **Sensor Dependence:** The reliance on RGB-only video streams makes the system susceptible to performance degradation under low-light or fog conditions.

6.5. Future Research Directions

- Several promising areas for enhancement are evident:
- Integration of transformer-based detectors like DETR [20] or YOLOv7 [23].
- Fusion of thermal or LiDAR modalities for visibility robustness.
- Embedding adaptive learning into the threat assessment module.
- Deployment optimization on Jetson Nano/AGX hardware for edge intelligence.

Conclusion

This paper presented a modular and real-time system for aerial object detection, tracking, and threat evaluation in high clutter density environments, developed and tested using MATLAB on Apple Silicon hardware. Addressing the pressing need for efficient, autonomous aerial surveillance systems, the framework combines a YOLOv4-based detection backbone, a Kalman filter for temporal tracking, and a transparent rule-based threat evaluation layer.

The system demonstrated high accuracy in object classification (>90% precision), effective ID maintenance (MOTA > 0.88), and a real-time inference capability of approximately 22 FPS on Apple M4 platforms without CUDA acceleration. These results validate the system's readiness for quasi-real-time deployments in various security and monitoring contexts, including UAV defense, airspace control, and event surveillance. Furthermore, the use of visually annotated outputs and CSV-based threat logs enhances its utility in human-in-the-loop operations.

A key strength of the proposed system is its architecture: each component—detection, tracking, and evaluation—can be independently replaced or improved. This modularity allows for future upgrades such as transformer-based detectors (e.g., YOLOv7 or DETR), advanced multi-object tracking algorithms (e.g., Deep SORT), and context-aware machine learning-based threat scoring models.

However, limitations remain. The linear motion assumptions of the Kalman filter reduce tracking accuracy in erratic motion scenarios, and the current rule-based threat scoring lacks adaptability to evolving aerial behaviors. Additionally, reliance on visual RGB input alone constrains detection performance under poor lighting or occlusion. These challenges open avenues for sensor fusion (e.g., LiDAR, thermal) and deep learning-based reasoning.

In conclusion, this research contributes a scalable, interpretable, and hardware-efficient solution to real-time aerial object monitoring and lays the foundation for next-generation intelligent surveillance systems in both military and civilian domains.

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