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AI-Driven GPS And Vision-Free Navigation for Military Drones: A Review of the CLAK Framework and Emerging Trends in GPS-Denied UAV Autonomy

Major Ankur Singh Pathania
Faculty of Combat Engineering, Military College of Telecommunication Engineering, Mhow

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ABSTRACT

Reliable navigation in Global Navigation Satellite System denied environments has emerged as a critical requirement for modern unmanned aerial vehicle operations, particularly in military scenarios characterized by electronic warfare, signal spoofing, and contested electromagnetic environments. Conventional UAV navigation systems rely extensively on GPS and optical sensing, making them vulnerable to jamming, low-visibility conditions, and adversarial countermeasures. This paper examines the CLAK framework, an artificial intelligence-based navigation architecture that enables drones to perform autonomous positioning without dependence on GPS or camera-based systems. The study analyzes the framework's sensor fusion approach, which integrates LiDAR, inertial measurement units, and barometric sensing with deep-learning architectures including convolutional neural networks, bidirectional long short-term memory (BiLSTM) networks, and attention mechanisms. The paper further situates CLAK within the broader evolution of GPS-denied navigation technologies, including inertial navigation systems, visual SLAM, visual-inertial odometry, and learning-based inertial navigation methods. Operational implications for military UAV applications such as autonomous swarming, urban reconnaissance, subterranean operations, and low-signature missions are evaluated. The study also discusses limitations related to domain adaptation, adversarial vulnerability, computational integration, and verification challenges. The paper concludes that AI-enabled non-visual navigation frameworks represent a significant advancement in resilient autonomous systems and are likely to become central components of future multi-domain military operations.

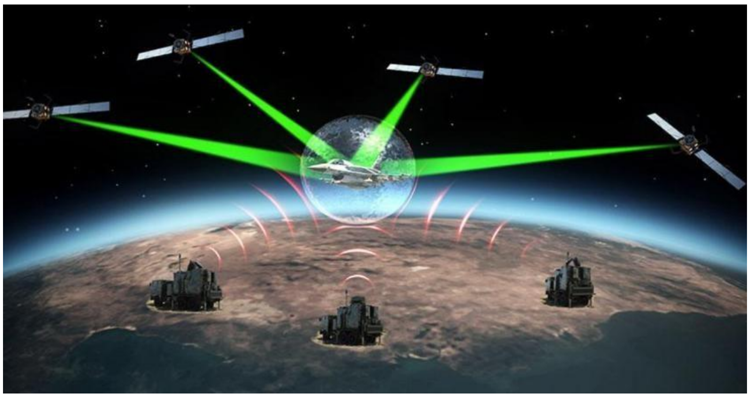
KEYWORDS
GPS-denied navigation; UAV autonomy; CLAK framework; LiDAR navigation; military drones; artificial intelligence; visual SLAM; electronic warfare.

1. INTRODUCTION

Modern military operations increasingly depend upon autonomous and semi-autonomous unmanned aerial vehicles (UAVs) for intelligence collection, surveillance, reconnaissance, target acquisition, and precision engagement missions. The effectiveness of these systems is strongly linked to reliable positioning, navigation, and timing (PNT) capabilities. However, contemporary operational environments are characterized by extensive electronic warfare activities, including jamming, spoofing, and degradation of Global Navigation Satellite System signals [8], [12]. As a result, traditional GPS-dependent UAV architectures face substantial operational vulnerabilities.

Despite significant advances in visual-inertial navigation systems, limited research has examined AI-enabled navigation frameworks capable of operating without dependence on both GPS and optical sensing. This study addresses that gap by evaluating the CLAK framework and its implications for future military UAV autonomy.

Figure 1. Autonomous UAV operating in a contested GPS-denied electromagnetic environment



In contested electromagnetic environments, disruption of satellite navigation can result in mission degradation, loss of situational awareness, or complete mission failure. Similar navigation challenges also arise in urban canyons, dense forests, underground environments, and indoor spaces where satellite visibility is naturally restricted. Consequently, the development of resilient GPS-independent navigation systems has become a strategic priority for both military and civilian UAV applications.

Recent advances in artificial intelligence and sensor fusion have accelerated the emergence of alternative navigation paradigms capable of functioning without direct reliance on satellite signals or optical sensing [5], [9]. Among these developments, the CLAK framework represents a significant innovation. Unlike conventional visual navigation systems, CLAK utilizes non-visual onboard sensors such as LiDAR, inertial measurement units, and barometric sensors combined with deep-learning architectures to estimate UAV position autonomously.

This paper presents a structured analytical review of the CLAK framework and evaluates its relevance within the broader evolution of GPS-denied UAV navigation systems. The study examines the framework's operational principles, compares it with existing navigation approaches, and assesses its potential military applications, technical limitations, and future research implications.

1.1 Contribution Statement

This paper contributes to the field of autonomous UAV navigation by

- synthesizing recent advances in GPS-denied and vision-free navigation technologies,
- providing a structured review of the CLAK framework and its sensor-fusion architecture, and
- evaluating its operational relevance for future military and multi-domain autonomous systems operating in contested electromagnetic environments.

2. LITERATURE REVIEW

2.1CLASSICAL GPS-DENIED NAVIGATION APPROACHES

Early GPS-independent navigation systems primarily relied upon inertial navigation systems, terrain-referenced navigation, and radio-based positioning methods. INS technologies estimate vehicle position by integrating acceleration and rotational motion data collected from onboard gyroscopes and accelerometers. Although effective for short-duration navigation, inertial systems experience cumulative drift errors over time, particularly when deployed on lightweight UAV platforms using low-cost MEMS sensors [9].

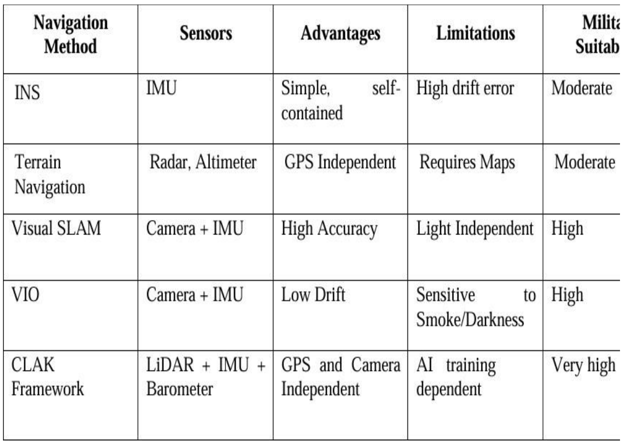
Terrain aided navigation approaches attempted to reduce this drift by comparing onboard sensor measurements with pre-existing terrain databases. However, these systems require highly accurate environmental maps and are sensitive to environmental changes, weather conditions, and intentional camouflage.

2.2VISION-BASEDNAVIGATION SYSTEMS

The emergence of visual odometry (VO), visual-inertial odometry (VIO), and simultaneous localization and mapping (SLAM) significantly improved GPS-denied UAV navigation capabilities. These systems utilize monocular, stereo, or RGB-D cameras to identify visual features across sequential image frames and estimate vehicle motion relative to the environment.

Visual SLAM systems additionally generate continuously updated environmental maps while simultaneously estimating vehicle position [4]. Recent developments integrating deep learning with visual navigation have enhanced robustness under moderate environmental degradation and dynamic motion conditions [3], [5].

Despite their effectiveness, visual navigation systems remain dependent on illumination, visibility, texture richness, and unobstructed line-of-sight conditions. Smoke, darkness, fog, dust, and optical countermeasures can substantially reduce their reliability in operational environments.



Navigation Method	Sensors	Advantages	Limitations	Milit Suitab
INS	IMU	Simple, self-contained	High drift error	Moderate
Terrain Navigation	Radar, Altimeter	GPS Independent	Requires Maps	Moderate
Visual SLAM	Camera + IMU	High Accuracy	Light Independent	High
VIO	Camera + IMU	Low Drift	Sensitive to Smoke/Darkness	High
CLAK Framework	LiDAR + IMU + Barometer	GPS and Camera Independent	AI training dependent	Very high

Table 1. Comparison of GPS-denied navigation methods

2.3AI-DRIVEN SENSOR FUSION FOR UAV NAVIGATION

Recent research has increasingly focused on artificial intelligence-based navigation architectures that integrate multiple sensor modalities using neural-network frameworks [5], [6], [9]. Deep learning methods are particularly effective in modeling nonlinear relationships between sensor observations and vehicle motion patterns.

The CLAK framework represents a transition toward non-visual AI-driven navigation [5], [6],[9]. Instead of relying upon camera imagery, the architecture processes LiDAR point clouds, inertial measurements, and barometric data to infer UAV position directly. By combining convolutional neural networks with recurrent temporal learning models and attention mechanisms, the framework enables autonomous navigation in environments where both GPS and visual sensing are degraded or unavailable.

3. METHODOLOGY

3.1 RESEARCH DESIGN

This study adopts a qualitative analytical review methodology based on secondary-source technical literature, defense technology reports, and contemporary research related to GPS-denied UAV navigation systems. The objective is to evaluate the operational significance and technological implications of the CLAK framework within modern autonomous military systems.

3.2 CLAK SENSOR ARCHITECTURE

The CLAK framework utilizes three principal sensor modalities:

3.2.1 LiDAR-based environmental sensing.

3.2.2 Inertial Measurement Units (IMUs).

3.2.3 Barometric altitude sensing.

LiDAR sensors provide geometric representations of surrounding terrain and structures through point-cloud generation. IMUs capture acceleration and angular velocity information required for short-term motion estimation, while barometric sensors provide altitude stabilization and vertical reference information.

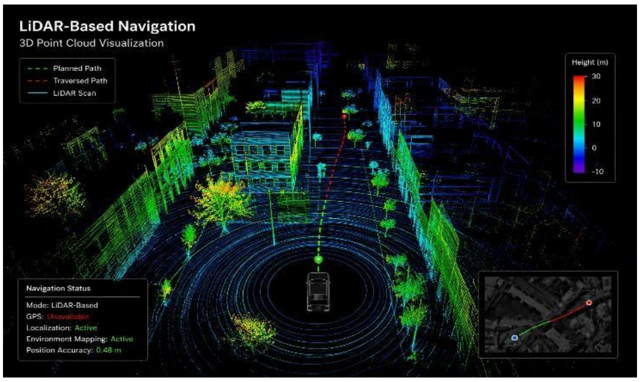
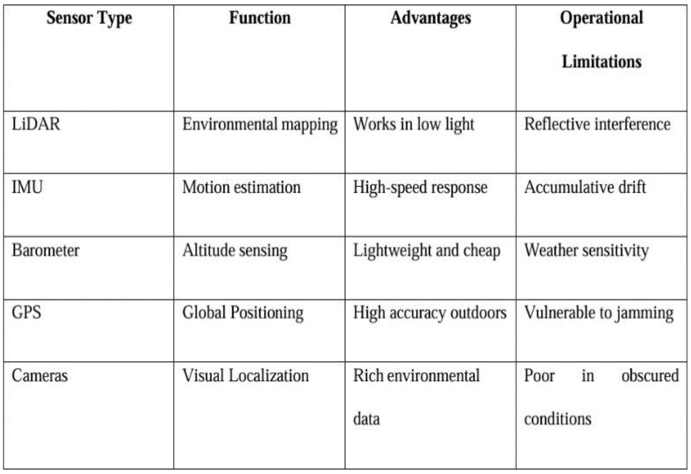


Figure 2. LiDAR-based environmental perception and point-cloud navigation representations

The integration of these sensing modalities enables the framework to maintain positional awareness without dependence on external navigation infrastructure.



Sensor Type	Function	Advantages	Operational Limitations
LiDAR	Environmental mapping	Works in low light	Reflective interference
IMU	Motion estimation	High-speed response	Accumulative drift
Barometer	Altitude sensing	Lightweight and cheap	Weather sensitivity
GPS	Global Positioning	High accuracy outdoors	Vulnerable to jamming
Cameras	Visual Localization	Rich environmental data	Poor in obscured conditions

Table 2. Sensor Comparison for autonomous UAV navigation

3.3 DEEP LEARNING PIPELINE

The CLAK architecture employs a multi-stage deep learning pipeline consisting of:

3.3.1 Convolutional neural networks for spatial feature extraction.

3.3.2 Bidirectional Long Short-Term Memory (BiLSTM) networks for temporal sequence modeling.

3.3.3 Attention mechanisms for prioritization of relevant sensor features.

3.3.4 Regression layers for coordinate estimation.

The network processes sequential sensor streams and estimates latitude, longitude, and altitude simultaneously. Training objectives focus on minimizing mean absolute positioning error between predicted and reference coordinates.

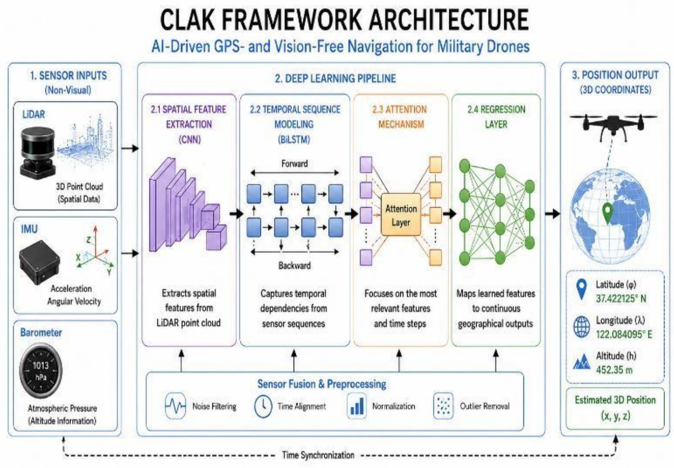


Figure 3. Sensor fusion and deep-learning architecture of the CLAK navigation framework

4. RESULTS AND ANALYSIS

Reported evaluations indicate that the CLAK framework achieves substantial improvements in navigation accuracy compared with baseline GPS-deniednavigation approaches. Experimental findings suggest reductions in positioning error exceeding 75% under simulated operational conditions. Similar improvements have been reported in recent deep-learning-based localization studies employing LiDAR and inertial sensor fusion techniques [6], [9],[11]. The framework demonstrates several significant operational characteristics:

4.1Robust performance under GPS-denied conditions.

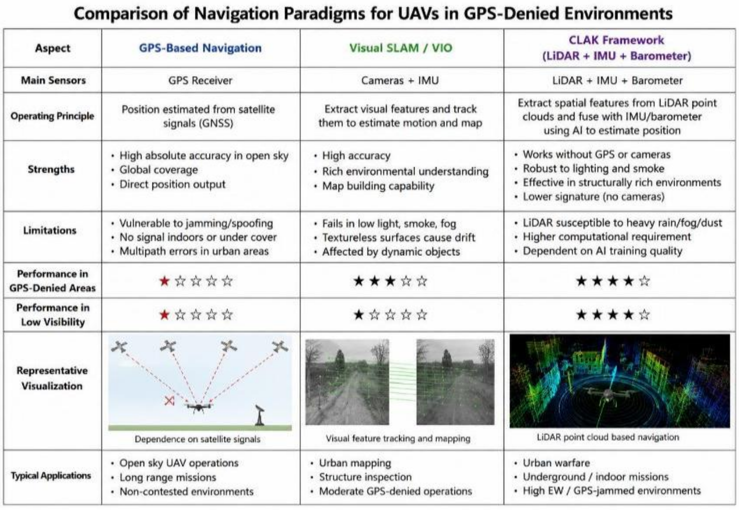
4.2Independence from camera-based sensing.

4.3Reduced susceptibility to low light and obscurant conditions.

4.4Compatibility with lightweight UAV platforms.

4.5Lower hardware complexity relative to advanced optical systems.

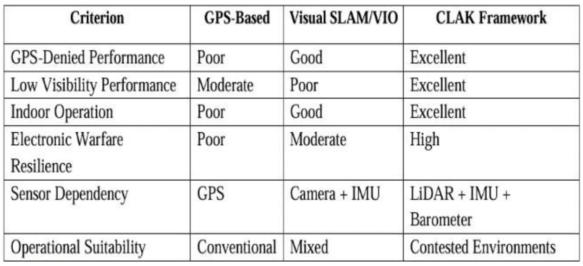
The use of non-visual sensing additionally improves resilience against optical countermeasures commonly encountered in contested military environments.



Comparison of Navigation Paradigms for UAVs in GPS-Denied Environments

Aspect	GPS-Based Navigation	Visual SLAM / VIO	CLAK Framework (LiDAR + IMU + Barometer)
Main Sensors	GPS Receiver	Cameras + IMU	LiDAR + IMU + Barometer
Operating Principle	Position estimated from satellite signals (GNSS)	Extract visual features and track them to estimate motion and map	Extract spatial features from LiDAR point clouds and fuse with IMU/barometer using AI to estimate position
Strengths	• High absolute accuracy in open sky • Global coverage • Direct position output	• High accuracy • Rich environmental understanding • Map building capability	• Works without GPS or cameras • Robust to lighting and smoke • Effective in structurally rich environments • Lower signature (no cameras)
Limitations	• Vulnerable to jamming/spoofing • No signal indoors or under cover • Multipath errors in urban areas	• Fails in low light, smoke, fog • Textureless surfaces cause drift • Affected by dynamic objects	• LiDAR susceptible to heavy rain/fog/dust • Higher computational requirement • Dependent on AI training quality
Performance in GPS-Denied Areas	★☆☆☆☆	★★★☆☆	★★★★☆
Performance in Low Visibility	★☆☆☆☆	★☆☆☆☆	★★★★☆
Representative Visualization	Dependence on satellite signals	Visual feature tracking and mapping	LiDAR point cloud based navigation
Typical Applications	• Open sky UAV operations • Long range missions • Non-contested environments	• Urban mapping • Structure inspection • Moderate GPS-denied operations	• Urban warfare • Underground / indoor missions • High EW / GPS-jammed environments

Figure 4. Comparison of GPS-Based, Visual SLAM, and CLAK Navigation Paradigms.



Criterion	GPS-Based	Visual SLAM/VIO	CLAK Framework
GPS-Denied Performance	Poor	Good	Excellent
Low Visibility Performance	Moderate	Poor	Excellent
Indoor Operation	Poor	Good	Excellent
Electronic Warfare Resilience	Poor	Moderate	High
Sensor Dependency	GPS	Camera + IMU	LiDAR + IMU + Barometer
Operational Suitability	Conventional	Mixed	Contested Environments

Table 3. Comparative Assessment of Navigation Paradigms

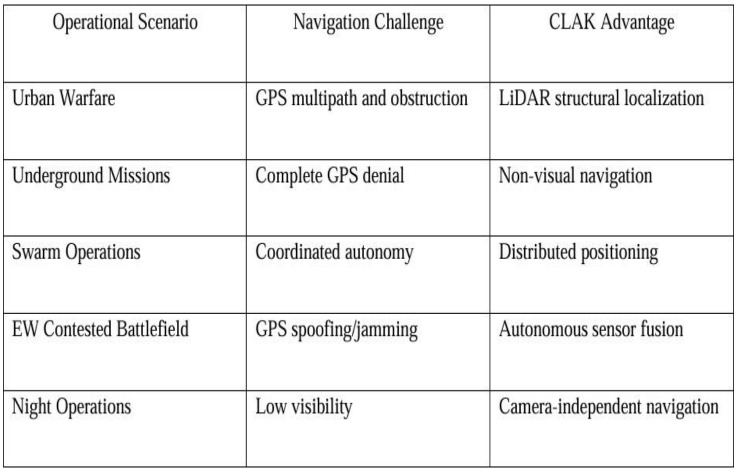
The comparative assessment indicates that CLAK-based architectures offer superior operational resilience in GPS-denied, low-visibility, and contested electromagnetic environments when compared with conventional GPS-dependent and visual SLAM-based approaches. However, these advantages are accompanied by increased dependence on high-quality training datasets and computational resources, highlighting the need for hybrid navigation architectures that balance robustness with operational practicality.

5. DISCUSSION

5.1MILITARY APPLICATIONS

AI-driven non-visual navigation architectures possess considerable strategic relevance for future military operations. In contested electromagnetic environments, autonomous UAVs equipped with GPS-independent navigation systems can continue reconnaissance, targeting, communication relay, and strike missions despite extensive electronic warfare interference.

Urban warfare environments represent another important application domain. Dense infrastructure, subterranean passages, and indoor structures frequently degrade both GPS and visual navigation systems. LiDAR-driven sensor fusion offers enhanced navigation reliability within these complex operational spaces.



Operational Scenario	Navigation Challenge	CLAK Advantage
Urban Warfare	GPS multipath and obstruction	LiDAR structural localization
Underground Missions	Complete GPS denial	Non-visual navigation
Swarm Operations	Coordinated autonomy	Distributed positioning
EW Contested Battlefield	GPS spoofing/jamming	Autonomous sensor fusion
Night Operations	Low visibility	Camera-independent navigation

Table 4. Operational applications of CLAK - Type Navigation Systems

5.2SWARM AUTONOMY AND DISTRIBUTED OPERATIONS

Autonomous swarming concepts supported by AI-enabled navigation architectures are increasingly being explored for future military operations [7]. GPS-denied navigation frameworks may enable decentralized swarm coordination without reliance on centralized navigation infrastructure.

By combining onboard sensor fusion with inter-platform communication, autonomous swarms could maintain coordinated behavior while operating in heavily contested electromagnetic environments.

5.3TECHNICAL LIMITATIONS

Despite its advantages, the CLAK framework faces several technical challenges. AI-based navigation models remain heavily dependent on training data quality and environmental diversity. Performance degradation may occur when deployed in environments significantly different from training conditions.

Additional concerns include:
5.3.1 Adversarial manipulation of sensor inputs [8].

5.3.2 LiDAR spoofing and reflective deception [11].

5.3.3 Computational resource limitations.
5.3.4 Verification and validation difficulties.

5.3.5 Limited explainability of deep learning decisions.

These limitations highlight the importance of hybrid navigation architectures combining data-driven and model-based approaches.

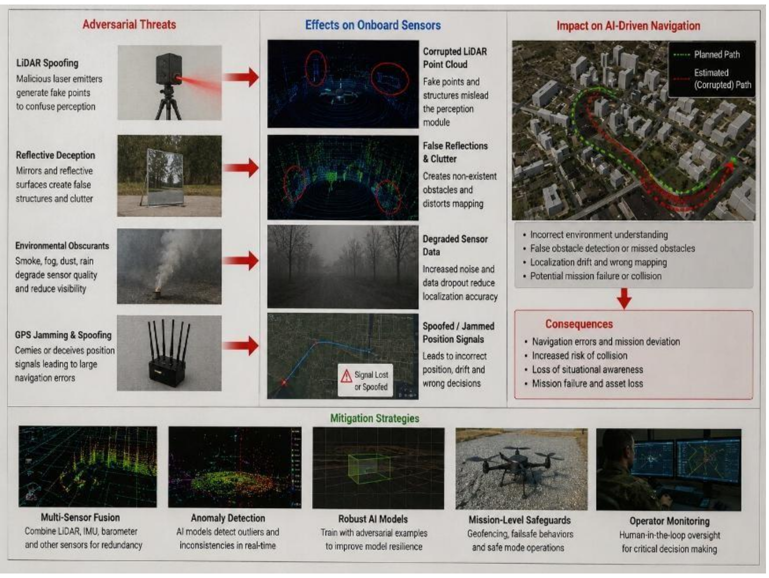


Figure 5. Adversarial manipulation and deceptive environmental effects against AI-driven UAV navigation systems

5.4ETHICAL AND STRATEGIC IMPLICATIONS

The advancement of resilient autonomous navigation technologies may accelerate the deployment of fully autonomous combat drones capable of operating without external guidance. Such developments raise important ethical, legal, and strategic questions related to escalation risks,accountability, and autonomous weapons governance.

Furthermore, widespread deployment of GPS-independent UAV systems could complicate civilian airspace regulation and surveillance mechanisms traditionally dependent on GNSS-based tracking.

6. STUDY LIMITATIONS

This study is based primarily on secondary-source analysis of publicly available technical literature and reported experimental findings. The absence of access to proprietary CLAK datasets and field-test results limits independent validation of performance claims. Consequently, conclusions should be interpreted as analytical assessments rather than experimental verification.

7. CONCLUSION

This review demonstrates that the CLAK framework represents a significant advancement in the evolution of GPS-denied UAV navigation technologies. By integrating LiDAR, inertial sensing, barometric measurements, and deep learning architectures, the framework demonstrates the feasibility of autonomous drone navigation without reliance on either satellite navigation systems or optical sensors.

The study indicates that AI driven non-visual navigation systems possess considerable operational relevance for future military applications, particularly within contested electromagnetic environments characterized by GPS disruption and degraded visibility conditions. Such technologies support resilient reconnaissance, autonomous swarming, subterranean operations, and low signature mission profiles.

However, important technical and strategic challenges remain unresolved, including robustness under domain shift, adversarial resilience, explainability, and certification for mission-critical deployment. Future research should prioritize hybrid navigation architectures, standardized evaluation benchmarks, edge AI optimization, and operational testing under realistic combat conditions.

As multi-domain operations continue to evolve, resilient AI-enabled navigation systems are likely to become foundational components of next-generation autonomous military platforms.

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DECLARATIONS

Conflict of Interest: The author declares no conflict of interest.

Funding: No external funding was received for this study.

Ethical Approval: This study does not involve human participants, human data, or animal subjects.

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