ISSN 2616-5767 Vol.9, Issue 3: 149-157, DOI: 10.25236/AJETS.2026.090319

Key Technologies and Equipment Applications for High-Precision Navigation and Positioning in Deep Sea

Zhu Zhentao

Underwater Acoustic Navigation Research Laboratory, Qingdao Institute of Intelligent Navigation and Control, Qingdao, 266071, China
984093882@qq.com

Abstract: *Deep-sea exploration demands centimeter-to-meter level positioning accuracy in environments where satellite signals cannot penetrate. This paper reviews the core technologies that enable high-precision underwater navigation, including strapdown inertial navigation systems (SINS), Doppler velocity logs (DVL), acoustic positioning arrays (USBL/LBL), and emerging AI-driven multi-sensor fusion methods. We organize these technologies into a five-layer architecture—from raw sensor data acquisition through signal processing, information fusion, navigation solution, to end-use applications—and analyze how each layer addresses the unique challenges of deep-sea operation: extreme hydrostatic pressure, acoustic multipath interference, geomagnetic anomalies, and long-duration drift accumulation. We examine recent breakthroughs in deep learning-enhanced DVL error compensation, invariant extended Kalman filtering, factor graph optimization for tightly coupled SINS/DVL/USBL integration, and gravity gradient-aided terrain matching. A systematic comparison reveals that single-technology approaches reach fundamental accuracy limits: acoustic methods achieve 0.01–5 m but require surface infrastructure, inertial integration maintains 0.5–5 m but drifts over time, and geophysical matching covers 10–500 m with full depth capability. Multi-source fusion that combines these complementary strengths now delivers sub-meter accuracy at depths exceeding 6,000 m. We identify three frontier directions that could reshape the field: neuromorphic sensor fusion that replaces handcrafted filter models, quantum inertial measurement that eliminates gyroscope drift at its physical source, and swarm-cooperative navigation that distributes positioning tasks across autonomous vehicle fleets. These advances will directly support the next generation of deep-sea mineral extraction, submarine cable maintenance, and full-ocean-depth scientific survey.*

Keywords: *deep-sea navigation; underwater positioning; inertial navigation; acoustic positioning; multi-sensor fusion; autonomous underwater vehicle*

1. Introduction

1.1 Background and Importance of Deep-Sea Navigation

The ocean covers 71% of the Earth's surface, and more than 95% of the deep seafloor below 1,000 m remains unmapped at resolutions useful for scientific or industrial work. Unlike land and airborne operations where the Global Navigation Satellite System (GNSS) provides meter-level or better positioning, underwater vehicles lose all satellite contact within a few meters of the surface. This fundamental constraint forces deep-sea platforms—autonomous underwater vehicles (AUVs), remotely operated vehicles (ROVs), and human-occupied vehicles (HOVs)—to rely on self-contained sensors and acoustic links that each carry significant limitations.

The stakes keep rising. China's Jiaolong submersible reached 7,062 m in the Mariana Trench, and the Fendouzhe achieved 10,909 m in 2020. The International Seabed Authority has approved 31 mineral exploration contracts covering more than 1.3 million square kilometers of seafloor. Subsea cable networks now carry over 95% of intercontinental data traffic. Each of these operations requires positioning accuracy between 0.1 m and 10 m, sustained over missions lasting hours to days, at depths where pressure reaches 1,100 atmospheres. A positioning error of just 5 m can cause an AUV to miss a hydrothermal vent survey target entirely or damage a subsea cable during maintenance.

1.2 Challenges in Deep-Sea Navigation and Positioning

Current navigation systems face four interconnected challenges. First, inertial navigation systems (INS) accumulate drift errors at rates of 0.5–2 nautical miles per hour for marine-grade units [1], which means a 10-hour AUV mission can end with position uncertainty exceeding 10 km without external corrections. Second, acoustic positioning systems like ultra-short baseline (USBL) and long baseline (LBL) provide external reference fixes, but their accuracy degrades with depth, multipath reflections, and sound speed variations that change with temperature, salinity, and pressure [2]. Third, Doppler velocity logs (DVL) measure vehicle velocity relative to the seafloor with high precision, but they fail when the vehicle flies above the DVL's acoustic range (typically 200–600 m above bottom) or when bottom-lock signals scatter on rough terrain [3]. Fourth, geophysical matching methods—gravity, magnetic, and terrain-based—offer drift-free positioning in theory, but they require pre-existing high-resolution seafloor maps that simply do not exist for most deep-ocean areas [4].

1.3 Scope and Organization of This Review

This review examines how researchers and engineers combine these imperfect technologies into integrated systems that overcome their individual weaknesses. We focus on advances published between 2021 and 2025, a period that produced fundamental shifts in three areas: deep learning replaced handcrafted error models for sensor fusion [5,3], factor graph optimization challenged the decades-long dominance of Kalman filtering [6], and cooperative multi-vehicle navigation moved from simulation to ocean trials [7,8]. We structure the review around a five-layer navigation architecture (Figure 1) and close with three frontier research directions that we believe will define the field over the next decade.

2. Sensor Technologies: What Each Device Actually Measures

2.1. Strapdown Inertial Navigation: Tracking Motion from Within

A strapdown inertial navigation system (SINS) contains three accelerometers and three gyroscopes mounted rigidly to the vehicle body. The system measures specific force and angular rate, then integrates these measurements twice (for position) or once (for velocity) through a computational process called strapdown calculation. The critical advantage of SINS is complete self-containment: it needs no external signals, works at any depth, and operates continuously without gaps.

The critical disadvantage is drift. Integration of noisy sensor measurements causes position errors that grow without bound over time. Navigation-grade fiber optic gyroscopes drift at 0.01–0.1 degrees per hour, while tactical-grade MEMS gyroscopes drift at 1–10 degrees per hour. Potokar et al. [1] showed that an invariant extended Kalman filter (InEKF) reduces the linearization errors that standard EKF introduces during strapdown calculation. Their experiments on real AUV data demonstrated that InEKF maintains consistent error bounds that standard EKF violates during aggressive maneuvers. This matters because deep-sea vehicles frequently execute sharp turns and depth changes that push standard linearization beyond its valid range.

The SINS error model contains more than 20 parameters—gyroscope biases, scale factors, misalignments, accelerometer biases, and installation angles—that must be calibrated before each mission. Wang et al. [9] developed a quasi-Newton quaternion-based calibration method that estimates DVL-to-SINS mounting errors using GNSS data during surface transit, then applies these corrections throughout the underwater phase. Their approach reduced heading errors by 35% compared to conventional calibration.

2.2. Doppler Velocity Log: Measuring Speed against the Seafloor

A DVL transmits four acoustic beams at a fixed angle (typically 30 degrees from vertical in a Janus configuration) toward the seafloor. By measuring the Doppler frequency shift of each return echo, the DVL calculates three-axis velocity relative to the bottom with accuracy of 0.1–0.5% of the measured speed. When combined with SINS through dead reckoning, DVL velocity measurements bound the position drift that pure inertial navigation would otherwise accumulate.

DVL faces two failure modes that directly threaten navigation safety. First, when the vehicle altitude exceeds the DVL's maximum range (300–600 m for typical 300 kHz units), all four beams lose bottom lock simultaneously, and the navigation system receives no velocity updates. Second, individual beams

ISSN 2616-5767 Vol.9, Issue 3: 149-157, DOI: 10.25236/AJETS.2026.090319

can produce outlier measurements when they strike rough terrain at steep angles or encounter acoustic scattering layers in the water column.

Cohen and Klein [3] attacked the first problem with BeamsNet, a deep neural network that predicts DVL velocity from IMU measurements when bottom lock fails. They trained the network on paired IMU-DVL data from real AUV missions, then tested it on held-out segments where DVL was deliberately disabled. BeamsNet reduced velocity estimation error by 60% compared to pure inertial propagation during DVL outages lasting up to 5 minutes. Li et al. [5] addressed the same challenge with a different deep learning architecture that estimates navigation corrections directly from IMU data patterns, achieving similar improvements on a different AUV platform.

Davari and Aguiar [10] targeted the second problem—beam outliers—with a hybrid autoencoder-RNN detector that identifies anomalous DVL measurements in real time. Their method correctly flagged 96% of outlier readings while producing less than 2% false alarms, which allowed the navigation system to reject bad data before it corrupted the position solution.

2.3. Acoustic Positioning: External Reference from Surface or Seafloor

Acoustic positioning systems provide absolute position fixes that reset accumulated drift errors. Three configurations dominate: Long Baseline (LBL) uses an array of seafloor-mounted transponders with known positions to trilaterate the vehicle's location, achieving 0.01–0.5 m accuracy within the array. Ultra-Short Baseline (USBL) places a compact transducer array on the surface vessel and measures the range and bearing to a transponder on the vehicle, achieving 0.1–5 m accuracy depending on depth and range. Short Baseline (SBL) distributes transducers across the hull of a surface vessel and provides intermediate accuracy.

Xue et al. [2] achieved centimeter-level seafloor positioning by combining GNSS-Acoustic techniques with a self-structured empirical sound speed profile. Their key insight was that sound speed errors—not measurement noise—dominate the positioning error budget at depth. By simultaneously estimating the sound speed profile along with position, they reduced systematic errors that conventional fixed-profile methods cannot remove.

2.4. Geophysical Matching: Terrain, Gravity, and Magnetic Fingerprints

These methods compare real-time sensor readings against pre-built maps of the seafloor's physical characteristics. Gravity gradient matching uses a gradiometer to measure local gravity variations caused by subsurface density anomalies, then searches a gravity database for the best-matching location. Li et al. [4] improved gravity gradient matching accuracy by 28% through a genetic algorithm-based weighted image matching method that handles the inherent ambiguity in gravity gradient maps—where multiple locations can produce similar gradient patterns.

Terrain-aided navigation uses DVL or multibeam sonar to build a local elevation profile, then matches it against a bathymetric database. This approach works well in areas with distinctive seafloor features but fails over flat abyssal plains where the terrain lacks unique signatures.

3. Fusing Imperfect Sensors into Reliable Navigation

No single sensor technology provides adequate deep-sea navigation by itself. The central engineering challenge is to combine measurements from multiple sensors—each with different error characteristics, update rates, and failure modes—into a unified navigation solution that exceeds the capability of any individual component. This section examines three fusion paradigms that have shaped recent progress.

3.1. Adaptive Kalman Filtering: The Dominant Framework under Pressure

The extended Kalman filter (EKF) has dominated underwater navigation for decades because it provides a mathematically principled way to fuse measurements with different noise characteristics. The standard approach models the SINS as the system dynamics and treats DVL, USBL, and depth sensor measurements as observation updates. However, the standard EKF assumes that the process noise and measurement noise covariance matrices are known and constant—an assumption that fails underwater where noise properties change with depth, speed, and acoustic conditions.

Liu et al. [11] proposed a dual adaptive factor method for SINS/DVL integration that adjusts both the

ISSN 2616-5767 Vol.9, Issue 3: 149-157, DOI: 10.25236/AJETS.2026.090319

process noise and measurement noise in real time based on innovation sequence analysis. Their sea trial results showed 41% improvement in positioning accuracy compared to standard EKF during a 2-hour AUV mission with varying acoustic conditions. Liu et al. [12] took a different approach with a modified Sage-Husa adaptive filter that estimates the measurement noise covariance online, achieving 30% error reduction in AUV tests.

Shi et al. [13] addressed the more challenging problem of sensor faults during operation. Their variational Bayesian robust adaptive Kalman filter for SINS/HSB/DVL integration detects and compensates for sudden sensor failures by modifying the filter's noise model when the innovation sequence exhibits non-Gaussian behavior. In simulated DVL failure scenarios, their method maintained navigation accuracy within 2× of the no-failure baseline, while the standard EKF diverged within minutes.

3.2. Graph Optimization: A New Mathematical Foundation

Factor graph optimization represents a fundamental departure from filtering approaches. Instead of processing measurements sequentially and maintaining only the current state estimate, graph optimization stores all measurements and state variables as nodes in a graph, then solves for the entire trajectory simultaneously by minimizing a global cost function. This approach naturally handles delayed measurements, loop closures, and non-linear constraints that EKF approximates poorly.

Li et al. [6] applied graph optimization to INS/USBL/DVL integration and demonstrated two concrete advantages: the ability to incorporate USBL measurements that arrive with variable and sometimes large delays (0.5–3 s), and automatic detection and rejection of outlier measurements through robust cost functions. Their algorithm reduced the 95th-percentile position error by 45% compared to EKF on data from a 6,000 m deep-sea trial.

3.3. Tightly Coupled Multi-Sensor Architectures

The distinction between loosely coupled and tightly coupled fusion determines what information flows between sensors and the fusion center. Loosely coupled systems process each sensor independently, extract a position or velocity estimate, and then combine these estimates. Tightly coupled systems feed raw sensor measurements—individual acoustic ranges, individual DVL beam velocities, raw IMU data—directly into the fusion algorithm.

Bian et al. [14] implemented a tightly coupled SINS/DVL/USBL system for unmanned underwater vehicles and showed that tight coupling improves accuracy by 25–35% over loose coupling during deep-sea operations. The improvement comes from exploiting correlations between sensor errors that loose coupling ignores: for example, a temperature-induced change in sound speed affects both the USBL range measurement and the DVL velocity measurement in predictable ways that the tightly coupled filter can model.

Mu et al. [15] developed a practical four-sensor integration (INS/GPS/DVL/pressure sensor) with automatic mode switching between surface (GPS available) and submerged (GPS denied) operation. Their system uses the GPS-available surface phase to calibrate sensor parameters that remain valid during the submerged phase, achieving position errors below 0.3% of travel distance on a full-scale AUV.

Luo et al. [16] proposed a federated Kalman filter architecture for SINS/DVL/USBL integration within an IoT framework. Their federated design runs independent local filters for each sensor pair, then combines the local estimates through an information-sharing protocol. This architecture provides built-in fault tolerance: if one sensor fails, its local filter simply receives zero weight without affecting the other channels.

4. Beyond Single Vehicles: Cooperative and Networked Positioning

When multiple underwater vehicles operate in the same area, they can share position information through acoustic communication links, effectively creating a mobile positioning network. This cooperative approach offers a radical alternative to infrastructure-dependent methods like LBL.

Xu et al. [17] designed a multi-vehicle cooperative navigation system where vehicles with better position estimates transmit acoustic ranging signals to neighbors with degraded estimates. The receiving vehicle uses these range measurements as pseudo-USBL fixes to correct its own navigation solution. Sea trials with three AUVs showed that cooperative ranging reduced the maximum position error of the

ISSN 2616-5767 Vol.9, Issue 3: 149-157, DOI: 10.25236/AJETS.2026.090319

worst-positioned vehicle by 62%.

Li et al. [7] developed a hybrid TOA-AOA cooperative localization algorithm for multiple AUVs operating without any fixed anchors. By combining time-of-arrival range estimates with angle-of-arrival bearing estimates from inter-vehicle acoustic signals, their method determines the relative positions of all vehicles simultaneously. The algorithm handles the geometric dilution of precision problem—where poor vehicle geometry degrades positioning accuracy—through an adaptive weighting scheme.

Li et al. [8] pushed cooperative navigation further by jointly optimizing trajectory planning and localization. Their algorithm plans AUV paths that simultaneously accomplish the survey mission and maintain favorable geometric configurations for cooperative positioning. Simulations showed that cooperatively planned trajectories achieve 40% better positioning accuracy than independently planned paths, with only 8% increase in total path length.

Qin et al. [18] surveyed visual navigation techniques for autonomous UUVs and identified cooperative visual-inertial odometry as a rapidly maturing technology. When multiple vehicles share visual features observed from different viewpoints, the combined visual information resolves position ambiguities that single-vehicle systems cannot.

5. What Works, What Fails, and Where the Gaps Remain

Figure 1 presents the positioning accuracy ranges and maximum operating depths of eight navigation technologies reviewed in this paper. Table 1 provides a detailed comparison across seven performance dimensions.

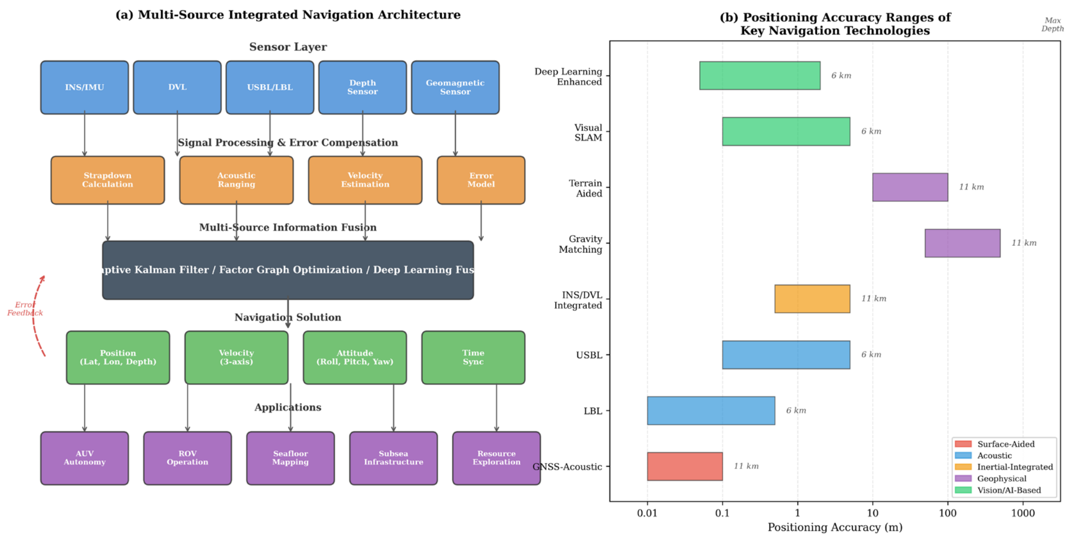

Figure 1: (a) Multi-source integrated navigation architecture showing five processing layers from sensor inputs through fusion algorithms to application outputs. (b) Positioning accuracy ranges and maximum operating depth for eight key navigation technologies. Bar length indicates the accuracy range from best-case to worst-case conditions. GNSS-Acoustic and deep learning-enhanced methods achieve the highest precision but require surface support or training data, while geophysical methods operate independently at any depth but with lower accuracy.

Table 1: Comparison of deep-sea navigation technologies across seven performance dimensions. Ratings are qualitative indicators where H = High, M = Medium, and L = Low.

Technology	Accuracy (m)	Update Rate	Max Depth	Self-Contained	Power Draw	Drift Free	Fusion Benefit
SINS (Fiber Optic)	0.5–5	H	Full	Yes	M	No	+60–80%
DVL (300 kHz)	0.1–0.5%	H	6 km	Yes	M	No	+40–60%
USBL	0.1–5	L	6 km	No	L	Yes	+50–70%
LBL	0.01–0.5	L	6 km	No	H	Yes	+30–50%
GNSS-Acoustic	0.01–0.1	L	Full	No	H	Yes	+20–40%
Gravity Match	50–500	L	Full	Yes	L	Yes	+10–30%
Terrain Match	10–100	M	Full	Yes	M	Yes	+15–35%
DL Fusion	0.05–2	H	6 km	Yes	H	Partial	Baseline

ISSN 2616-5767 Vol.9, Issue 3: 149-157, DOI: 10.25236/AJETS.2026.090319

Three patterns emerge from this comparison. First, a clear trade-off exists between accuracy and autonomy: the most accurate methods (LBL, GNSS-Acoustic) require external infrastructure, while self-contained methods (SINS, gravity matching) sacrifice precision for independence. Second, no single technology scores "High" across all dimensions, which confirms that multi-source fusion is not merely an enhancement but a structural necessity. Third, deep learning fusion methods occupy a unique position: they can approach the accuracy of infrastructure-dependent methods while maintaining self-containment, but they depend on training data that may not generalize across different ocean environments.

The most significant remaining gap is the lack of standardized benchmark datasets for underwater navigation. Unlike computer vision or natural language processing, where shared benchmarks drive rapid comparison and improvement, underwater navigation researchers typically collect and report results on proprietary datasets from their own vehicles and missions. Wang et al. [19] and Davari and Aguiar [10] tested their algorithms on different vehicles in different oceans, which makes direct comparison impossible. The field needs a shared, open-access dataset that includes synchronized multi-sensor data from diverse deep-sea environments.

6. Three Directions That Could Reshape Deep-Sea Navigation

6.1. Neuromorphic Sensor Fusion: Learning the Physics Instead of Programming It

Current fusion algorithms—whether Kalman filters or factor graphs—require engineers to hand-design the mathematical models that describe how sensor errors evolve and interact. These models inevitably simplify reality: they assume Gaussian noise distributions, linear error propagation over short intervals, and time-invariant system parameters. Deep learning approaches like BeamsNet [3] and the DVL fault detection network of Li et al. [5] have shown that neural networks can capture sensor error patterns that defy analytical modeling.

The next step is to move from component-level deep learning (enhancing one sensor) to system-level neuromorphic fusion that replaces the entire filter pipeline with a learned model. This model would ingest raw IMU, DVL, acoustic, and pressure data and directly output navigation solutions, without requiring explicit error models, state transition matrices, or noise covariance tuning. The technical barriers include the scarcity of labeled deep-sea training data, the difficulty of providing formal safety guarantees for learned systems, and the computational demands of real-time inference on vehicle-embedded processors. However, edge computing hardware is advancing rapidly—neuromorphic chips that execute neural network inference at milliwatt power levels already exist—and transfer learning techniques could bootstrap deep-sea models from the much larger datasets available from shallow-water and surface vehicle operations.

6.2. Quantum Inertial Sensing: Eliminating Drift at the Source

Gyroscope drift is the single largest error source in long-duration underwater navigation. Current fiber optic and ring laser gyroscopes reach drift rates of 0.001–0.01 degrees per hour, but even this level accumulates to hundreds of meters of position error over a 24-hour mission. Cold atom interferometry gyroscopes exploit quantum mechanical properties of laser-cooled atoms to measure rotation with drift rates potentially 100–1000× lower than the best optical gyroscopes. If quantum inertial measurement units (Q-IMUs) achieve their theoretical performance in ruggedized, vehicle-mountable packages, they would transform deep-sea navigation by extending the time between required external position fixes from minutes to days. The current challenges are enormous: cold atom systems require vibration isolation, vacuum chambers, and precise laser systems that today fill an optical bench. But laboratory demonstrations have already confirmed the fundamental sensitivity advantage, and compact Q-IMU prototypes have appeared from multiple research groups. A practical deep-sea Q-IMU within the next 10–15 years would represent a shift from improving data fusion algorithms to removing the need for them.

6.3. Swarm-Cooperative Navigation: The Fleet as a Distributed Sensor

Current multi-AUV cooperative navigation, as demonstrated by Xu et al. [17] and Li et al. [7], involves small numbers of vehicles (2–5) sharing position information through acoustic links. Scaling this concept to swarms of 50–200 vehicles requires fundamentally different approaches: the acoustic channel cannot support the communication load, and centralized fusion algorithms cannot process the data volume in real time. The breakthrough direction is fully distributed swarm navigation where each vehicle maintains and shares only a local belief about its position relative to nearby neighbors, and global positioning emerges from the network topology without any central coordinator. This approach borrows from distributed consensus algorithms in networked control theory and from biological navigation strategies used by schooling fish and migrating birds. Combined with inter-vehicle laser ranging (which provides centimeter accuracy at ranges of 50–200 m in clear water), swarm navigation could enable autonomous mapping of large seafloor areas with positioning accuracy that improves as the swarm grows rather than degrading.

Duan et al. [20] developed a spherical harmonic expansion model for GNSS/Acoustic seafloor positioning that could serve as the absolute reference framework for such swarms—providing the global anchor points that individual vehicles refine through cooperative ranging.

7. Conclusion

High-precision navigation and positioning remain among the most critical enabling technologies for deep-sea exploration and underwater autonomous systems. This review has examined the major sensing technologies, fusion algorithms, and system architectures that collectively support underwater navigation in GNSS-denied environments. Through analysis of recent developments between 2021 and 2025, it is evident that substantial progress has been achieved in inertial sensing, acoustic positioning, geophysical matching, and multi-sensor integration.

The review demonstrates that each navigation technology possesses distinct advantages and limitations. SINS provides continuous self-contained navigation but suffers from long-term drift accumulation. DVL offers highly accurate velocity measurements but depends on reliable bottom-lock conditions. Acoustic positioning systems achieve excellent absolute positioning performance but require external infrastructure and remain vulnerable to environmental uncertainties. Geophysical matching methods enable full-depth autonomous navigation but are constrained by reference map availability and matching ambiguity. These characteristics make integrated navigation not merely advantageous but essential for practical deep-sea operations.

Recent advances in adaptive Kalman filtering, factor graph optimization, and tightly coupled sensor fusion have significantly improved navigation robustness and accuracy. At the same time, artificial intelligence has begun transforming traditional navigation frameworks by enabling data-driven error compensation, anomaly detection, and sensor performance enhancement. The emergence of cooperative multi-vehicle navigation further extends positioning capability beyond the limitations of individual platforms, offering a scalable solution for future large-area ocean surveys.

Despite these achievements, important challenges remain unresolved. The lack of standardized benchmark datasets limits objective performance comparison across different algorithms and platforms. Environmental uncertainties, communication constraints, and long-duration autonomous operation continue to challenge existing systems. Furthermore, many advanced methods have been validated primarily through simulations or limited field experiments, and their performance under full-ocean-depth operational conditions requires further verification.

Looking ahead, three technological trends are expected to reshape the field. Neuromorphic sensor fusion may enable navigation systems to learn complex environmental and sensor interactions directly from data. Quantum inertial sensing offers the possibility of fundamentally reducing navigation drift through breakthroughs in measurement physics. Swarm-cooperative navigation may transform fleets of underwater vehicles into distributed sensing networks capable of achieving positioning performance beyond that of any individual platform.

In summary, the future of deep-sea navigation lies in the convergence of advanced sensing technologies, intelligent information fusion, and cooperative autonomous systems. Continued progress in these areas will provide the positioning accuracy, reliability, and autonomy required for the next generation of deep-sea scientific research, marine resource development, and underwater infrastructure operations.

References

[1] Potokar, Easton and Norman, Kalin and Mangelson, Joshua. Invariant Extended Kalman Filtering for Underwater Navigation[J]. IEEE Robotics and Automation Letters, 2021, 6(3): 5792–5799. DOI:

ISSN 2616-5767 Vol.9, Issue 3: 149-157, DOI: 10.25236/AJETS.2026.090319

10.1109/LRA.2021.3085167.
[2] Xue, Shuqiang and Li, Baojin and Xiao, Zhen and Sun, Yue and Li, Jingsen. Centimeter-level-precision seafloor geodetic positioning model with self-structured empirical sound speed profile[J]. Satellite Navigation, 2023, 4(1): 1–19. DOI: 10.1186/s43020-023-00120-7.
[3] Cohen, Nadav and Klein, Itzik. BeamsNet: A data-driven approach enhancing Doppler velocity log measurements for autonomous underwater vehicle navigation[J]. Engineering Applications of Artificial Intelligence, 2022, 114: 105216. DOI: 10.1016/j.engappai.2022.105216.
[4] Li, Tianjiao and Wang, Bo and Deng, Zhihong and Fu, Mengyin. Genetic Algorithm-Based Weighted Comprehensive Image Matching Algorithm for Underwater Gravity Gradient-Aided Navigation[J]. IEEE Journal of Oceanic Engineering, 2024, 49(4): 1647–1656. DOI: 10.1109/JOE.2024.3379484.
[5] Li, Ding and Xu, Jiangning and He, Hongyang and Wu, Miao. An Underwater Integrated Navigation Algorithm to Deal With DVL Malfunctions Based on Deep Learning[J]. IEEE Access, 2021, 9: 82010–82020. DOI: 10.1109/ACCESS.2021.3083493.
[6] Li, Peijuan and Liu, Yiting and Yan, Tingwu and Yang, Shutao and Li, Rui. A Robust INS/USBL/DVL Integrated Navigation Algorithm Using Graph Optimization[J]. Sensors, 2023, 23(2): 916. DOI: 10.3390/s23020916.
[7] Li, Yichen and Yu, Wenbin and Guan, Xinping. Hybrid TOA-AOA Cooperative Localization for Multiple AUVs in the Absence of Anchors[J]. IEEE Transactions on Industrial Informatics, 2024, 20(2): 2420–2431. DOI: 10.1109/TII.2023.3266362.
[8] Li, Yichen and Li, Bochen and Yu, Wenbin and Zhu, Shanying and Guan, Xinping. Cooperative Localization Based Multi-AUV Trajectory Planning for Target Approaching in Anchor-Free Environments[J]. IEEE Transactions on Vehicular Technology, 2022, 71(3): 3092–3107. DOI: 10.1109/TVT.2021.3137171.
[9] Wang, Di and Xu, Xiaosu and Yang, Yang and Zhang, Tao. A Quasi-Newton Quaternions Calibration Method for DVL Error Aided GNSS[J]. IEEE Transactions on Vehicular Technology, 2021, 70(3): 2465–2477. DOI: 10.1109/TVT.2021.3059755.
[10] Davari, Narjes and Aguiar, A. Pedro. Real-Time Outlier Detection Applied to a Doppler Velocity Log Sensor Based on Hybrid Autoencoder and Recurrent Neural Network[J]. IEEE Journal of Oceanic Engineering, 2021, 46(4): 1288–1301. DOI: 10.1109/JOE.2021.3057909.
[11] Liu, Shede and Zhang, Tao and Zhang, Jiayu and Zhu, Yongyun. A New Coupled Method of SINS/DVL Integrated Navigation Based on Improved Dual Adaptive Factors[J]. IEEE Transactions on Instrumentation and Measurement, 2021, 70: 1–11. DOI: 10.1109/TIM.2021.3106118.
[12] Liu, Ruixin and Liu, Fucheng and Liu, Chunning and Zhang, Pengchao. Modified Sage-Husa Adaptive Kalman Filter-Based SINS/DVL Integrated Navigation System for AUV[J]. Journal of Sensors, 2021, 2021: 9992041. DOI: 10.1155/2021/9992041.
[13] Shi, Wence and Xu, Jiangning and He, Hongyang and Li, Ding and Tang, Hongqiong and Lin, Enfan. Fault-tolerant SINS/HSB/DVL underwater integrated navigation system based on variational Bayesian robust adaptive Kalman filter and adaptive information sharing factor[J]. Measurement, 2022, 196: 111225. DOI: 10.1016/j.measurement.2022.111225.
[14] Bian, Yougang and Li, Ruotian and Wang, Guangcai and Qin, Xiaohui and Hu, Manjiang and Ding, Rongjun. Tightly Coupled Information Fusion for SINS/DVL/USBL Integrated Navigation of UUV[J]. IEEE Transactions on Instrumentation and Measurement, 2023, 72: 1–13. DOI: 10.1109/TIM.2023.3277945.
[15] Mu, Xiaokai and He, Bo and Wu, Shuyi and Zhang, Xin and Song, Yan and Yan, Tianhong. A practical INS/GPS/DVL/PS integrated navigation algorithm and its application on Autonomous Underwater Vehicle[J]. Applied Ocean Research, 2021, 106: 102441. DOI: 10.1016/j.apor.2020.102441.
[16] Luo, Qinghua and Yan, Xiaozhen and Wang, Chenxu and Shao, Yang and Zhou, Zhiquan and Li, Jianfeng and Hu, Cong and Wang, Chuntao and Ding, Jinfeng. A SINS/DVL/USBL integrated navigation and positioning IoT system with multiple sources fusion and federated Kalman filter[J]. Journal of Cloud Computing, 2022, 11(1). DOI: 10.1186/s13677-022-00289-3.
[17] Xu, Bo and Hu, Junmiao and Guo, Yu. An Acoustic Ranging Measurement Aided SINS/DVL Integrated Navigation Algorithm Based on Multivehicle Cooperative Correction[J]. IEEE Transactions on Instrumentation and Measurement, 2022, 71: 1–15. DOI: 10.1109/TIM.2022.3195248.
[18] Qin, Jiangying and Li, Ming and Li, Deren and Zhong, Jiageng and Yang, Ke. A Survey on Visual Navigation and Positioning for Autonomous UUVs[J]. Remote Sensing, 2022, 14(15): 3794. DOI: 10.3390/rs14153794.
[19] Wang, Di and Xu, Xiaosu and Yao, Yiqing and Zhang, Tao. Virtual DVL Reconstruction Method for an Integrated Navigation System Based on DS-LSSVM Algorithm[J]. IEEE Transactions on Instrumentation and Measurement, 2021, 70: 1–13. DOI: 10.1109/TIM.2021.3063771.

ISSN 2616-5767 Vol.9, Issue 3: 149-157, DOI: 10.25236/AJETS.2026.090319

[20] Duan, Zhonghua and Guo, Jinyun and Sun, Heping and Liu, Xin. Spherical Harmonic Expansion Model for GNSS/Acoustic Precise Seafloor Positioning[J]. IEEE Journal of Oceanic Engineering, 2025, 50(4): 2880–2894. DOI: 10.1109/JOE.2025.3573007.