AI-enhanced Sky Surveillance Mobile Multisensor Imaging System

Loukas Athanasekos[1], Dimitrios Nodaros[1], Nikolaos Dimitriou[2] and Aris S. Lalos[3]

[1]AKMON S.A., 44th Str. Nr. 4, 13341, Ano Liosia - Industrial Area, Athens, Greece
[2]Center for Research and Technology, Hellas, 57001 Thessaloniki, Greece
[3]Industrial Systems Institute, Athena Research and Innovation Center, 265 04 Patras, Greece
E-mail: l.athanasekos@akmonsa.gr , d.nodaros@akmonsa.gr, nikdim@iti.gr, lalos@athenarc.gr

Abstract
Drones are one of the most emerging threats for the future operations, as they can detect and attack ground targets, including soldiers, vehicles or infrastructures without being detected soon in advance so as to avoid damage. The concept relates to a mobile multisensor system incorporating thermal, day camera and LIDAR, mounted on the helmet of the soldier or on top of a vehicle and able to detect threats coming from the sky in real time, in order to provide prompt alert to stakeholders. By leveraging AI, computer vision and ML algorithms, the system provides stakeholders with seamless access to data feeds that allow for more informed and precise decision-making. Furthermore, we propose the adaptation of Cooperative Multi-Object Tracking (CoMOT) frameworks—originally developed for autonomous vehicle perception—to ground-based surveillance systems targeting the airspace.

Introduction
In modern warfare, the rapid proliferation of unmanned aerial vehicles (UAVs) and other airborne threats has significantly increased the demand for advanced detection and surveillance systems. Traditional air defense relies on large, stationary radar systems and ground-based sensors, which, while effective, often suffer from coverage limitations and vulnerability to countermeasures. Moreover, the increasing use of low-observable and terrain-masking tactics by adversaries makes it difficult for conventional systems to provide continuous and reliable aerial surveillance. As a result, there is a growing need for decentralized, mobile, and adaptable solutions that can provide real-time threat awareness in dynamic combat environments.
Electro-optical (E/O) systems have become integral to modern defense strategies, offering high-resolution imaging capabilities. These technologies are widely employed in air defense systems, but their implementation is mostly limited to fixed installations, aircraft, or ground vehicles. Mobile/portable E/O systems equipped with multiple sensors could provide a new dimension of situational awareness. By enabling individual soldiers or small units to detect and track aerial threats in real-time, such a system could significantly enhance operational effectiveness in contested environments.

Background
The rapid evolution of unmanned aerial vehicles (UAVs) has introduced new challenges for military and security forces, necessitating advanced detection and countermeasure systems. Traditional air defense strategies, which rely heavily on radar-based detection, struggle to identify small, low-altitude drones with minimal radar cross-sections. Recent research highlights the growing inadequacy of conventional air defense radars in countering contemporary drone threats, emphasizing the need for multi-sensor approaches to enhance detection capabilities[1]. The increasing complexity of drone threats, including swarm attacks and electronic warfare tactics, has further accelerated the demand for next-generation surveillance solutions that leverage sensor fusion and artificial intelligence (AI)-driven analytics[2,3].

Current surveillance architectures primarily rely on ground-based radar, electro-optical (EO) tracking stations, and centralized command-and-control networks. While these systems provide effective coverage in open battlefields, their effectiveness is reduced in urban, forested, and mountainous terrains due to line-of-sight constraints. Additionally, adversarial forces have developed electronic countermeasures (ECM) to jam or deceive radar systems, further limiting their effectiveness[4]. In response, EO/IR (electro-optical/infrared) sensors have been widely integrated into air defense platforms, offering passive detection capabilities that are immune to radar jamming[5]. However, the fixed installation of most EO/IR tracking stations reduces adaptability in dynamic combat situations, where soldier- or vehicle-mounted systems could provide localized real-time threat awareness.

One emerging multi-sensor approach involves the fusion of thermal infrared cameras and LiDAR, an integration that has already been explored in autonomous vehicle perception systems[6]. LiDAR provides precise 3D mapping and distance measurement, enhancing target classification by distinguishing between drones, birds, and environmental objects—a key limitation of purely optical or thermal imaging methods. Studies demonstrate that LiDAR-based UAV tracking significantly improves target recognition accuracy, particularly when paired with AI-based classification models[7]. However, LiDAR-based detection solutions have traditionally been large-scale installations, and their deployment in wearable or vehicle-mounted formats remains underexplored.

Advanced image processing techniques, particularly those based on wavelet transforms, have gained traction for enhancing EO/IR sensor capabilities in UAV detection. Wavelet-based methods provide multi-scale image analysis, improving object detection and feature extraction in cluttered environments. Research demonstrates that wavelet transforms enable superior image denoising and edge enhancement, crucial for thermal and low-visibility imaging conditions[8,9]. These methods, when integrated with AI-driven real-time recognition algorithms, significantly enhance UAV detection accuracy in diverse operational environments.

Furthermore, the future evolution of aerial threats suggests that drones will continue to play a dominant role in asymmetric warfare, reconnaissance, and autonomous strike missions[10]. Adversaries are expected to leverage stealth drone technologies, autonomous navigation, and AI-driven swarm coordination, requiring military forces to adopt adaptive, mobile, and decentralized surveillance solutions. A wearable or vehicle-integrated EO system, combining thermal imaging, visible-light cameras, and LiDAR, would provide a flexible and resilient approach to countering these threats. Such a system would bridge the gap between traditional large-scale air defense systems and the real-time situational awareness needs of soldiers in the field. Research into counter-UAV strategies must therefore prioritize the miniaturization of LiDAR-based solutions, AI-enhanced real-time threat classification, and efficient data fusion across multiple sensor modalities[11].

The integration of multi-sensor surveillance systems into wearable and vehicle-mounted platforms represents the next frontier in UAV threat mitigation. By leveraging sensor fusion, real-time AI analytics, and wavelet-enhanced image processing, the proposed system offers a scalable and adaptable approach to modern battlefield surveillance and counter-drone defense.

System Architecture

The proposed electro-optical (E/O) surveillance system is designed as a multi-sensor platform for detecting and classifying aerial threats in real time. It integrates three primary sensors—thermal imaging, a day camera, and LiDAR—along with an onboard processing unit and a communication module. This configuration ensures comprehensive situational awareness by leveraging the strengths of multiple detection technologies while mitigating individual limitations. Designed for both wearable and vehicle-mounted configurations, the system is lightweight and modular, allowing flexibility in deployment.

At the core of the system is the sensor module, which houses the thermal camera, day camera, and LiDAR unit. The thermal camera detects heat signatures, making it highly effective in low-light environments or when visual obstructions such as smoke or fog are present. The day camera provides high-resolution imagery for target identification under normal lighting conditions. Meanwhile, the LiDAR sensor generates precise three-dimensional spatial data, enabling accurate ranging and tracking of aerial threats. Together, these sensors form a robust detection suite adaptable to various environmental conditions.

The processing unit plays a crucial role in sensor fusion, data analysis, and target recognition. Advanced AI-based algorithms integrate inputs from all three sensors to enhance detection accuracy while minimizing false positives. Object recognition and classification models differentiate between drones, birds, and other airborne objects, significantly improving situational awareness. Real-time data processing ensures rapid detection, which is critical in combat scenarios where response time determines mission success.

Augmented Reality and AI for Sky Surveillance

In addition, a real-time information ecosystem is proposed that connected users with command centers. By leveraging computer vision algorithms and machine learning, the system provides stakeholders with seamless access to AI-enhanced data feeds that allow for more informed and precise decision-making[12,13]. Through AR-powered visual overlays, users can quickly assess aerial threats, identify individuals of interest, and act with greater confidence and accuracy.

One of the key technologies is the AI-driven computer vision system, designed to operate in real-time on embedded and edge computing devices. This system enabled users to analyze complex real-world scenarios instantaneously, significantly enhancing their ability to respond to unfolding events.

The system is built around several key capabilities. Instance segmentation enables the recognition and categorization of aerial objects in the system's field of view such as UAVs and other items of interest[14]. Object tracking allows users to monitor objects over time, ensuring that aerial threats could be continuously assessed even in dynamic environments. These AI capabilities dramatically improve aerial surveillance efficiency by reducing the cognitive load on physical military personnel. Instead of having to manually assess and interpret every aerial element in their environment, officers can rely on AI-assisted insights, allowing them to focus their attention where it matters most.

Additionally, the system incorporates an AI-powered Identification Friend or Foe (IFF) system, which quickly identifies ally and adversary aerial assets in high-stakes situations, reducing the likelihood of misidentification and unnecessary confrontation.

The ability to overlay this real-time information onto an AR display represents a major leap forward. By extending officers' perception by using a diverse set of sensors way beyond their physical abilities, the proposed system significantly improves their ability to assess aerial threats and coordinate tactical operations with greater confidence.

The methodology behind the system includes three key processes: data collection, signal processing, and machine learning-based threat identification. The system continuously captures data from its three integrated sensors, ensuring robust detection across different lighting conditions and environmental scenarios. Pre-processing techniques enhance signal clarity, while sensor fusion algorithms align multi-modal data for accurate object representation. AI-driven classification models, trained on diverse datasets, ensure real-time and reliable threat identification.

The user interface (UI) is designed for intuitive operation, ensuring that soldiers receive actionable intelligence without cognitive overload. The wearable (helmet mounted) configuration includes an AR HUD displaying real-time threat overlays, while the vehicle-mounted system features a ruggedized monitor with integrated threat markers. Secure data links transmit information to remote operators for coordinated responses. By integrating AI-driven analytics, AR visualization, and robust communication protocols, the system significantly enhances modern defense capabilities in dynamic combat environments.

Cooperative Ground-Based Tracking of Aerial Threats for Defense Applications

In response to the escalating need for advanced aerial threat detection and situational awareness in defense, we additionally propose the adaptation of **Cooperative Multi-Object Tracking (CoMOT)** frameworks—originally developed for autonomous vehicle perception[15,16,17]—to ground-based surveillance systems targeting the airspace. Mobile LiDAR-equipped ground units form a distributed sensor network capable of persistently scanning the sky for potential threats, such as hostile UAVs, drones, or other unidentified aerial platforms[18,19].

By leveraging a fully connected graph topology among multi-agent LiDAR detections, our approach applies **Graph Signal Processing (GSP)** techniques[20,21] to refine the 3D positioning of detected aerial objects. This enables the system to mitigate noise, reduce positional uncertainty, and fuse partially occluded or incomplete detections across agents into coherent tracking data[22,23].

The refined detections are subsequently processed through a one- or two-stage association mechanism—optionally enhanced with **Kalman filtering** to generate accurate and consistent object trajectories. Unlike traditional radar or single-sensor optical systems, this CoMOT-based architecture offers increased robustness to electronic interference, weather-induced signal degradation, and line-of-sight limitations. It draws on cooperative perception concepts demonstrated in vehicle-to-vehicle (V2V) systems[24], extending them vertically into aerial surveillance.

As such, it provides a scalable, real-time solution for **persistent airspace monitoring** around critical infrastructure, military installations, or border zones. This framework significantly enhances early warning capabilities, target tracking accuracy, and overall battlefield awareness—supporting **proactive threat mitigation** and secure defense operations[25].

Key Performance Indicators

To evaluate the effectiveness and reliability of the proposed E/O surveillance system, the following key performance indicators (KPIs) are suggested:

Detection Accuracy: Percentage of correctly detected aerial threats compared to actual threats present. Ensures the system reliably detects aerial threats while minimizing missed detections.

False Alarm Rate (FAR): Percentage of false positive detections (e.g., misclassifying birds as threats). Reduces unnecessary alerts and improves decision-making efficiency for users.

Threat Classification Accuracy: Correct classification of identified threats (e.g., differentiating between military drones, commercial UAVs, and birds). Ensures accurate identification of threats, preventing misclassification.

Detection Range: Maximum distance at which aerial threats can be detected. Determines the effective coverage area and early warning capability of the system.

Power Consumption and Battery Life: Operational runtime on a full charge (for wearable configuration). Ensures prolonged field usability without frequent recharging.

Environmental Adaptability: System performance across different environmental conditions (e.g., night, fog, rain). Ensures reliability in diverse battlefield environments.

System Weight and Portability: Total weight of the wearable system (helmet-mounted configuration). Ensures user comfort and ease of mobility for soldiers.

Implications for Military Applications

The integration of **day camera, thermal camera, and LiDAR** in the proposed E/O surveillance system provides a **multi-modal sensing approach**, ensuring robust detection and classification of aerial threats in various environmental and operational conditions. Each sensor brings unique strengths that compensate for the limitations of the others, leading to **higher accuracy, reduced false positives, and enhanced situational awareness**.

The **day camera**, typically a high-resolution CMOS or CCD sensor, captures images in the visible spectrum (400–700 nm) and plays a crucial role in:

- **Object Recognition and Classification:** The day camera provides high-fidelity images that allow AI models to identify the shape, color, and structural features of UAVs, distinguishing them from birds, debris, or other non-threat objects.
- **Visual Confirmation:** Soldiers and operators can visually confirm detections made by thermal and LiDAR sensors, reducing false alarms.
- **Long-Range Detection in Clear Conditions:** The day camera performs best in good lighting conditions, allowing early detection of drones at a longer range compared to thermal imaging.
- **Optical Zoom for Detailed Inspection:** Zoom capabilities enable detailed inspection of UAV payloads, which is useful for identifying potential weapons or surveillance equipment on enemy drones.

However, the day camera is limited by lighting conditions (e.g., low visibility at night, fog, or smoke) and can be ineffective against drones with camouflage or low contrast backgrounds (e.g., a white drone against a cloudy sky). This is where the thermal camera and LiDAR become crucial.

The **thermal imaging camera** detects infrared radiation emitted by objects in the long-wave infrared (LWIR) spectrum, typically 8–14 µm, and is highly effective in scenarios, such as:

- **Night-Time Operations:** Since drones often emit heat from their motors, battery packs, and electronics, thermal imaging enables 24/7 detection capability, independent of ambient light.
- **Detecting Drones with Stealth Coatings or Low Visibility:** UAVs designed to be low-contrast in visible light (e.g., matte black or sky-colored drones) can still be detected based on their heat signature.
- **Penetrating Fog, Smoke, and Haze:** Unlike visible light, thermal radiation can pass through some obscurants, allowing drone detection in environments where the day camera would fail.

However, thermal cameras do not provide fine visual details such as drone shape, markings, or payload type, which makes identification difficult without additional data from the day camera or LiDAR. Additionally, small drones with low heat output or those operating at ambient temperature can be harder to detect.

LiDAR (Light Detection and Ranging) uses laser pulses to measure distance and create real-time 3D point cloud maps of the environment. It complements both the day and thermal cameras in multiple ways:

- **3D Object Tracking:** LiDAR **provides precise distance, size, and shape data, allowing accurate tracking of drones regardless of lighting or temperature conditions.**
- **Altitude and Speed Estimation:** Unlike cameras, which rely on pixel-based estimations, LiDAR can directly measure a drone's height and velocity, crucial for threat classification.
- **Independent of Lighting Conditions:** Since LiDAR works by measuring the time-of-flight of laser pulses, it remains effective in complete darkness, bright daylight, or adverse weather.
- **Differentiation Between Objects:** While cameras may struggle to distinguish drones from birds, LiDAR provides precise shape data, allowing AI models to differentiate between them based on size, flight pattern, and structure.

However, LiDAR has some limitations:

- **Limited Range Compared to Optical Sensors:** While advanced LiDAR can detect drones at medium distances, it typically has a shorter range than high-powered optical cameras.

- **Decreased Performance in Heavy Fog or Rain:** While LiDAR is robust, extreme weather conditions (such as heavy rain or dense fog) can scatter laser pulses, affecting accuracy.
- **Weight:** Since LIDAR is of moderate weight, its use is limited to the vehicle-mounted variant of the proposed system.

A comparison table, highlighting the complementarity of the proposed technologies, is shown below:

Feature	Day Camera	Thermal Camera	LiDAR
Detection (Daylight)	Excellent	Moderate	Good
Detection (Night)	Poor	Excellent	Good
Detection (Fog/Smoke)	Poor	Good	Reduced
Detection (Long-Range)	Excellent	Good	Moderate
Classification	Yes	No	Yes
Motion Tracking	Yes	Yes	Yes
Speed Estimation	Approximate	Approximate	Precise
Ambient Light absence effectiveness	No	Yes	Yes

One of the most significant advantages of the proposed system is the **enhanced situational awareness**. Traditional air defense relies on centralized radar networks and fixed surveillance stations, which may be ineffective in detecting low-altitude or small UAV threats. By equipping individual soldiers and mobile units with a real-time detection system, the proposed solution decentralizes surveillance capabilities, enabling frontline personnel to identify threats independently. This shift in detection strategy ensures that soldiers are no longer reliant solely on command-and-control centers, reducing reaction time and improving battlefield responsiveness.

Another key benefit is the **portability and ease of deployment**. Unlike large-scale radar or fixed electro-optical tracking systems, this solution is designed to be compact and lightweight, making it suitable for both wearable and vehicle-mounted configurations. The helmet-mounted variant ensures that soldiers maintain full mobility without being burdened by excessive weight, while the vehicle-mounted version enhances reconnaissance and perimeter security for convoys and forward-operating bases. This flexibility makes the system ideal for deployment in urban warfare, remote operations, and dynamic battlefield environments where traditional surveillance infrastructure is unavailable.

The system also contributes to **improved defensive strategies** by offering multi-sensor data fusion for increased detection accuracy. By combining thermal imaging, visible-light cameras, and LiDAR, the system mitigates the limitations of any single sensor. For example, thermal imaging is effective in low-light conditions but may struggle with non-heat-emitting drones, while LiDAR provides precise distance measurements but can be affected by environmental factors like heavy rain or fog. The integration of these technologies results in a robust detection mechanism that enhances the military’s ability to counter emerging aerial threats such as drone swarms and loitering munitions.

Additionally, the system supports **seamless integration with existing military defense networks**. The communication module enables real-time data transmission to command centers or other personnel, facilitating coordinated responses to aerial threats. If coupled with counter-drone systems such as electronic jamming or directed-energy weapons, the system can serve as an early-warning mechanism that triggers automated defensive actions, significantly reducing the risk posed by hostile UAVs.

Its modular design, which allows deployment in both **vehicle-mounted** and **helmet-mounted** configurations, makes it adaptable to a wide range of mission types, including the following:

Convoy Security in Hostile Environments, Critical Infrastructure Protection, Special Forces Urban Operations, Border Surveillance and Anti-Smuggling Operations, Naval Operations and Maritime Security, Protection of High-Ranking Personnel and VIPs and Military Base Protection in a Warzone, to name a few.

Challenges and Limitations

The system faces several challenges, including false positives, power constraints, connectivity issues, environmental factors, cost, and user training. Distinguishing actual threats from benign objects remains a challenge despite AI improvements, as false alarms can lead to inefficiencies. Power limitations, especially for wearable versions, require optimization techniques, though advances in battery technology may be needed for extended use. Connectivity issues arise in electronic warfare scenarios, necessitating autonomous operation and secure communication methods. Environmental conditions like extreme weather can degrade sensor performance, requiring redundancy and adaptive filtering. High production costs may hinder widespread deployment, but modular design and phased rollout can help. Finally, effective user training and an intuitive interface are crucial to ensuring soldiers correctly interpret alerts and integrate the system into operations.

Conclusion

The proposed wearable and vehicle-mounted E/O surveillance system represents a significant advancement in real-time aerial threat detection for modern warfare. By offering enhanced situational awareness, portability, and multi-sensor detection capabilities, the system provides a critical advantage in countering emerging drone threats. However, challenges such as false positives, power constraints, and environmental limitations must be addressed to ensure its optimal performance. Through continuous refinement, AI model improvements, and integration with existing military defense networks, the system has the potential to become an indispensable tool for soldiers and tactical units operating in increasingly drone-dominated battlefields.

Recommendations for Future Research

The proposed electro-optical (E/O) surveillance system represents a major step forward in aerial threat detection, but further research is needed to enhance its capabilities. **Improving sensor fusion techniques** can boost detection accuracy and reduce false positives by integrating additional sensors such as radar or acoustic detection systems. **Advanced Deep Learning models** could refine sensor weighting dynamically based on environmental conditions and threat characteristics. Additionally, ongoing development of AI algorithms is essential to distinguish between friendly and hostile UAVs by analyzing behavioral patterns. Federated Learning approaches may improve classification accuracy while maintaining data security and scalability.

Beyond detection, **integrating counter-drone technologies** could create a more effective defense system by linking surveillance with automated response mechanisms like electronic jamming or directed-energy weapons. AI-driven predictive analytics could improve interception accuracy by anticipating drone movements. To ensure real-world effectiveness, large-scale field trials in diverse environments such as urban, desert, and maritime settings are crucial. Insights from military personnel can refine usability and interface design. Additionally, **cost reduction strategies**, including modular sensor alternatives, 3D-printed components, and AI optimization for lightweight processors, could make the system more affordable and scalable for widespread military deployment.

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