Proceedings of CONF-SPML 2026 Symposium: The 2nd Neural Computing and Applications Workshop 2025
DOI: 10.54254/2755-2721/2026.TJ30153

A Review of Technologies Related to the Application of Inertial Navigation on Unmanned Aerial Vehicles

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Abstract. Swarm collaborative navigation of Unmanned Aerial Vehicles (UAVs) is critical for both civilian (e.g., agricultural machinery fleets, urban drone logistics) and military (e.g., tactical formations, search-and-rescue) applications. However, it faces significant challenges in Global Navigation Satellite System (GNSS)-denied environments: traditional GNSS signals are easily compromised by jamming, spoofing, or non-line-of-sight (NLOS) conditions, while standalone Inertial Navigation Systems (INS) suffer from inevitable error accumulation over time, making long-duration operation impractical. To address these limitations, INS fusion strategies have become the core of reliable swarm navigation. This review focuses on three mainstream INS fusion strategies for UAV swarm collaborative navigation in GNSS-denied scenarios: distributed GNSS/INS-Ultra-Wideband (UWB) fusion, swarm intelligence-optimized INS error modelling, and anti-interference-enhanced fusion architecture. It systematically analyses the underlying principles, advantages, limitations, and optimal application scenarios of each strategy by synthesizing recent experimental data (e.g., centimetre-level positioning accuracy of distributed UWB-INS fusion, 70% error reduction of swarm intelligence-based modelling) and technical insights. The review fills the existing gap of lacking systematic trade-off analysis among robustness, cost, and scalability of these strategies, and provides a practical guide for selecting appropriate fusion schemes based on specific swarm requirements (e.g., GNSS availability, cost budget, communication conditions). This work aims to support the development of more resilient and adaptable UAV swarm navigation systems in complex GNSS-denied environments.

Keywords: Inertial Navigation, GNSS denied scenarios, UAV swarm collaborative navigation

1. Introduction

Swarm collaborative navigation has emerged as a critical technology for diverse applications, ranging from civilian tasks like agricultural machinery fleet operations and urban drone logistics to military scenarios such as tactical formation missions and search-and-rescue operations [1]. Unlike single-platform navigation, swarm systems rely on inter-agent coordination to enhance robustness, but they face unique challenges: Global Navigation Satellite System (GNSS) signals—traditional staples for high-precision positioning—are often compromised by jamming, spoofing, or non-line-

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DOI: 10.54254/2755-2721/2026.TJ30153

of-sight (NLOS) conditions (e.g., urban canyons, dense farmland, or contested battlefields) [2]. Standalone Inertial Navigation Systems (INS), while independent of external signals, suffer from inevitable error accumulation over time (e.g., position drift of 1.5–2% per hour for low-cost INS), making long-duration unaided operation impractical [3]. To address these limitations, INS fusion strategies—integrating INS with inter-swarm sensing, intelligent algorithms, or auxiliary signals—have become the core of reliable swarm navigation.

Current INS fusion strategies for swarms follow distinct technical paths, each tuned to specific constraints (e.g., cost, environmental interference, communication latency). The first is distributed GNSS/INS-UWB fusion, which uses Ultra-Wideband (UWB) inter-agent ranging to bridge GNSS outages. Filters such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) fuse INS pre-integration with UWB relative-distance measurements, achieving meter-level positioning in GNSS-denied settings [4]. Its strength is strong anti-interference performance; its weakness is susceptibility to UWB NLOS errors, which necessitates added detection and compensation (e.g., chi-square testing), increasing complexity [1].

A second path focuses on swarm intelligence-optimized INS error modelling, designed for low-cost swarms (e.g., consumer-grade drones or small agricultural robots). Techniques such as the Artificial Bee Colony (ABC) algorithm optimizing Backpropagation (BP) neural networks calibrate INS drift by learning from GNSS/BDS (BeiDou Navigation Satellite System) data during signal availability [4]. This strategy reduces hardware costs (using MEMS INS instead of tactical-grade sensors) and maintains acceptable accuracy (position error <30 m for farm machinery), but it depends heavily on initial GNSS initialization and performs poorly in prolonged GNSS denial [4].

The third category comprises anti-interference-enhanced fusion architectures that address dense-swarm computation bottlenecks and communication latency. Factor-graph frameworks with Sigma-Point Filtering (SPF) enable distributed confidence propagation, cutting computational load by almost half for swarms exceeding 100 agents [3]. Modular Cubature Kalman Filter (CKF) designs with data buffers accommodate time-varying communication delays (up to 200 milliseconds), limiting error divergence in electromagnetically contested environments [4]. These gains come at the cost of higher on-board computing demands, constraining use in resource-limited micro-swarms.

Despite notable advances, a systematic comparison of these strategies—balancing robustness, cost, and scalability—remains scarce. This review addresses that gap by analyzing three mainstream INS fusion approaches for swarm collaborative navigation: their principles, advantages, limitations, and best-fit scenarios. By synthesizing recent experimental results and technical insights, it guides the selection of fusion schemes based on specific swarm requirements (e.g., GNSS availability, cost budget, communication conditions), supporting the development of more resilient swarm navigation systems.

2. Review on latest relevant research

The field of inertial navigation systems (INS) is experiencing rapid advancements, fuelled by breakthroughs in multi-sensor fusion, MEMS (Micro-Electro-Mechanical Systems) miniaturization, and artificial intelligence (AI) integration. In autonomous driving—one of the most demanding INS application areas—tightly coupled GNSS (Global Navigation Satellite System)/INS/wheel odometry systems have become mainstream. For instance, Baidu Apollo's navigation solution employs factor graph optimization to fuse real-time IMU (Inertial Measurement Unit) pre-integration data with visual feature matching results, enabling centimetre-level positioning even at complex, heavily occluded intersections [5]. This robustness is further enhanced by progressive two-source fusion

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frameworks (GNSS/INS), which dynamically adjust sensor weights based on environmental confidence levels, reducing the positioning failure probability to smaller extent [6].

MEMS-based IMUs have now achieved full automotive-grade maturity, with commercial products delivering both performance and reliability. TDK's IAM-20685, for example, complies with ASIL-B safety standards in a compact 4.5×4.5mm form factor, while offering 20g RMS vibration tolerance and a 15-year operational lifespan—critical for supporting automated parking and drive-by-wire systems [7]. Chinese manufacturers have also made significant strides: their 6-axis MEMS IMUs integrate AI-driven real-time temperature drift compensation algorithms, maintaining a bias stability of 0.01°/hour at only one-third the cost of Bosch's equivalent products [8].

Deep learning is revolutionizing INS error mitigation strategies by addressing long-standing challenges in dynamic error modelling. Long Short-Term Memory (LSTM) networks, for instance, capture the temporal correlation of gyroscope bias drift, reducing such drift by 37% through predicting zero-offset fluctuations under dynamic temperature variations [9]. In specialized scenarios like underwater navigation, hybrid CNN (Convolutional Neural Network)-attention models fuse IMU data with underwater camera feeds; these models use attention mechanisms to prioritize motion-correlated visual features, cutting trajectory estimation error to 6.38% even in turbulent sea conditions [10].

Quantum and visual-aided solutions address GNSS vulnerability. Cold atom interferometers, as explored in recent studies, cool atoms to microkelvin temperatures to measure three-dimensional motion via atomic interference patterns, promising sub-millimetre precision. Huawei's experimental quantum-IMU module builds on this, using atom trap arrays to achieve 0.001°/hour stability [11]. For contested environments, Inertial Labs' VINS combines IMU pre-integration with visual SLAM map matching, maintaining 35m horizontal accuracy by correcting drift through environmental feature registration—critical for UAV operations amid rising GPS jamming possibility [12].

These advancements position INS as a cornerstone of resilient positioning systems. With the global automotive inertial navigation market has already exceeded USD 5.47 billion in 2024 [13]. Ongoing standardization efforts and AI-enhanced adaptive filtering will further expand applications in autonomous mobility, robotics, and aerospace.

3. Comparative analysis of existing combination paths in different scenarios

3.1. Advantages of distributed GNSS/INS-UWB fusion technology

The distributed GNSS/INS-UWB fusion technology is well-suited for scenarios where high-precision positioning is required amid GNSS denial, including urban canyons with dense high-rises (which severely block satellite signals), complex indoor environments such as large underground shopping malls and subway tunnels, collaborative operations of UAV swarms (e.g., formation-based agricultural spraying and search-and-rescue missions), and military electronic warfare zones. Operating on a hierarchical collaborative positioning framework, it leverages UWB's inherent advantages—operating in the 3.1–10.6 GHz frequency band, adopting time-hopping spread spectrum (TH-SS) and pulse coding technologies—to effectively counter narrowband interference and multipath effects. To mitigate positioning errors, it employs Factor Graph Optimization (FGO) to dynamically adjust the weight distribution between INS and UWB data; for instance, in tunnel scenarios, this reduces the circular error probable (CEP) to less than 0.8 meters. It also uses an event-triggered communication mechanism, transmitting data only when positional deviations exceed 5 cm, which significantly lowers network bandwidth consumption. Representative cases

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include Tsinghua University's 3D UWB array system, which achieved a dynamic positioning error of less than 0.1 meter in a 20m×25m×4m test site with multi-floor obstructions, and the Lingyun U15 UAV, which maintained centimetre-level positioning accuracy (0.8 cm) even under strong electromagnetic jamming.

3.2. Advantages of INS error modelling

The INS error modelling based on swarm intelligence optimization excels in dynamically complex environments where INS drift is prone to exacerbation, such as mountainous areas with rugged terrain, jungles with dense vegetation, autonomous navigation of mobile robots (e.g., self-guided handling robots in warehouse logistics), long-endurance missions of Underwater Unmanned Vehicles (UUVs) (e.g., deep-sea resource exploration), and penetration operations of military tactical teams (e.g., reconnaissance missions in uncharted jungle areas). This approach simulates biological group behaviours—such as particle swarms and lion prides—to achieve global optimization: for example, the Particle Swarm Optimization (PSO) algorithm balances global exploration and local exploitation via velocity update formulas, converging within 50 iterations even in complex terrain, and improving path planning efficiency by 40%. It builds an online learning framework using reinforcement learning to real-time adjust INS error compensation parameters (e.g., zero bias and scale factor) and adopts lightweight neural networks like MobileNetV2 for edge-device inference, ensuring a latency of less than 50 ms. Through distributed weighted projection algorithms, multiple nodes mutually calibrate errors; a case study by MIT showed that the positioning error of a 10-UAV swarm was 70% lower than that of a single UAV. Another typical application is the SINS/DVL integrated navigation system developed by the Institute of Acoustics, Chinese Academy of Sciences, which achieved a voyage error rate of 0.5% at a water depth of 200 meters.

3.3. Advantages of anti-jamming enhanced fusion architecture

The anti-jamming enhanced fusion architecture is primarily designed for high-interference GNSS-denied environments, including military electronic warfare zones (e.g., areas with enemy GNSS spoofing and jamming), crowded urban locations like large exhibitions and stadiums (where civilian signals such as Wi-Fi and Bluetooth cause severe interference), industrial Internet of Things (IIoT) scenarios (e.g., collaborative navigation of robotic arms and AGVs in smart factories), and UAV swarm combat missions (e.g., jamming enemy radars while maintaining self-positioning). It integrates multi-source data from INS, visual sensors, and radio frequency (RF) fingerprints, and adopts a multi-layer anti-jamming strategy: at the physical layer, it uses 2.4 GHz dual-band frequency hopping (FHSS) at 100 hops per second and direct sequence spread spectrum (DSSS); at the protocol layer, it relies on the adaptive CSMA/CA mechanism of the IEEE 802.15.4-2020 standard, reducing collision probability by 72%; at the algorithm layer, it implements anti-spoofing model updates via Federated Learning, with a GNSS spoofing detection accuracy of 96% using Variational Autoencoders (VAE). It also supports real-time switching of modulation schemes and coding strategies through software-defined radios (e.g., USRP B210). A notable case is the INS/terrain matching system supporting the Russian military's "Bolei-21" electronic warfare system, which maintained a voyage error of less than 50 meters within a 100 km-radius GNSS denial zone. The ZigBee 10.0 industrial network, another example, shortened network reconfiguration time to 35 ms and achieved a node handover success rate of 98.7%.

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4. Conclusion

In feature comparison, distributed GNSS/INS–UWB fusion delivers centimetre-level precision and supports multi-node collaboration but encounters bottlenecks in node synchronisation (requiring microsecond-level accuracy) and communication bandwidth, with medium-to-high cost due to UWB base-station deployment. Swarm-intelligence-optimised INS error modelling adapts well to dynamic environments and resists model uncertainty, yet depends on real-time computing resources and training data, with moderate cost centred on algorithm optimisation. Anti-jamming-enhanced fusion architectures offer high robustness and multi-modal anti-jamming capability, but impose high hardware complexity (anti-jamming RF chips and multi-sensor integration) and face spectrum resource competition, resulting in high costs. In practice, scenarios demanding high precision (e.g., indoor warehouse robots) prioritise distributed UWB–INS fusion; dynamically complex environments (e.g., mountain rescue) suit swarm-intelligence-optimised INS error modelling; and high-interference settings (e.g., military operations) favour anti-jamming-enhanced fusion. These solutions can also be combined as needed to ensure reliable navigation in GNSS-denied environments.

Looking ahead, INS fusion for unmanned aerial vehicle clusters in GNSS-denied settings can advance along four lines: (1) overcoming current bottlenecks—for example, using AI to improve UWB NLOS error compensation and node synchronisation, reducing group-intelligence modelling's reliance on GNSS via self-supervised learning, and lowering anti-interference hardware complexity with low-power SDR; (2) expanding cross-scenario and multi-domain applications by building a scene-aware framework for dynamic switching of fusion algorithms and enabling coordinated air–sea–land navigation; (3) deepening intelligent upgrades through end-to-end pre-trained models and federated, reinforcement-learning-driven autonomous evolution; and (4) promoting standardisation by formulating multi-sensor fusion protocols, establishing universal test benchmarks, reducing the cost of high-performance components, and accelerating deployment in civilian and critical domains to build a more robust and efficient cluster navigation system.

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