

REVIEW

Multi-Source Data Fusion for Underwater Geophysical Field Matching Navigation: A Systematic Review of Methodologies, Challenges, and Future Trends

Jiaqi Mi¹, Congcong Ma², Xinrui Li¹, Sixu Huang¹ and Kunpeng He^{1,*}

¹College of Artificial Intelligence, Nankai University, Tianjin, China

²Hebei Provincial Engineering Research Center for Power System Generative AI Technology, Baoding, China

*Corresponding Author: Kunpeng He. Email: seaskyexplorer@163.com

Received: 20 May 2026; Accepted: 11 August 2026; Published: 22 October 2026

ABSTRACT: In underwater environments where global navigation satellite systems are unavailable, autonomous underwater vehicles and other underwater vehicles require autonomous navigation methods, among which matching navigation based on seafloor topography, gravity anomalies, and geomagnetic anomalies can effectively mitigate the cumulative errors of inertial navigation systems. To exploit the complementary characteristics of different geophysical fields, multi-source data fusion has become a key technique for improving the robustness and accuracy of underwater matching navigation. This review systematically examines recent advances in underwater geophysical-field data fusion. First, existing methods are categorized into three levels: map-level, feature-level, and decision-level fusion, and a standardized preprocessing pipeline is summarized. On this basis, the core fusion strategies at each level are distilled. Map-level fusion focuses on spatial interpolation and multi-source joint inversion. Feature-level fusion covers the evolution from traditional descriptors to lightweight deep representations and decision-level fusion discusses filtering-based mechanisms, factor graph-based frameworks, and robust matching strategies. Furthermore, a comprehensive testing and benchmarking scheme is proposed, covering datasets, task definitions, and evaluation metrics. Finally, emerging directions, including the integration of physical modeling with learning-based enhancement and adaptive uncertainty management, are discussed. This review aims to provide a unified and reproducible reference for future research and system implementation in underwater geophysical-field fusion navigation.

KEYWORDS: Underwater navigation; geophysical-field matching; data fusion; seafloor topography; gravity anomaly; geomagnetic anomaly; robust matching; benchmarking

1 Introduction

In Global Navigation Satellite System (GNSS) restricted or denied marine and polar environments, autonomous underwater vehicles (AUVs) commonly rely on inertial navigation system (INS)/Doppler velocity log (DVL) integrated navigation or ultra-short baseline (USBL) acoustic navigation [1–4]. However, INS/DVL navigation suffers from time-accumulating inertial errors and possible DVL performance degradation in deep-water conditions, whereas USBL navigation depends on a limited and high-cost acoustic transponder network, making it unsuitable for large-scale or covert missions. Geophysical-field matching navigation, which exploits inherent physical fields such as seafloor topography, geomagnetism, and gravity, provides an autonomous positioning paradigm that does not depend on external infrastructure [5–9]. Therefore, the term underwater geophysical-field matching navigation in this review specifically refers

to the self-localization, drift correction, and trajectory correction of AUVs and other underwater vehicles operating in GNSS-denied underwater environments. Nevertheless, single-field matching has limited robustness in areas with ambiguous field characteristics or strong external disturbances. Therefore, fusing multi-source geophysical fields to establish a cooperative matching framework has become a key approach for improving navigation accuracy, reliability, and environmental adaptability. This paper systematically reviews the methodological framework and research progress of multi-field data fusion in underwater matching navigation.

In recent years, researchers have attempted to fuse multiple geophysical fields to enhance underwater matching navigation performance. Representative combinations include bathymetry–gravity and gravity–geomagnetism [10–13], as well as bathymetry–gravity–geomagnetism and related multi-source configurations [14–16]. These studies indicate that both direct multi-field fusion and improved single-field matching modules are important foundations for robust underwater geophysical-field matching navigation. According to the fusion strategy, existing methods can be categorized into three levels: map-level fusion, feature-level fusion, and decision-level fusion. At the map level, representative studies include the fusion of multi-source gravity anomaly data using optimal interpolation or kriging [17], as well as the construction of high-resolution base maps through joint inversion using both gravity and geomagnetic data [18]. For feature-level fusion, gradients, wavelet coefficients, and statistical features are extracted from bathymetric, gravity, and geomagnetic fields to construct combined feature vectors for matching [19]; recent studies have also explored lightweight neural networks to automatically learn cross-field features [20]. For decision-level fusion, common strategies include fusing the matching results from different physical fields through weighted averaging, Bayesian estimation, or factor graphs [21], as well as directly incorporating multi-field observations into extended Kalman filter (EKF) or particle filter (PF) frameworks [22]. These methods have demonstrated the advantages of multi-field fusion over single-field matching under specific sea-area or simulation conditions, for example, by improving the matching success rate or suppressing long-term drift.

However, existing methods still face several key challenges that have not been systematically addressed in the literature. To further clarify the novelty and scope of this review, Table 1 compares the present work with representative related review articles. The comparison demonstrates that, unlike previous surveys, this review focuses specifically on underwater geophysical-field matching navigation and provides a comprehensive analysis covering three-level fusion strategies, uncertainty management, and standardized evaluation benchmarks. First, cross-source heterogeneity remains significant. The units, coordinate systems, and vertical datums of geomagnetic-field, gravity-field, and bathymetric data differ from one another. Moreover, the removal methods for main or reference fields, such as the International Geomagnetic Reference Field (IGRF), the World Magnetic Model (WMM), and the Earth Gravitational Model (EGM), have not been unified. Directly superimposing these datasets may introduce systematic biases and scale inconsistencies. Recent marine gravity and magnetic mapping studies further show that different survey sources, data processing strategies, and map-generation procedures can significantly affect the consistency and navigation usability of the resulting reference maps [14,23]. Second, spatial resolution and spectral content are often mismatched. In practical navigation, high-precision onboard sensors, such as sonar and inertial measurement units (IMUs), often provide finer-scale and higher-frequency information, whereas regional gravity and geomagnetic background maps are typically provided on relatively coarse angular grids. Conventional interpolation methods may therefore lead to information loss or distortion. Recent studies on gravity-map refinement and multi-source gravity-field fusion also indicate that short-wavelength details and long-wavelength consistency must be handled jointly, rather than through naive interpolation alone [24–26]. At present, no widely accepted standard approach is available for smoothly merging long- and short-wavelength components to achieve cross-scale consistency. Third, base maps generally lack pixel-level uncertainty characterization. Most maps

report only nominal or global accuracy, without pixel-level error bounds, confidence layers, or quality masks that can be directly used in computation. As a result, fusion weights and gating thresholds are often tuned empirically, and uncertainty cannot be effectively propagated into the matching likelihood function or the filter noise model. Recent uncertainty-aware magnetic and gravity navigation studies have shown that map uncertainty, local information density, and matching confidence strongly influence the stability of filtering and map matching [27,28]. Fourth, dynamic environments and sensor drift require online adaptability. Geophysical-field observations are affected by dynamic disturbances such as ocean currents and temperature variations, as well as by sensor drift. Traditional fusion methods often assume static or weakly time-varying conditions, making them prone to weight mismatch and estimation bias in dynamic environments. Recent work on magnetic navigation and gravity-gradient matching further suggests that weak anomaly signals, vehicle-induced disturbances, temporal geomagnetic variations, and multi-component map-matching errors need to be explicitly considered in robust navigation frameworks [29,30].

Table 1: Comparison between this review and previous related reviews.

Review	Geophysical Fields	Fusion Strategy	Evaluation	Uncertainty	Benchmark
Paull et al. 2014 [1]	No	No	Limited	No	No
Ma et al. 2023 [31]	Terrain	Limited	Partial	No	No
Merveille et al. 2024 [32]	Multi sensors	Sensor fusion	Yes	Limited	No
Heshmat et al. 2025 [33]	Multi-modal	Learning fusion	Yes	No	No
Ours	Terrain + gravity + geomagnetism	Map + Feature + Decision	Yes	Yes	Yes

In response to the above challenges, the main contributions of this paper are summarized as follows:

- Existing multi-field data fusion methods are systematically summarized. The objectives, representative methods, applicable scenarios, advantages, and limitations of map-level, feature-level, and decision-level fusion are clarified, providing a principled basis for selecting appropriate fusion strategies under different task requirements.
- A systematic data-processing and interface specification is proposed to facilitate engineering implementation. The corresponding preprocessing pipeline covers calibration and correction, reference-field removal, coordinate and datum unification, scale alignment and resampling, and standardized filtering. This pipeline helps improve interoperability among system components and reduces the difficulty of deployment in real environments.
- A reproducible evaluation system is constructed. Specifically, a multi-dimensional performance assessment framework is established, covering accuracy, convergence rate, mismatch ratio, computational cost, and energy consumption. This framework supports quantitative, comparable, and reproducible evaluation of navigation performance, thereby contributing to the goal of bounded-error navigation.

The remainder of this paper is organized as follows. [Section 2](#) describes the review methodology, and [Section 3](#) presents the overall three-level fusion framework. [Section 4](#) summarizes the data preprocessing pipeline and interface specifications. [Sections 5–7](#) review map-level, feature-level, and decision-level fusion methods, respectively. [Section 8](#) describes the evaluation system and experimental baselines, [Section 9](#) provides a discussion, and [Section 10](#) concludes the paper with an outlook on future directions.

2 Review Methodology

To ensure that the literature search, screening, and subsequent analysis were conducted in a systematic and objective manner, this review was guided by the following research questions (RQs):

- **RQ1:** What are the major multi-source geophysical-field fusion strategies employed in underwater matching navigation?
- **RQ2:** How are heterogeneous geophysical-field data (e.g., bathymetry, gravity, and geomagnetism) processed and integrated at different fusion levels?
- **RQ3:** What are the advantages, limitations, and applicable scenarios of map-level, feature-level, and decision-level fusion methods?
- **RQ4:** What evaluation criteria, benchmark datasets, and performance metrics are commonly adopted to assess multi-source geophysical-field matching navigation methods?
- **RQ5:** What open challenges and future research directions remain for robust multi-source geophysical-field fusion in underwater navigation?

To answer the above research questions in a transparent and reproducible manner, the literature search and screening process was designed with reference to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [34,35]. The review protocol was designed to ensure that the identified studies could provide sufficient evidence to address the proposed research questions regarding fusion strategies, data processing, evaluation methodologies, and future research directions. The literature search was conducted mainly in Web of Science, Scopus, IEEE Xplore, ScienceDirect, SpringerLink, and China National Knowledge Infrastructure(CNKI). The search covered studies published from 2010 to May 2026, with particular attention given to recent work published since 2020 on underwater geophysical field matching navigation and multisource data fusion. The database-specific search fields and Boolean search strings are summarized in Table 2. The syntax was adapted to the search interface of each database while retaining the same three conceptual groups.

Table 2: Database-specific search fields and Boolean search expressions used for literature retrieval.

Item	Search Field or Concept	Search Block or Database-Specific Expression
Common search blocks		
N	Navigation objects and scenarios	“underwater navigation” OR “AUV navigation” OR “underwater vehicle navigation” OR “autonomous underwater vehicle localization” OR “geophysical-field matching navigation” OR “terrain-aided navigation” OR “gravity-aided navigation” OR “geomagnetic navigation”
F	Fusion methods	“data fusion” OR “multi-source fusion” OR “map-level fusion” OR “feature-level fusion” OR “decision-level fusion” OR “Bayesian fusion” OR “Kalman filter” OR “particle filter” OR “factor graph”
G	Geophysical-field data types	“seafloor topography” OR bathymetry OR “gravity anomaly” OR “geomagnetic anomaly” OR “magnetic anomaly map”

(Continued)

Table 2 (continued)

Item	Search Field or Concept	Search Block or Database-Specific Expression
Database-specific search expressions		
Web of Science	Topic	TS=(N AND F AND G)
Scopus	Title, abstract, and keywords	TITLE-ABS-KEY(N AND F AND G)
IEEE Xplore	All metadata	N AND F AND G
ScienceDirect	Title, abstract, or author-specified keywords	N AND F AND G
SpringerLink	Title, abstract, and keywords, where available	N AND F AND G
CNKI	Topic	Chinese equivalents of N AND F AND G

Note: N, F, and G denote the complete parenthesized search blocks defined in the upper part of the table. During the database searches, these symbols were replaced by their corresponding complete term blocks. For CNKI, the corresponding Chinese search terms were used, whereas their English translations are presented in this table. The searches covered publications from January 2010 to May 2026. Quotation marks were used for phrase searching where supported, and the search syntax and searchable fields were adapted to the interface of each database.

As shown in Table 2, the database-specific search strings were constructed from three groups of concepts and combined using Boolean operators. Terms within each concept group were connected using the operator “OR”, whereas the navigation, fusion-method, and geophysical-field blocks were connected using “AND”. The first group focused on navigation objects and application scenarios, including underwater navigation, AUV navigation, underwater vehicle navigation, autonomous underwater vehicle localization, geophysical-field matching navigation, terrain-aided navigation, gravity-aided navigation, and geomagnetic navigation. The second group focused on fusion methods, including data fusion, multi-source fusion, map-level fusion, feature-level fusion, decision-level fusion, Bayesian fusion, Kalman filter, particle filter, and factor graph. The third group focused on geophysical-field data types, including seafloor topography, bathymetry, gravity anomaly, geomagnetic anomaly, and magnetic anomaly maps. The three groups were complementary search dimensions rather than mutually exclusive categories; therefore, an included study could address an underwater navigation scenario, a fusion or matching method, and one or more geophysical-field data types simultaneously. In addition, the reference lists of important review articles and representative studies were manually traced to reduce the possibility of missing relevant publications.

The inclusion criteria were as follows. First, the study had to be directly related to geophysical field aided navigation, matching localization, or related data fusion problems in underwater or marine environments. Second, the study had to involve at least one physical field, such as seafloor terrain, gravity anomaly, or geomagnetic anomaly, or discuss methods related to multi-field cooperative mapping, feature extraction, matching decision, or state estimation. Third, the study had to provide a clear methodological framework, experimental validation, data source, or technical details that could support the classification and comparison in this review. Fourth, priority was given to journal articles, recent high quality conference papers, representative public datasets, and engineering application studies. The exclusion criteria included studies focused only on geological interpretation or resource exploration without a direct connection to

navigation, studies discussing sensor hardware without involving matching, fusion, or localization algorithms, duplicated publications, studies with incomplete bibliographic information, and papers with limited relevance to the topic of this review.

The screening process consisted of four steps. First, duplicate records were removed from the initial search results. Second, clearly irrelevant studies were excluded based on their titles and abstracts. Third, full texts were examined to determine whether the studies met the inclusion criteria. Finally, the included studies were categorized according to data preprocessing, map-level fusion, feature-level fusion, decision-level fusion, evaluation baselines, and engineering applications. These categories were subsequently used to synthesize the evidence and answer the proposed research questions in the Discussion section. The literature identification, screening, eligibility assessment, and final inclusion process used to address the proposed research questions is summarized in Fig. 1. The completed PRISMA 2020 Checklist is provided as Supplementary Table S1. It should be noted that the three concept groups used to construct the search strategy represent complementary Boolean search dimensions rather than mutually exclusive categories of studies. Therefore, a single article may be associated with more than one concept group. Detailed study-level mappings for navigation scenarios, fusion methods, and geophysical-field data types are provided in Supplementary Tables S2–S4, respectively.

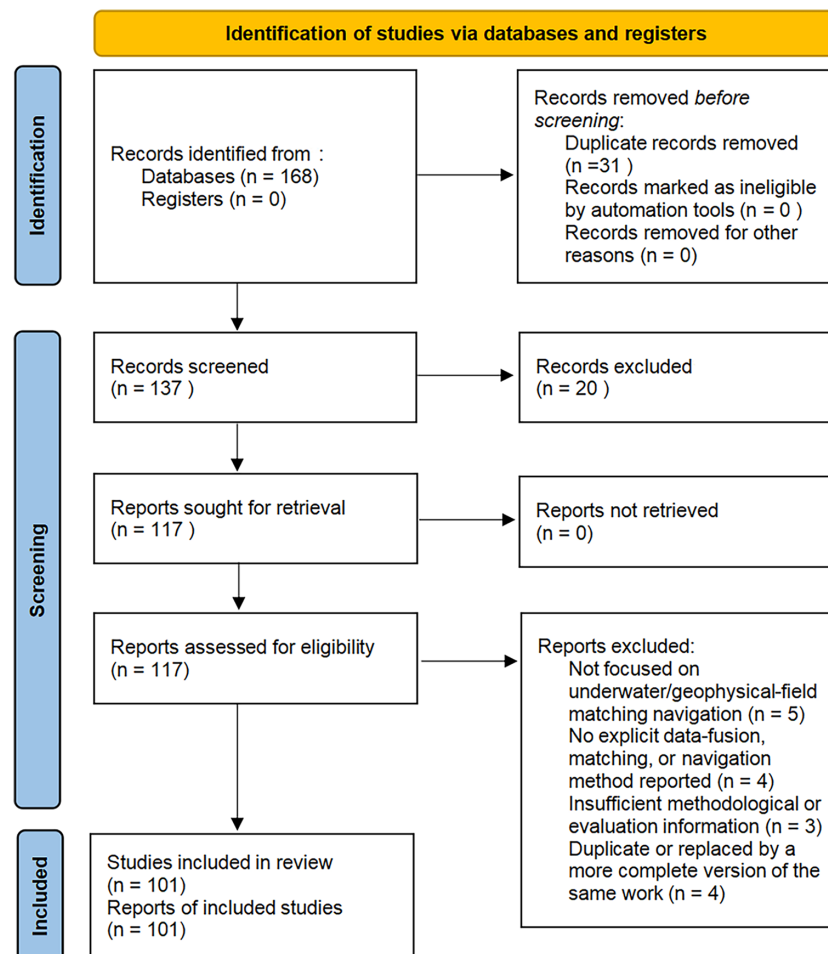


Figure 1: PRISMA 2020 flow diagram of the literature identification, screening, eligibility assessment, and inclusion process used in this systematic review. A total of 168 records were initially identified from databases, 137 records were screened after duplicate removal, and 101 studies were finally included for qualitative synthesis.

To further show the publication distribution and recent development trend of the reviewed methods, Fig. 2 summarizes 58 method-related studies published from 2021 to 2025. Each study represented in the figure was assigned to one primary category according to its main methodological contribution, including map-level fusion, feature-level fusion, decision-level fusion, and competitive frameworks. Competitive frameworks include INS/DVL-based integrated navigation, single-field matching navigation, underwater simultaneous localization and mapping (SLAM), general sensor-fusion frameworks, and learning-based geophysical localization methods used as baselines or comparative references. Non-methodological records, such as PRISMA reporting guidelines, global reference-field model descriptions, data portals, and generic algorithmic foundations, were not counted in this figure. As shown in Fig. 2, recent studies increasingly focus on map construction and refinement, feature-level learning, decision-level robust estimation, and competitive multi-sensor navigation frameworks, indicating the expanding research scope and application potential of underwater geophysical-field matching navigation.

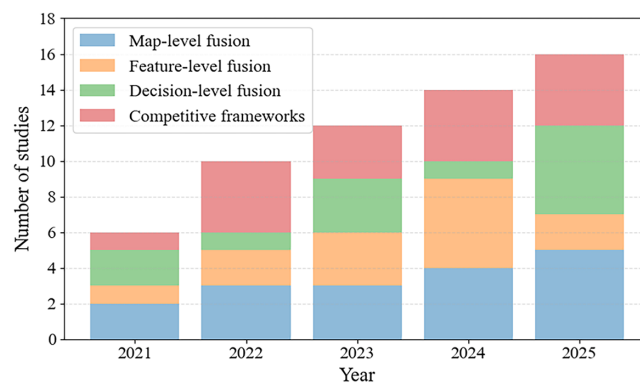


Figure 2: Annual distribution of 58 method-related studies by primary methodological category from 2021 to 2025.

3 Overall Framework of Three-Level Fusion

To systematically review data fusion methods in underwater geophysical field matching navigation, this paper categorizes existing studies into three levels: map-level fusion, feature-level fusion, and decision-level fusion. These three types of methods are not isolated from one another. Instead, they represent different fusion pathways built upon a unified data preprocessing foundation. Map-level fusion focuses on constructing unified multisource maps in the spatial or frequency domain. Feature-level fusion emphasizes the extraction of more discriminative matching features from multiple physical fields. Decision-level fusion integrates the matching results, likelihood distributions, or navigation observations derived from different physical fields into a unified state estimation framework. Fig. 3 presents the overall three-level fusion framework adopted in this review.

As shown in Fig. 3, terrain, gravity anomaly, and geomagnetic anomaly data are first processed through a unified preprocessing procedure, including coordinate and datum unification, trend processing, normalization, and quality assessment. The preprocessed multisource data can then be introduced into different fusion modules. Map-level fusion usually generates fused maps or multi-channel maps, providing a unified background field for subsequent matching. Feature-level fusion further extracts texture, gradient, entropy, wavelet, or deep features to construct feature tensors and similarity constraints. Decision-level fusion realizes the final navigation state update through probabilistic fusion, dynamic weighting, filtering, or factor graph optimization. These three levels can either form independent navigation solutions or constitute a progressive fusion chain from maps to features and finally to decisions.

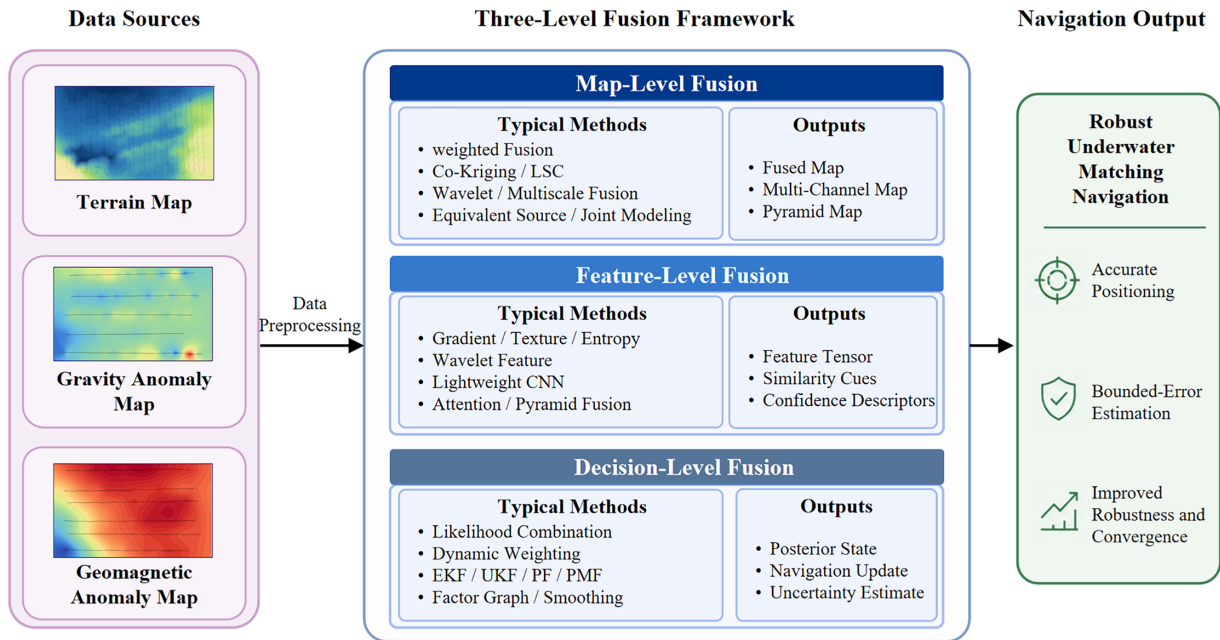


Figure 3: Overall three-level fusion framework for underwater geophysical field matching navigation.

4 Data Preprocessing

Whether multi-field cooperation can deliver stable positioning gains depends first on whether the data are aligned before entering the fusion stage. Over the past five years, research on data preprocessing has converged to a common pipeline: unifying spatial coordinates and datums, subtracting the main or theoretical field to obtain anomaly quantities, performing amplitude normalization and scale harmonization, and propagating pixel-level uncertainties into the matching and filtering modules. Based on this consensus, this section distills a standardized preprocessing workflow, as detailed below and illustrated in Fig. 4.

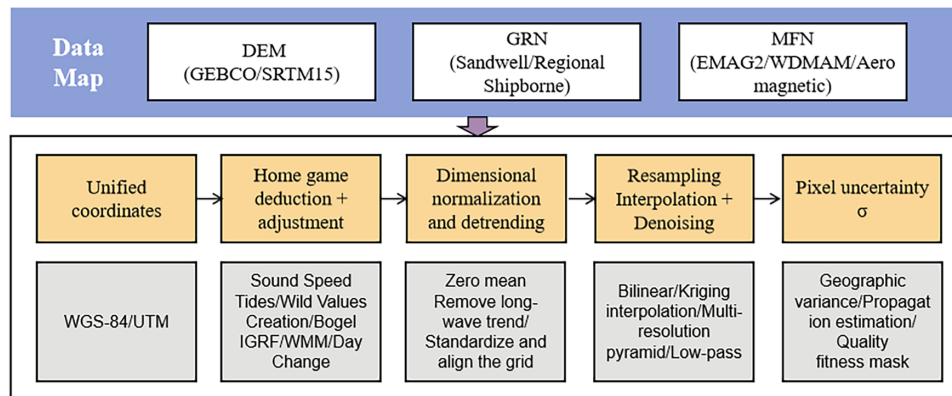


Figure 4: Preprocessing workflow for geophysical-field data. The preprocessing of three input data types begins with unified coordinate and vertical datum alignment, followed by the removal of main and theoretical fields and the application of relevant corrections. The data then undergo amplitude normalization and detrending, and are subsequently resampled and denoised. This process ultimately produces standardized and spatially co-registered raster data.

The first step is coordinate and datum harmonization. The literature on terrain, gravity, and magnetic navigation consistently stresses the need for a common horizontal reference frame and a common vertical datum [31]. The World Geodetic System 1984 (WGS 84) is typically adopted as the horizontal datum, and mean sea level or the geoid is typically used as the vertical datum. Measured depths must be reduced to the same vertical datum as the chart, and gravity data should be referenced to the geoid before anomaly computation. Failure to do so introduces a site-independent constant bias, forcing the matching algorithm to absorb non-positional errors, which slows convergence and increases the risk of mismatches. After datum unification, the correlation between measured profiles and map profiles increases markedly, reducing the number of Kalman updates required for convergence [7]. For gravity data, crossover adjustment between survey lines and data sources is also required to remove systematic offsets [36].

Next, spatial resolution, interpolation, and registration should be addressed. Bathymetric maps typically have meter- to decameter-level resolution in local surveys, while global products such as the General Bathymetric Chart of the Oceans (GEBCO) and the Shuttle Radar Topography Mission-based 15 arc-second global relief model (SRTM15+) are commonly provided at 15 arc-second resolution [37–39]. Naive upsampling or downsampling introduces spurious details or discards the texture needed for localization. The prevailing strategy is multiscale and hierarchical: global convergence is first ensured at coarse scales, and the solution is then refined at finer scales. For gravity matching, a multi-resolution sequential scheme improves convergence under large initial errors [40]. For multi-source fusion, wavelet decomposition is used to trust wide-coverage and stable satellite or model data in low-frequency bands, while airborne or shipborne measurements are trusted in high-frequency bands [36,41]. In practice, bilinear or spline interpolation is commonly adopted in the observation model to avoid numerical discontinuities caused by grid stair-stepping. Applying a low-pass constraint compatible with the target grid before upsampling low-resolution layers is a practical way to mitigate aliasing [36].

Removing the main or theoretical field is essential for obtaining matchable anomalies. For the magnetic field, the International Geomagnetic Reference Field or the World Magnetic Model is used to compute and subtract the core main field [42–44], and diurnal variation and magnetic storms are corrected. This process compresses the main field from about fifty thousand nanotesla (nT) to anomalies on the order of tens to hundreds of nT, thereby greatly improving spatial discriminability [45,46]. For gravity, normal gravity is subtracted and, where needed, Bouguer and terrain corrections are added to form anomalies that reflect subsurface density contrasts [47–49]. Recent marine gravity models further demonstrate the contribution of multi-mission altimetry to anomaly-map construction [50–52]. For bathymetry, moderate large-scale trend removal helps highlight relative relief [46]. Recent practice favors newer models, such as the thirteenth-generation International Geomagnetic Reference Field (IGRF-13) or the World Magnetic Model 2020 (WMM-2020), and reserves small bias states within the filter to absorb residual modeling errors [53].

Amplitude and unit normalization are used primarily in cross-source fusion and learning-based methods to prevent any single channel from dominating the fusion due to its larger numerical range. Classical correlation-based matching employs zero-mean and unit-variance standardization to emphasize shape similarity rather than absolute magnitude [54]. In learning-based methods, normalizing latitude, longitude, elevation, and magnetic components to comparable scales improves training stability [9]. For modalities with significantly different spectral content, mild whitening or band-pass shaping can be applied to suppress over-dominant single-scale energy [36].

As important as the value itself is the confidence, namely the reliability of each map-pixel estimate. Recent studies increasingly generate per-pixel error or quality labels and propagate them into the likelihood function and filter-noise tuning. Geostatistical interpolation naturally yields an estimation variance that can be used directly as a weight [36]. Classification methods based on variance, gradient, and entropy provide

a localizability mask that reduces mismatches [55]. Incorporating map error into the observation variance prevents overconfident updates that cause filter jumps [7]. For multi-source fusion, pixel-level variance weighting is more robust than heuristic weighting and facilitates reproducibility.

In summary, this paper proposes a standardized preprocessing workflow: unifying datums and coordinates; correcting tides and sound-speed effects; subtracting the main geomagnetic and gravity fields; detrending bathymetry; performing amplitude normalization and spectral shaping; registering all datasets to a target grid anchored by the highest-accuracy source; building a coarse-to-fine multiscale pyramid; and generating per-pixel error layers with metadata records. Table 3 summarizes commonly used global geophysical data sources, including seafloor bathymetry, marine gravity, and magnetic anomalies, and lists their resolutions, units, and reference-field versions. Global magnetic anomaly products such as EMAG2v3 and WDMAM provide essential anomaly-map references for magnetic matching navigation [56,57]. This workflow has been validated in recent studies [9,36,40]: a disciplined preprocessing chain reduces mismatch rates, accelerates convergence, provides objective weights for multi-source fusion, and supports fair cross-region and cross-algorithm comparison as well as reproducible research.

Table 3: List of global physical-field data sources. GEBCO stands for the General Bathymetric Chart of the Oceans; SRTM15+ denotes the SRTM-based 15'' global relief model; SIO denotes the Scripps Institution of Oceanography; GMGA denotes Global Marine Gravity Anomaly; DTU17 denotes the 2017 Technical University of Denmark global marine gravity model; EMAG2 denotes the Earth Magnetic Anomaly Grid; and WDMAM denotes the World Digital Magnetic Anomaly Map. The mGal denotes milligal and nT denotes nanotesla.

Category	Dataset	Spatial Resolution	Unit	Main/Reference Field Version
Seafloor bathymetry	GEBCO	15'' global	m	Not applicable
Seafloor bathymetry	SRTM15+	15'' global	m	Not applicable
Marine gravity	SIO global marine free-air gravity	1' global	mGal	Already free-air anomaly
Marine gravity	GMGA	1' (60° S–60° N)	mGal	Already free-air anomaly
Marine gravity	DTU17 global marine gravity	1' global	mGal	Already free-air anomaly
Magnetic anomaly	EMAG2 v3	2' global	nT	Main field removed
Magnetic anomaly	WDMAM v2.0	3' global	nT	Main field removed

5 Map-Level Fusion Methods

At the map level, multi-source data fusion integrates heterogeneous datasets such as geomagnetic, gravity, and bathymetric data into a unified reference frame or grid, thereby eliminating differences in physical scale and spatial distribution across sources and significantly improving the accuracy and robustness of map matching localization [58]. Unlike feature-level and decision-level fusion, map-level fusion operates directly in the spatial domain of the geophysical fields themselves, providing more stable and consistent localization constraints. It offers unique advantages for large-scale, long-duration continuous positioning. This chapter reviews recent advances, focusing on the fusion and interpolation of multi-source gridded data

as well as joint modeling techniques, and analyzes how different fusion strategies affect matching accuracy, convergence behavior, and overall reliability.

The most direct method is the linear combination or weighted average of different geophysical fields. In the gravity-geomagnetic combined aided navigation framework proposed by Zheng et al., an optimal weight assignment principle dynamically allocates the contributions of gravity-based and geomagnetic-based matches according to each field's information content, and the two position estimates are fused via a weighted average [58], leveraging the complementary strengths of gravity's high precision and geomagnetism's high resolution. Similarly, Li et al. used Bayesian optimization to determine source weights for fusing multi-source Bouguer gravity anomalies, producing a product that retains the local accuracy of terrestrial gravity surveys while benefiting from the broad coverage and long-wavelength fidelity of satellite gravity models [59]. This weight-based approach is particularly suitable when source characteristics differ markedly. However, its success depends on prior knowledge; unclear error statistics or improper weight settings can introduce bias. Moreover, optimizing weights is computationally intensive, and adaptively adjusting weights remains challenging. In recent years, adaptive uncertainty management has introduced real-time uncertainty propagation, allowing dynamic adjustment of observation variances and fusion weights according to spatial-temporal context [7,36]. For instance, Ma et al. used an experience-driven weighted average to fuse marine gravity and magnetic data, validating the effectiveness of weighted fusion while noting that suboptimal weights degrade performance [60]. Ma et al. further proposed dynamically adjusting weights based on data quality and measurement uncertainty, improving the reliability of the fused outcomes [61]. To handle time-varying disturbances such as magnetic storms or sensor drift, researchers have proposed an online closed-loop scheme of noise learning and consistency diagnostics, which can trigger covariance inflation or weight reallocation upon detecting abnormal innovations, thereby preventing overconfidence and bias [7,62]. Fig. 5 illustrates a wavelet-domain fusion method that combines a smooth gravity background map with fine-scale trackline information: the low-frequency background field dominates the large-scale structure, while high-frequency trackline information is injected within a transition band, and the final fusion result preserves regional consistency while enhancing local anomaly details.

Cokriging is a multivariate geostatistical method that exploits spatial correlations between a primary variable and one or more auxiliary variables to improve interpolation accuracy. When gravity correlates with bathymetry or depth, bathymetry can assist the interpolation of gravity anomalies. Studies have shown that fusing satellite and terrestrial gravity data by cokriging preserves both local details and long-wavelength trends [59]. This method requires accurate covariance modeling, entails relatively high computational cost, and imposes strict demands on data spatial distribution and quality. To systematically compare existing map-level fusion methods, Table 4 summarizes their key characteristics, including physical consistency, computational cost, advantages, and disadvantages for spatial weighting, geostatistical fusion, multi-scale fusion, equivalent source, and joint inversion. Spatial weighting is simple and efficient but requires careful consistency control; geostatistical fusion provides medium-high physical consistency at medium-high computational cost, whereas multi-scale fusion provides a medium-consistency, medium-cost trade-off; equivalent source and joint inversion can achieve seamless cross-field consistency but are computationally expensive and prone to overfitting, which may limit real-time applicability. In recent years, machine learning approaches have also been widely adopted. Li et al. used convolutional neural networks to fuse multi-constellation altimetry data and produce more accurate gravity anomaly grids [63]. Other work feeds multi-channel inputs such as gravity gradients and gravity anomalies into deep neural networks to predict seafloor bathymetry, achieving higher depth estimation accuracy than inversions based solely on gravity [64]. These data-driven methods implicitly perform multi-field fusion and interpolation, can generalize well, but they suffer from weaker interpretability, which may affect user confidence in the results.

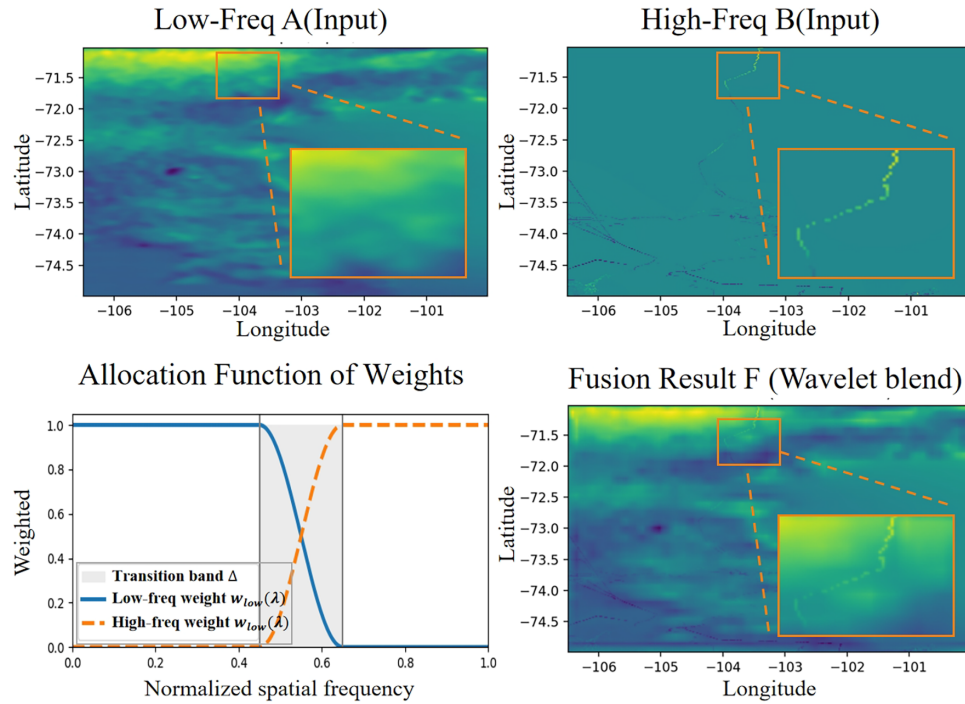


Figure 5: Wavelet-based weighted fusion of marine gravity anomalies. Inputs consist of a long-wavelength background field and a short-wavelength component extracted from survey measurements; both are free-air gravity anomalies in mGal. The weight curves indicate how contributions are allocated across scales, with a smooth transition from background-dominated low-frequency content to detail-enhanced high-frequency content. The fused map combines regional continuity with locally supported anomalies. The data are from the Marine Geoscience Data System (MGDS) and consist of Bohai Sea marine gravity products, including a gridded background field and shipborne trackline measurements.

Table 4: Qualitative comparison of map-level fusion methods.

Method	Phys.	Cost	Unc.	Core Idea
Spatial weighting	M	L	O	Weighted blending in overlap regions
Geostatistical fusion	MH	MH	Y	Model spatial covariance to fuse or interpolate fields
Multi-scale fusion	M	M	O	Separate low- and high-frequency components and recombine them
Equivalent source	H	H	O*	Fit a source model to enforce physical-field continuation
Joint inversion	VH	VH	O*	Solve a coupled inverse problem for cross-field consistency

Note: Phys. denotes physical consistency, Cost denotes computational cost, and Unc. denotes uncertainty availability. L, M, MH, H, and VH denote low, medium, medium-high, high, and very high, respectively. Y means that uncertainty is directly provided, O means that uncertainty is not inherent and requires additional analysis, and O* means that uncertainty is usually obtained indirectly and depends on the modeling or inversion setup.

Different from the aforementioned fusion methods based on weighted averaging, interpolation, or data-driven approaches, another important line of work introduces physical constraints from multiple fields directly at the model construction stage, thereby achieving a higher level of fusion. Rather than merely coordinating heterogeneous information at the data level, these methods enforce intrinsic consistency among different geophysical fields in the model parameter space through techniques such as equivalent source inversion, joint inversion, or cross-gradient constraints, yielding higher fusion accuracy and physical interpretability. Specifically, equivalent source inversion places hypothetical sources on a unified reference surface and adjusts their parameters so that their synthesized fields match the observed data, treating

multiple physical fields as an interconnected system for fusion. This method can perform interpolation, continuation, and multi-parameter transforms within a single physically consistent inversion model, and directly handles irregular point data. The multi-layer equivalent source scheme of Gao et al. integrates ground and airborne magnetic anomalies into a single model, ensuring homology and consistency across different measurement altitudes [65]. This method can also impose geological priors, for example, linking density and susceptibility through constraints that co-locate high-density bodies with high-susceptibility regions, enhancing interpretability. Classical joint inversion simultaneously fits multiple datasets such as gravity and magnetic data to generate a consistent subsurface model, optimizing shared parameters such as density and susceptibility [66–68]. Cross-gradient or Gramian constraints are commonly used to couple inversions of different datasets. For instance, Del Razo Gonzalez and Yutsis used cross-gradient constraints to obtain a subsurface model where density and susceptibility are strongly correlated in spatial structure [68]. Another line of work introduces cross-field constraints while modeling a single field, such as adding sonar depth priors to gravity-based bathymetry inversion, or conditioning magnetic anomaly matching on coarse position constraints from gravity. Multi-field consistency filtering exploits the common geological origin of gravity and magnetic measurements: when both time series are available, the anomaly match from one field can be constrained by the other within the navigation filter, stabilizing the position estimate. Such joint modeling strategies typically require quantitative knowledge of inter-field relationships; when model uncertainties are large, they may introduce systematic bias.

In summary, map-level fusion methods encompass a wide range of techniques, from simple weighted combinations to complex joint inversion. Weighted fusion and interpolation methods are simple to implement and computationally efficient, making them suitable for scenarios with high real-time requirements. In contrast, physics-based joint modeling methods, although algorithmically complex and computationally demanding, provide stronger physical consistency and matching discriminability, and are especially applicable to tasks with rich prior information or stringent accuracy requirements. In practical navigation systems, different methods should be selected or combined appropriately according to available data quality, computational resources, and mission needs. It is worth emphasizing that reproducible practice relies on open data and code. For example, the open-source framework for scalar-field cooperative localization simulation provided by Yang et al. [69] lays a foundation for fair comparison and replication of map-level fusion methods.

6 Feature-Level Fusion Methods

After map-level fusion provides a unified basemap, feature-level fusion methods encode discriminative information into stable, lightweight matchable representations, directly affecting convergence speed and disturbance rejection. Over the past five years, feature-level fusion has progressed along two main threads: one systematically exploits classical image and signal features and combines them across modalities, while the other pursues learning-based fusion using lightweight deep networks augmented with attention and multi-scale architectures. The two lines are not mutually exclusive: handcrafted features can serve as auxiliary channels to deep networks, and the attention weights learned by those networks can in turn guide the selection of handcrafted cues.

On the handcrafted side, texture statistics, gradients, and spectral/wavelet features remain dominant. Haralick textures derived from the gray-level co-occurrence matrix extract energy (angular second moment), contrast, and entropy, producing information maps that reflect seabed roughness and the complexity of gravity/magnetic anomalies [70–73]. Portes et al. computed 13-dimensional Haralick descriptors separately for magnetic and gravity anomalies and concatenated them for unsupervised multi-physics feature discovery [74]. Among gradient and edge features, the analytic signal amplitude and the enhanced total

gradient are sensitive to weak gradient breaks and are suitable for extracting matchable contours in gently varying regions [75]. The wavelet-entropy scheme effectively highlights boundaries and fine details in potential-field data, aiding structural extraction from magnetic or gravity anomalies [76]. In underwater terrain matching, local descriptors such as scale-invariant feature transform often suffer performance degradation due to differences between sonar imagery and bathymetric grids, requiring domain filtering and scale tuning [77]. Handcrafted features are interpretable and computationally efficient, but they are sensitive to noise and scale changes and suffer from unit and dynamic-range imbalance across modalities.

For learning-based feature extraction, lightweight backbones, attention mechanisms, and multi-scale pyramids are used together [78–82]. Constrained by the computational budget of underwater platforms, MobileNet or EfficientNet are often adopted as feature extractors, augmented with squeeze-and-excitation blocks or convolutional block attention modules to adaptively re-weight features. Chen et al. introduced an attention-guided fusion block and multi-scale channel attention to replace vanilla encoder-decoder skip connections, significantly improving the discriminability and noise robustness of fused features [83]. Gidugu et al. trained a random forest to map magnetic anomalies to position over a $30 \text{ km} \times 30 \text{ km}$ area, achieving a circular error probable of about 50 m in field tests, demonstrating that even shallow models with proper input normalization can be practically useful [9]. Knowledge distillation, pruning, and quantization can compress large models to embedded platforms. Learning-based features are powerful but rely on high-quality training data; for deployment in unmapped waters, they should be combined with uncertainty quantification and online weight adjustment [84].

In terms of fusion strategies, early approaches used feature concatenation or weighted averaging. Prior normalization of each channel is essential to prevent dynamic-range differences from dominating the matching result [77]. Weighted fusion assigns weights according to local variance, gradient energy, or entropy. Dai et al. formulated the two matching residuals of gravity and geomagnetism as a bi-objective optimization and solved it jointly with an improved artificial bee colony algorithm, reducing mismatches [19]. Graph attention mechanisms and Transformers have been introduced to model higher-order cross-modal dependencies: one line treats modality-specific features as graph nodes and learns inter-modal weights; another tokenizes multi-modal feature maps into sequences and uses cross-attention to learn semantic correspondences [85]. Matching criteria have also expanded to mutual information and hybrid likelihood functions, improving robustness in multi-modal or weak-texture regions [8].

Fig. 6 illustrates the multi-field, multi-channel feature construction pipeline: z-score standardized grids of bathymetry, gravity, and geomagnetism, together with descriptors such as local entropy, gradient magnitude, and wavelet energy, are stacked along the channel dimension to form a fused feature tensor. Feature-level fusion accelerates convergence: coarse-scale gravity or terrain cues constrain large-area drift, while fine-scale magnetic or gravity-gradient details achieve precise alignment; simultaneously, positions where multiple channels exhibit high similarity are unique, reducing false alarms and jumpy solutions [9,19,77]. **Table 5** compares handcrafted and learning-based features across dimensions such as representation, data requirements, robustness, explainability, computational cost, fusion approach, maintenance cost, and failure modes, serving as a reference for system design.

Overall, the core value of feature-level fusion is to transform raw geophysical fields into more discriminative and robust matchable representations. Handcrafted features remain irreplaceable in scenarios with scarce data, limited computational resources, and strong geophysical signals. Learning-based features exhibit stronger adaptability in cross-scale, high-noise, and multi-modal complex environments. The two approaches are complementary rather than opposing: practical systems can adopt handcrafted features to provide an interpretable baseline and then use lightweight deep networks to refine residuals or uncertain regions. Current trends indicate that hybrid architectures combining both, online learning with uncertainty

propagation, and generalization enhancement for unmapped waters will be key directions for future development of feature-level fusion.

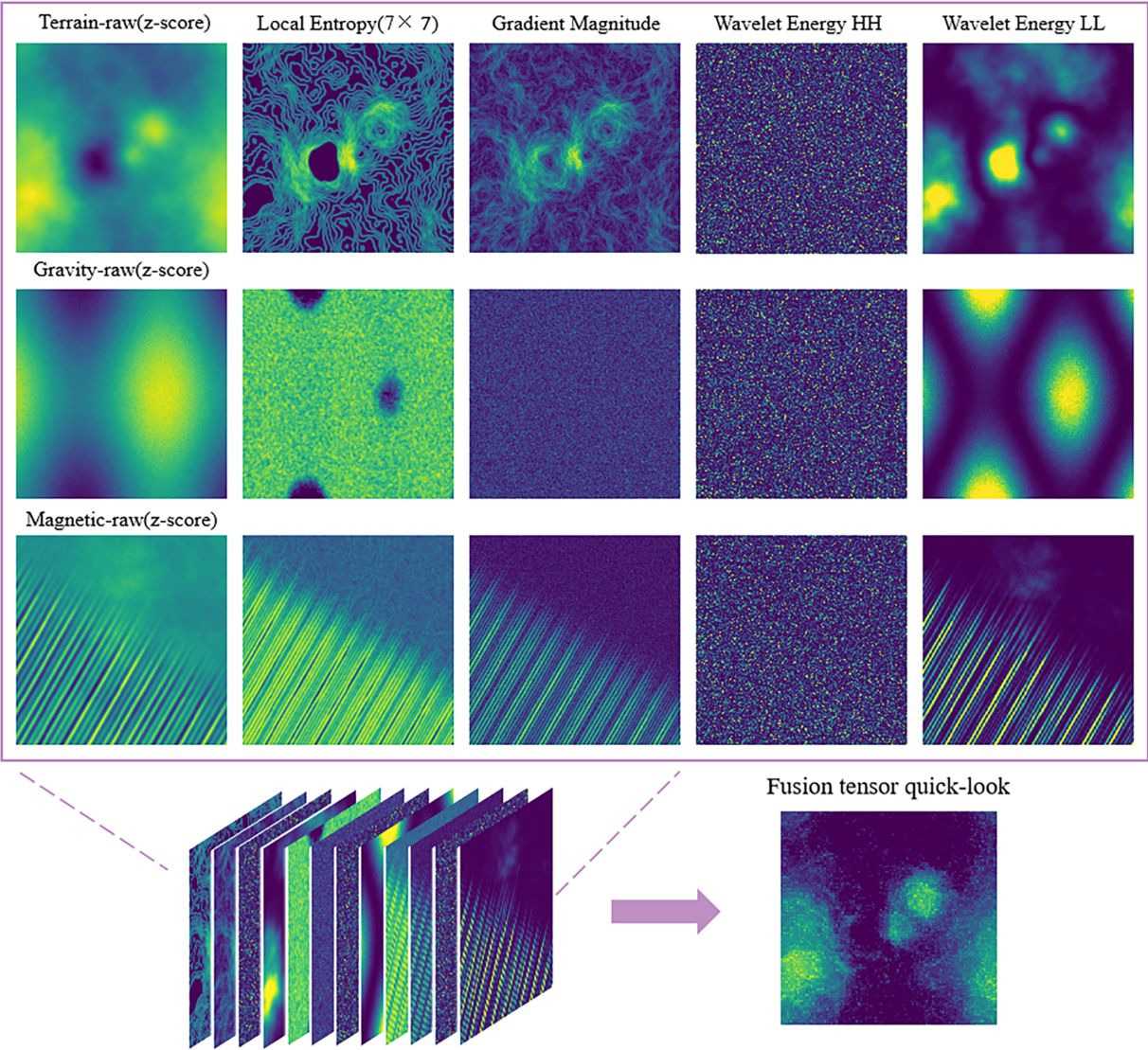


Figure 6: Multi-field, multi-channel feature construction and tensorization. The top three rows present the raw grids of bathymetry, gravity, and geomagnetism, z-score standardized, together with representative descriptors: local entropy (7×7) window, gradient magnitude, wavelet high-frequency energy (HH), and low-frequency approximation (LL). The bottom panel shows all features stacked along the channel dimension to form a fused feature tensor for subsequent matching, filtering, or deep-learning models. The quick-look inset in the lower right displays a composite saliency map derived from this tensor.

Table 5: Comparison of different feature methods for feature-level fusion in underwater geophysical fields.

Dimension	Handcrafted Features	Learning-Based Features
Representation	Explicit physical descriptors	Learned latent embeddings
Data requirements	No training data required	Training data required

(Continued)

Table 5 (continued)

Dimension	Handcrafted Features	Learning-Based Features
Noise and cross-domain robustness	Noise-sensitive, with limited invariance	Better invariance, but with OOD risk
Explainability	High physical interpretability	Moderate, usually requiring post-hoc explainers
Computing and deployment	Real-time execution on CPU	Acceleration or compression is usually required
Cross-modal fusion approach	Concatenated or weighted channels	Attention-based adaptive fusion
Maintenance cost	Low, with few tunable parameters	Requires retraining and monitoring
Failure mode	Ambiguous matches in low-contrast regions	Overconfidence under distribution shift

Note: OOD denotes out-of-distribution, CPU denotes central processing unit.

7 Decision-Level Fusion Methods

Decision-level fusion converts the matching information provided by different geophysical fields into a joint estimate of the platform state. Its core idea is to integrate the matching similarities, likelihood distributions, or candidate position solutions output by terrain-aided navigation, gravity-aided navigation, and magnetic-field-aided navigation into a unified state estimation framework. Over the past five years, research has evolved along three primary workflows: tightly coupled Bayesian filtering, which incorporates multi-field observations into a unified measurement model to jointly update the inertial navigation system; loosely coupled decision fusion, where each field independently performs matching and the results are merged via weighting, voting, or probabilistic fusion; and factor-graph or smoothing-based fusion, which represents inertial, map, and sensor constraints in a joint optimization framework. Learning-based adjustment of observation noise, fusion weights, and quality thresholds is treated as a cross-cutting enhancement to these workflows rather than as a separate workflow.

Representative tightly coupled work emphasizes a unified state estimation framework. In terrain-gravity integration, Khalilabadi simultaneously incorporate altimeter-derived terrain observations and gravity anomaly observations into a Kalman-filter-based measurement model. Both sea trials and simulations indicate that the dual-field scheme sustains convergence and improves accuracy even in gently varying terrain or weak gravity regions [31,54]. A key advantage is natural weighting: the measurement noise covariance directly determines each field's contribution, so an increase in one field's noise is automatically down-weighted by the filter. The limitation is sensitivity to linearization and prior noise modeling; if map and sensor errors are not properly accounted for, tight coupling can become overconfident and yield inconsistent estimates [7]. An earlier representative approach by Wu and Weng introduced a neural-network-assisted adaptive unscented Kalman filter (UKF) that estimates noise parameters online and, at the decision layer, fuses gravity-gradient and geomagnetic-vector filter outputs, improving stability under time-varying noise conditions [62].

When the initial error is large, the likelihood is multi-modal, or the system is strongly nonlinear, particle filters, point-mass filters, and probability grid formulations tend to be more robust [5,86–89]. Early point-mass filter work has already demonstrated wide-basin convergence in terrain-aided navigation [6,86]. For multi-field fusion, Lee et al. proposed a hybrid database referenced navigation algorithm that runs point-mass-filter-based estimation using terrain height and gravity anomaly databases, and then combines the estimation results according to the kurtosis of the posterior probability density function. Their simulation results showed that the proposed multi-database fusion method outperformed navigation based on individual databases [21]. The key advantage of this line is explicit preservation of multiple hypotheses: likelihood peaks produced by different fields at different locations can be retained through joint resampling, avoiding premature collapse to an incorrect mode. The trade-off is increased computational cost, which necessitates engineering compromises among particle count, candidate windows, and hierarchical search strategies [31]. A closely related approach is Viterbi or hidden Markov model path matching, which treats per-epoch matching scores as emission probabilities and uses dynamic programming to find the most probable trajectory; this helps suppress sporadic false peaks in gravity- or magnetically low-texture regions [8,90,91].

Factor graphs have become an increasingly popular tool for fusing inertial odometry with multi-field matching cues [92–96]. A factor graph is a probabilistic graphical model that represents variables (e.g., position, velocity, attitude) as nodes and constraints such as sensor measurements, map information, or prior knowledge as factors [31,96]. It is typically used for maximum a posteriori or least-squares optimization, with the goal of finding the most likely state trajectory given the observations. In multi-field navigation, gravity and magnetic observations are added as factors to the graph, and the inertial preintegration is jointly optimized with external measurements to achieve globally consistent state estimation.

Loosely coupled decision fusion remains a pragmatic engineering compromise: each modality independently performs matching to produce position estimates, probability maps, or likelihood peaks, which are then combined at the top level via weighting or probability products. Common strategies include quality-based weighting using posterior peak height, peak width, peak-to-valley ratio, mutual information, or local entropy as confidence measures; probabilistic products or Bayesian fusion under conditional independence assumptions to obtain a joint posterior [97]; and Dempster-Shafer evidence theory or covariance intersection, which fuse under unknown correlations without becoming overconfident. Zheng et al.'s gravity-magnetic combination employs dynamic weight allocation and leverages cross-field complementarity to improve success rates and reduce errors across regions [58]. While the loosely coupled architecture is clear, modular, and easy to integrate atop existing single-source blocks, it does not fully exploit inter-field correlations and can be suboptimal in highly nonlinear regimes or under strongly correlated noise.

The main decision-level fusion workflows are summarized in Fig. 7. The figure distinguishes tightly coupled filtering, loosely coupled decision combination, and factor-graph or smoothing-based fusion, which correspond to different assumptions on measurement modeling, source independence, and posterior consistency.

Based on a comprehensive comparison of the different technical routes, the field has converged on the following consensus. First, quality thresholds and adaptive weighting are pivotal for robust multi-field fusion. Per-pixel uncertainties and feature quality indicators should be mapped into measurement covariances or fusion weights, so that weak-information regions are automatically down-weighted or masked. Second, coarse-to-fine spatiotemporal stratification addresses both large initial errors and real-time constraints: low-frequency or low-resolution fields first drive global convergence, followed by high-frequency or fine-scale fields for fine alignment. Third, consistency diagnostics and fault isolation are necessary system capabilities. Metrics such as normalized innovation statistics, posterior Kullback-Leibler(KL) divergence, or the overlap of posteriors across fields can trigger weight resets, measurement rejection, or fallback to

single-source updates, preventing system-wide degradation due to anomalies in any single modality. Fourth, learning-based augmentation should be coupled with physical constraints: neural and machine learning models are well suited for tasks like noise estimation, weight prediction, and region suitability assessment, while the core state estimation should remain filter- or graph-optimization-based to preserve verifiability and reproducibility.

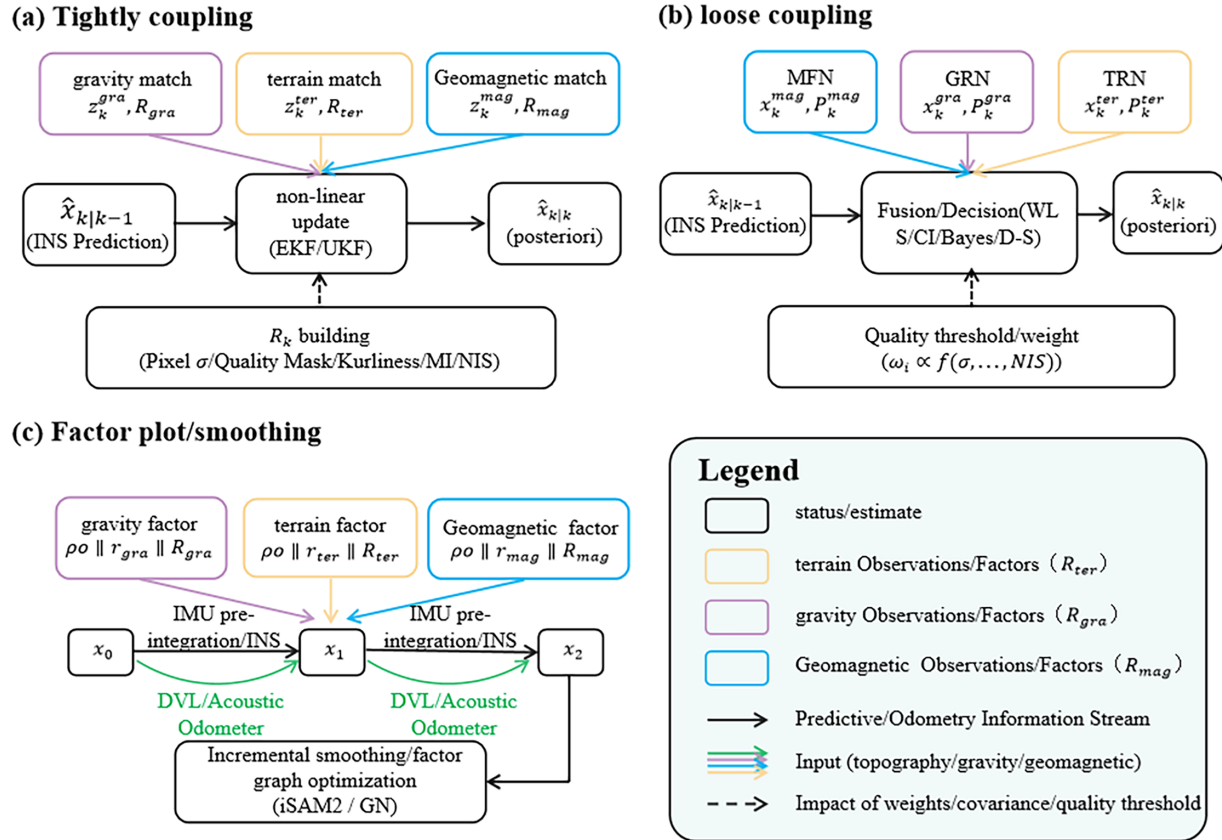


Figure 7: Schematic of decision-level fusion methods. This figure illustrates alternative strategies and workflows at the decision layer. Panel (a) shows a tightly coupled scheme based on Kalman filtering (EKF/UKF), where gravity, bathymetry (terrain), and geomagnetic observations are jointly modeled; modality-dependent weighting is effected through the measurement noise covariance, and nonlinear posterior updates are used to realize state prediction and fusion. Panel (b) depicts a loosely coupled scheme in which each modality first produces its own match or solution; weighted least squares (WLS), Bayesian fusion, Dempster-Shafer (D-S) evidence theory, or covariance intersection (CI) then combine these results according to their quality and uncertainty to yield the navigation decision. Panel (c) presents a factor-graph/smoothing approach, where error-correction factors are added and optimized via incremental prediction-update over a sliding window; by fusing IMU, DVL and geophysical measurements as graph factors, the method achieves consistent state estimation and trajectory optimization.

Table 6 summarizes common decision-level fusion strategies. The probability product is simple and effective when modalities are nearly independent, but correlation can lead to overconfidence. Covariance intersection remains consistent under unknown correlation but is conservative. Dempster-Shafer evidence theory can represent uncertainty and partial evidence, yet it is sensitive to high conflict. Dynamic weighting is adaptive but depends on gate design and may introduce delay. Taken together, the reviewed studies suggest a literature-derived implementation pattern rather than a newly validated algorithm. This pattern combines point-mass or particle filtering for coarse localization with Kalman-filter-family updates for local

refinement [5,21,54,86]; it then combines modality-specific evidence using quality-aware probabilistic fusion or dynamic weighting [7,58,97]. Regional localizability and confidence measures can be used to adjust the participating modalities and update frequency, thereby reducing ineffective or overconfident updates in weak-information regions [27,28,55]. These elements are summarized here as engineering design guidance and require experimental validation before being treated as a specific navigation architecture.

Table 6: Comparison of decision-level fusion methods. D-S denotes Dempster-Shafer.

Strategy	Advantages	Disadvantages
Probability product	Simple; strong under independence	Correlation overconfidence; fragile under multimodal posteriors
Covariance intersection	Consistent under unknown correlation	Conservative; fusion-weight tuning is required
D-S evidence fusion	Represents ignorance and partial evidence	Sensitive to conflict; parameterization is relatively heavy
Dynamic weighting	Adaptive and context-aware	Sensitive to gate design; may introduce latency

8 Evaluation and Baselines

Currently, the bottleneck in terrain-gravity-geomagnetic cooperative navigation is not a lack of methodological innovation, but the absence of a reproducible, comparable, and transferable systematic evaluation framework. This chapter synthesizes existing practices in underwater navigation evaluation, covering task definitions, performance metrics, baseline algorithms, and scenario stratification, to support more consistent research reporting.

Task settings are recommended to be divided into two categories: offline replay matching and online integrated navigation. The former performs sliding-window or particle search over a fixed map to evaluate matching performance in a controlled environment. The latter feeds the likelihood outputs of multi-field matching into an estimator (such as extended or unscented Kalman filter, particle filter, point-mass filter, or factor graph) and couples it in real time with an inertial navigation system and a Doppler velocity log. To ensure comparability, the following conditions should be uniformly reported: initial pose errors, speed, depth and altitude above the seafloor, sensor noise and loss-of-lock models, map resolution, and whether external disturbances are injected. It is also recommended to conduct a pre-experiment analysis of anomaly amplitude, spectral content, and map uncertainty in the test area to distinguish method performance from region-specific information content.

To make the benchmark setting more explicit, the evaluation objectives should be defined before selecting specific metrics or baseline algorithms. A benchmark for underwater geophysical-field matching navigation should not only compare final position errors, but should also reflect the complete navigation chain from local map matching to closed-loop state correction and onboard implementation. Therefore, this review organizes the benchmark objectives into five levels, as summarized in Table 7: matching localization, closed-loop navigation, robustness under disturbance, real-time deployment, and cross-region transferability. These objectives correspond to different evaluation modes and should not be mixed into a single accuracy score.

Table 7: Recommended benchmark objectives for underwater geophysical-field matching navigation.

Objective	Purpose	Recommended Metrics	Typical Baselines
Matching localization	Evaluate whether the local measurement window is correctly associated with the reference map	Matching success rate, mismatch rate, top- k recall, candidate position error, posterior peak sharpness	Cross-correlation, mutual information, ICCP, single-field matching
Closed-loop navigation	Evaluate whether matching updates suppress INS drift	RMSE, CEP50, CEP95, maximum error, time to first fix, convergence time, NIS, NEES	INS/DVL, EKF, UKF, PF, PMF, factor graph
Robustness under disturbance	Evaluate stability under weak fields, map errors, sensor drift, and heading errors	Failure rate, recovery time, outlier rejection rate, robustness under injected disturbances	Single-field matching, robust PF, RBPF, covariance inflation, measurement rejection
Real-time deployment	Evaluate onboard feasibility under limited computation and storage	Per-frame latency, update frequency, memory usage, map-tile I/O load, power consumption	Hierarchical search, map tiling, lightweight learning, sparse factor graph
Cross-region transferability	Evaluate generalization across sea areas, map resolutions, and sensor settings	Within-region error, cross-region error, degradation ratio, out-of-distribution failure rate	Classical non-learning baselines, learning-based models, hybrid physics-learning models

Note: ICCP denotes iterative closest contour point; INS/DVL denotes inertial navigation system/Doppler velocity log; RMSE denotes root mean square error; CEP50 and CEP95 denote 50% and 95% circular error probable; NIS and NEES denote normalized innovation squared and normalized estimation error squared; EKF, UKF, PF, PMF, and RBPF denote extended Kalman filter, unscented Kalman filter, particle filter, point-mass filter, and Rao-Blackwellized particle filter, respectively; I/O denotes input/output.

As shown in [Table 7](#), different benchmark objectives emphasize different aspects of navigation performance. Offline replay matching mainly supports the matching-localization objective, where success rate, mismatch rate, and posterior peak sharpness are more informative than final trajectory error alone. Online integrated navigation is more suitable for evaluating closed-loop drift suppression, estimator consistency, and convergence behavior. Robustness tests should deliberately inject large initial errors, weak-field regions, map noise, heading errors, sensor drift, missing observations, or Doppler velocity log dropouts to evaluate failure rate and recovery capability. For engineering applications, real-time feasibility and cross-region transferability are equally important, because an accurate method may still be unsuitable for autonomous underwater vehicles if it cannot run onboard or if it fails when transferred to a new sea area. Therefore, a complete benchmark should jointly report positioning accuracy, robustness, consistency, computational cost, and generalization performance, together with map resolution, sensor-noise assumptions, vehicle speed, altitude above the seafloor, update rate, and ground-truth availability.

Evaluation metrics need to balance positioning accuracy, consistency, and engineering feasibility. For positioning accuracy, it is recommended to report 50% and 95% circular error probable (CEP50 and CEP95), along-track and cross-track root mean square error (RMSE), time to first fix, steady-state error, match success and mismatch rates, and recovery time under intermittent observations [7,88,90]. For consistency, the normalized innovation squared and normalized estimation error squared can be supplemented by chi-square threshold monitoring and outlier detection. From an engineering perspective, per-frame latency, update frequency, power consumption, and tiled map input-output load should also be recorded [31]. Model confidence analysis is equally important: when matching confidence falls below a threshold, re-localization, measurement rejection, or a backup navigation strategy can be triggered, as demonstrated in confidence-aware gravity- and magnetic-aided navigation studies [27,28].

Table 8 presents a quantitative comparison of representative methods. For brevity, standard technical abbreviations are used: Kalman filter, extended Kalman filter, unscented Kalman filter, and error-state Kalman filter are denoted as KF, EKF, UKF, and ESKF, respectively. Key sensors and algorithms include Doppler velocity log (DVL), particle swarm optimization (PSO), iterative closest contour point (ICCP), terrain contour matching (TERCOM), probabilistic multi-hypothesis tracking (PMHT), Rao-Blackwellized particle filter (RBPF), and extreme learning machine (ELM). Because the reviewed studies differ in scenarios, field types, map resolutions, noise settings, and evaluation metrics, the results should be interpreted as a literature-based comparison rather than a strictly unified benchmark. Khalilabadi's tightly coupled Kalman filter increased the effective navigation probability from 79% to 99.8% [54]. Xu et al.'s staged PSO-ICCP-KF pipeline reduced position error from 1318.83 to 23.51 m [98]. Wang et al.'s probabilistic multi-hypothesis tracking plus unscented Kalman filter achieved a bounded position error of 408 m in long-range simulation [90]. Zhang et al.'s Rao-Blackwellized particle filter attained a root mean square error of 3.62 m [88]. Huang et al.'s extreme learning machine aided matching achieved a mean absolute error of 6.38 m [99]. These representative results, together with the broader studies reviewed in Sections 3–5, indicate that underwater matching navigation is evolving from single-field correlation or filter refinement toward multi-stage, hierarchical, uncertainty-aware, and learning-augmented architectures [16,88,90,99]. Therefore, the trend summarized here is not derived solely from the limited entries in Table 8, but from the combined evidence of representative quantitative studies, map-level fusion studies, feature-level fusion studies, and decision-level fusion studies.

Table 8: Quantitative comparison of representative underwater matching navigation methods and related competitive frameworks.

Category	Methods	Scenario & Data	Architecture	Reported Result
Single-field	Xu et al. 2022 [98]	Simulation with a geomagnetic map	PSO + ICCP + KF	Error reduced from 1318.83 to 23.51 m
Map-level	Bai et al. 2016 [36]	Multi-source gravity anomaly data	Wavelet-based multi-source gravity fusion	Improved multi-source gravity map consistency and reduced uncertainty for subsequent matching

(Continued)

Table 8 (continued)

Category	Methods	Scenario & Data	Architecture	Reported Result
Map-level	Zheng et al. 2013 [58]	Gravity and geomagnetic fields	Gravity-geomagnetic combined aided navigation with optimal weight assignment	Gravity and geomagnetic information were combined to improve navigation accuracy compared with single-field matching
Map-level	Chen et al. 2024 [14]	Altimetry-derived and shipborne gravity data	Marine gravity anomaly fusion	Improved consistency between satellite-derived and shipborne gravity anomalies
Map-level	Li et al. 2024 [63]	Multi-mission satellite altimetry	CNN-based marine gravity-field fusion	Improved marine gravity-field recovery through multi-mission data fusion
Feature-level	Chen et al. 2024 [83]	3D gravity inversion	Attention-based feature fusion	Improved inversion representation through attention-guided feature fusion
Feature-level	Huang et al. 2025 [99]	Complex geomagnetic region	Improved ELM-aided geomagnetic matching	Average absolute error of 6.38 m; maximum error reported under noise $\sigma = 5$ nT
Decision-level	Khalilabadi 2020 [54]	Gravity and terrain	KF-based tight coupling	Valid navigation probability increased from 79% to 99.8%
Decision-level	Wang et al. 2023 [90]	Long-range simulation with gravity map	PMHT + UKF updates	Best position error of 408 m
Decision-level	Zhang et al. 2023 [88]	Simulation and field tests with terrain data	Outlier-robust RBPF	Best position RMSE of 3.62 m

(Continued)

Table 8 (continued)

Category	Methods	Scenario & Data	Architecture	Reported Result
Graph-based	Ma et al. 2021 [60]	Simulation and semi-physical tests	Factor-graph multisensor fusion	Better positioning performance than EKF-based fusion
Learning-augmented	Gidugu et al. 2024 [9]	Geomagnetic-field AUV navigation	Bio-inspired machine-learning localization	Field-test circular error probable of about 50 m
Learning-augmented	Quan et al. 2025 [16]	Underwater geomagnetic navigation	Inertial-constraint-aided geomagnetic matching	Improved robustness of geomagnetic matching using inertial constraints

To further compare the related characteristics of different underwater matching navigation frameworks, Fig. 8 presents a radar-chart summary of six representative categories, including INS/DVL-only navigation, single-field matching, map-level fusion, feature-level fusion, decision-level fusion, and learning-augmented fusion. The comparison considers six aspects: accuracy potential, robustness, real-time feasibility, computational efficiency, interpretability, and engineering applicability. The scores are qualitative ratings summarized from the reviewed literature, where a higher score indicates stronger capability in the corresponding aspect. To make the criteria consistent, computational cost is inversely mapped into computational efficiency. As shown in Fig. 8, decision-level fusion generally provides stronger robustness and accuracy potential due to its ability to integrate likelihoods, confidence measures, and state estimation. Map-level fusion shows better interpretability and engineering stability, while feature-level and learning-augmented methods provide stronger representation capability but require careful treatment of training data, generalization, and onboard computational constraints.

For baseline algorithms, we recommend a horizontal comparison across single-field, dual-field, and triple-field levels [32,33]. Single-field baselines include extended Kalman filter matching, particle filter matching, Viterbi sequence decoding, and cross-correlation or mutual information matching, which can be applied to terrain, gravity, or geomagnetic maps. Dual-field baselines encompass dynamic weighting or probability product, extended Kalman filter tight coupling, and coarse-to-fine pipelines such as multi-resolution sequential gravity matching. As an implementation-neutral triple-field baseline, terrain, gravity, and geomagnetic likelihoods can be normalized and combined using either an equal-weight probability product or uncertainty-based weights; a hierarchical alternative can use terrain for coarse localization followed by gravity and geomagnetic refinement. Learning-based reference methods include geomagnetic localization models based on lightweight networks or random forests (typical CEP50 around 50 m) as well as advanced fusion architectures like graph attention or Transformers. All learning methods should be compared against classical baselines under identical maps and noise settings to ensure fair evaluation.

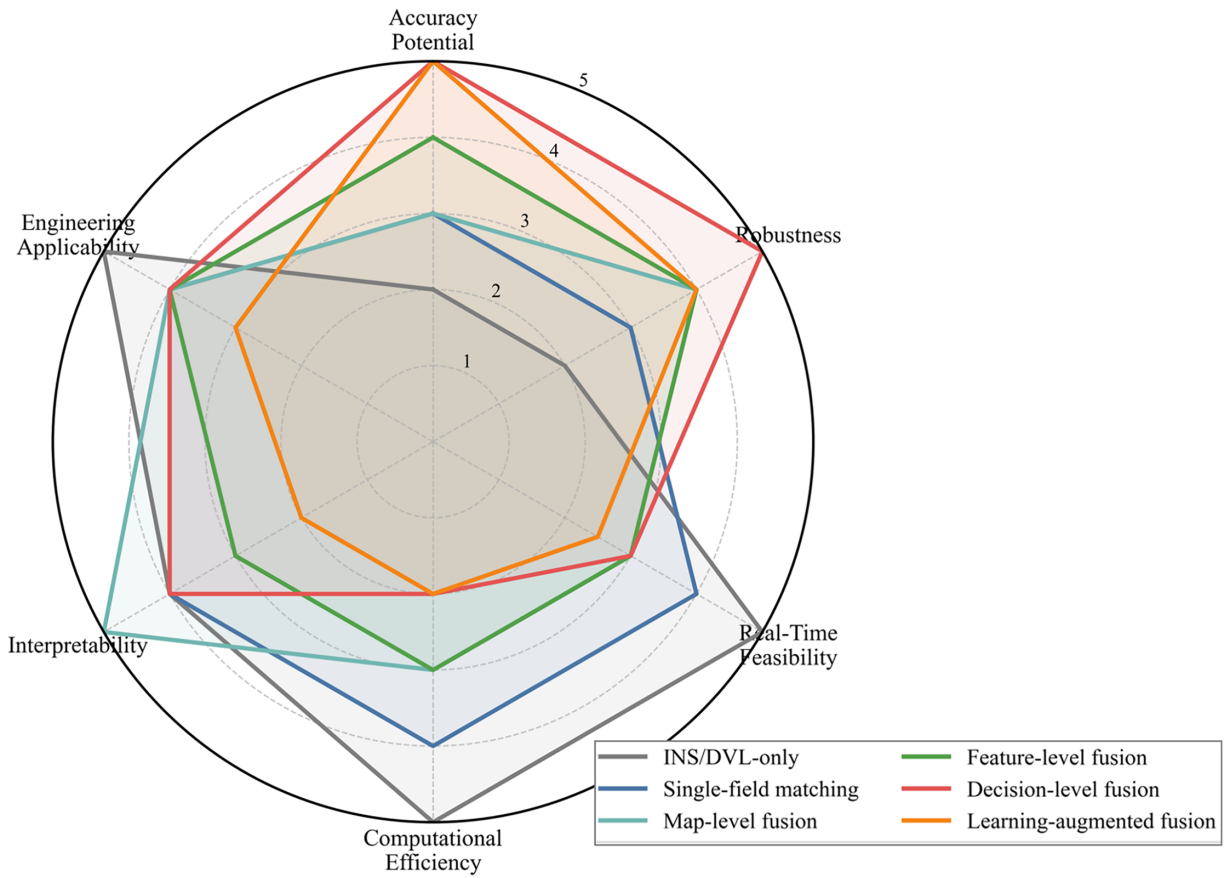


Figure 8: Radar-chart comparison of representative underwater matching navigation frameworks in terms of accuracy potential, robustness, real-time feasibility, computational efficiency, interpretability, and engineering applicability. Scores are qualitative ratings summarized from the reviewed literature, where 1 indicates low capability and 5 indicates high capability. Computational efficiency is obtained by inversely mapping the computational cost score.

9 Discussion

9.1 Answers to the Research Questions

Based on the study-level mappings provided in Supplementary Tables S2–S4, the research questions proposed in the Review Methodology section can be answered as follows. **RQ1:** Existing multi-source geophysical-field fusion methods can be principally classified into map-level, feature-level, and decision-level fusion. **RQ2:** Heterogeneous bathymetric, gravity, and geomagnetic data are generally unified through coordinate and datum alignment, reference-field removal, normalization, registration, resampling, and uncertainty characterization, and are subsequently integrated as maps, features, or navigation observations. **RQ3:** Map-level fusion offers strong physical interpretability but depends on map quality and registration; feature-level fusion improves matching discriminability but is sensitive to noise, training-data coverage, and distribution shifts; decision-level fusion supports adaptive state estimation but relies on reliable confidence and covariance modeling. **RQ4:** Fair evaluation requires joint assessment of positioning accuracy, matching success, convergence, robustness, estimator consistency, computational cost, and cross-region transferability under clearly reported experimental conditions. **RQ5:** The principal unresolved challenges are heading and attitude robustness, the verifiable integration of physics-based and learning-based methods, end-to-end uncertainty propagation, real-time onboard implementation, and benchmark standardization.

Heading robustness is a major cause of failure in feature-level fusion, especially because map matching performance is sensitive to rotation, local ambiguity, and the spectral characteristics of the reference field [45]. Existing work has roughly followed two paths. One handles geometric differences before matching, using heading correction, window rotation, and feature alignment to map observations to the basemap reference frame. The other enhances invariance on the feature or model side, e.g., via rotation augmentation, rotation-invariant descriptors, or equivariant convolutions. The former is interpretable and engineering controllable, but depends on heading quality and alignment accuracy; errors enter the likelihood as systematic bias. The latter covers disturbances more comprehensively, but the training data must cover a sufficient distribution of attitudes, otherwise it still degrades under out-of-distribution headings. These observations indicate that heading and attitude robustness remains an unresolved bottleneck for applying feature-level fusion in dynamic underwater navigation.

The deep integration of physics and data has moved from end-to-end replacement to modular enhancement, but its effective boundary requires clearer engineering consensus. Successful practices generally follow the principle: keep the physical chain (matching plus filtering or graph optimisation) interpretable and verifiable, while learning modules handle parts that are difficult to model explicitly, such as region suitability discrimination, weight or threshold scheduling, noise estimation, or feature enhancement. The weakness lies in poor generalisation across different sea areas; learning modules tend to become overconfident under map errors or sensor anomalies, and attention-like structures are costly on embedded platforms. Therefore, a key limitation of current learning-enhanced fusion is not only model accuracy, but also the lack of a stable and verifiable boundary between physical modeling, data-driven representation, and onboard implementation.

Uncertainty management is the core that turns multi-field complementarity into stable gains, and is also the part most lacking a unified interface. Existing methods often introduce quality metrics (interpolation variance, wavelet energy, entropy, gradient energy) at local stages for region screening or weighting, and the filtering layer uses innovation statistics or posterior peak shape for gating and resetting. The problem is that these quantities are often empirical and difficult to propagate end to end, making the credibility of the same data incomparable across different algorithms. This limitation makes uncertainty one of the most important obstacles to reproducible comparison and reliable transfer of multi-field fusion methods across different regions and platforms.

9.2 Research Challenges and Future Trends

First, robust matching under dynamic navigation remains a fundamental challenge. In practical AUV operations, heading, attitude, velocity, and altitude may change continuously, causing rotation, deformation, and scale inconsistency between the measured profile or local window and the reference map [100]. Future methods should combine explicit heading modeling with learning-based invariant representations. For example, heading angles can be introduced into feature construction or matching scores as continuous variables, while lightweight equivariant structures can be used to learn residual deformations. More importantly, heading uncertainty should be propagated into the likelihood function or observation covariance, so that robustness is controlled by measurable uncertainty rather than empirical parameter tuning.

Second, future research should further clarify the boundary between physics-based modeling and data-driven learning. A fully end-to-end black-box strategy is difficult to verify and risky for safety-critical underwater navigation. A more feasible trend is physics-informed lightweight learning, where the core navigation chain remains filter-based or graph-optimization-based, while learning modules are used for region suitability assessment, feature enhancement, noise estimation, quality gating, and fusion-weight scheduling. Physical consistency constraints, such as cross-gradient consistency and structural coherence among terrain, gravity, and magnetic anomalies, can be introduced into the training objective to suppress

unreasonable cross-field couplings. For onboard deployment, an offline-heavy and online-light scheme is preferable: large models learn cross-field relationships offline, while compact distilled models perform online coefficient adjustment under AUV computational and power constraints.

Third, uncertainty propagation from map pixels to navigation decisions should become a standard component of future fusion systems. Map errors, interpolation variance, sensor noise, matching confidence, and posterior consistency should not be treated as isolated quantities [45,101]. Instead, pixel-level uncertainty should be aggregated into window-level confidence and then mapped into likelihood functions, filter covariance, particle weights, or factor-graph residual weights. A closed-loop consistency diagnosis mechanism is also required. When abnormal innovations, insufficient cross-field posterior overlap, or sudden changes in posterior peak shape are detected, the system should trigger covariance inflation, weight reallocation, measurement rejection, or conservative fusion strategies such as covariance intersection. Such an uncertainty-aware interface is essential for preventing overconfident updates and mismatch-induced trajectory jumps.

Fourth, real-time onboard implementation and benchmark standardization are critical for moving multi-field fusion from algorithmic demonstration to operational use [100]. High-complexity methods, such as large-scale particle filtering, long-window factor graph smoothing, and deep attention networks, may be difficult to deploy directly on resource-constrained AUVs, including small vehicles and some medium platforms, because of limited computation, power, and storage. Therefore, future systems should emphasize hierarchical search, map tiling, sparse updates, model compression, pruning, quantization, and adaptive update scheduling. At the same time, the community still lacks open benchmark datasets, unified task definitions, and standardized metrics for terrain, gravity, and geomagnetic fusion navigation. Establishing shared datasets, baseline algorithms, uncertainty annotations, and reproducible evaluation scripts will be necessary for fair cross-method comparison and for accelerating the engineering application of underwater geophysical field matching navigation.

From an operational perspective, the choice of fusion strategy should also be matched to the size, endurance, and onboard computing capacity of the AUV. For small or power-limited AUVs, lightweight methods such as hierarchical correlation matching, map tiling, EKF/UKF-based updates, and quality-gated single- or dual-field fusion are usually more practical. For compute-capable AUVs, including some medium and large platforms with stronger processors and longer endurance, particle-filter-based global search, sliding-window factor graph optimization, and lightweight learning-enhanced fusion become more feasible, especially when sparse updates and adaptive triggering are used. In contrast, dense particle filtering over large map areas, long-window smoothing, and large attention-based networks may be difficult to deploy directly onboard unless model compression, pruning, quantization, or offline-heavy/online-light computation is adopted. Therefore, operational use requires a tradeoff among positioning accuracy, robustness, map-storage cost, update frequency, energy consumption, and failure-recovery capability. A full real-world deployment comparison across different AUV classes is beyond the scope of this review, but it represents an important direction for future engineering validation.

10 Conclusion

Based on the systematic review presented above, this paper provides a full-chain overview of multi-source data fusion methods for underwater geophysical field matching navigation, covering preprocessing, map-level, feature-level, and decision-level fusion, along with a standardized evaluation framework. The study shows that single-field matching has limited robustness in complex environments, and the key to successful multi-field cooperation lies in three aspects: first, establishing unified data benchmarks and pixel-level uncertainty characterization to make heterogeneous data comparable and weightable; second,

adopting coarse-to-fine hierarchical fusion strategies to balance wide-area convergence and fine alignment; third, propagating uncertainty end-to-end to the filtering and decision layers to enable adaptive gating and conservative fusion. The field is now converging around a consensus framework of “quality awareness, hierarchical progression, and adaptive decision-making”, where the performance ceiling is shifting from algorithmic forms to uncertainty modeling capabilities. Looking forward, deeply integrating physical priors with lightweight learning models and establishing open benchmark datasets and evaluation pipelines are two core directions for advancing this technology from laboratory research to engineering-reproducible and cross-region transferable applications.

Acknowledgement: Not applicable.

Funding Statement: The authors received no specific funding for this study.

Author Contributions: The authors confirm their contributions to the paper as follows: conceptualization, Jiaqi Mi and Kunpeng He; methodology, Jiaqi Mi; literature search and data curation, Jiaqi Mi, Congcong Ma, Xinrui Li and Sixu Huang; formal analysis, Jiaqi Mi, Congcong Ma, Xinrui Li and Sixu Huang; writing—original draft preparation, Jiaqi Mi; writing—review and editing, Kunpeng He and Jiaqi Mi; supervision, Kunpeng He. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: The data and materials supporting the findings of this study are available from the corresponding author, Kunpeng He, upon reasonable request.

Ethics Approval: Not applicable. This study did not involve human participants or animals.

Conflicts of Interest: The authors declare no conflicts of interest.

Supplementary Materials: The supplementary material is available online at <https://www.techscience.com/doi/10.32604/cmc.2026.085901/sl>.

References

1. Paull L, Saeedi S, Seto M, Li H. AUV navigation and localization: a review. *IEEE J Oceanic Eng.* 2014;39(1):131–49. doi:10.1109/JOE.2013.2278891.
2. Kinsey JC, Eustice RM, Whitcomb LL. A survey of underwater vehicle navigation: recent advances and new challenges. In: *Proceedings of the IFAC Conference of Manoeuvring and Control of Marine Craft*; 2006 Sep 20–22; Lisbon, Portugal. p. 1–12.
3. Stutters L, Liu H, Tiltman C, Brown DJ. Navigation technologies for autonomous underwater vehicles. *IEEE Trans Syst Man Cybern Part C (Appl Rev)*. 2008;38(4):581–9. doi:10.1109/TSMCC.2008.919147.
4. Bahr A, Leonard JJ, Fallon MF. Cooperative localization for autonomous underwater vehicles. *Int J Rob Res.* 2009;28(6):714–28. doi:10.1177/0278364908100561.
5. Anonsen KB, Hallingstad O. Terrain aided underwater navigation using point mass and particle filters. In: *Proceedings of the IEEE/ION Position, Location, and Navigation Symposium*; 2006 Apr 25–27; San Diego, CA, USA. p. 1027–35.
6. Claus B, Bachmayer R. Terrain-aided navigation for an underwater glider. *J Field Robot.* 2015;32(7):935–51. doi:10.1002/rob.21563.
7. Wang H, Wu L, Chai H, Bao L, Wang Y. Location accuracy of INS/gravity-integrated navigation system on the basis of ocean experiment and simulation. *Sensors.* 2017;17(12):2961. doi:10.3390/s17122961.
8. Li W, Gilliam C, Wang X, Kealy A, Greentree AD, Moran B. Gravity-aided navigation using Viterbi map matching algorithm. *J Navig.* 2024;77(3):307–21. doi:10.1017/S0373463324000030.
9. Gidugu AR, Vandavasi BNJ, Narayanaswamy V. Bio-inspired machine-learning aided geomagnetic field based AUV navigation system. *Sci Rep.* 2024;14(1):17912. doi:10.1038/s41598-024-68950-2.

10. Palmier C, Dahia K, Merlinge N, Laneuville D, Del Moral P. Bathymetry and atomic gravimetry sensor fusion for autonomous underwater vehicle. In: Proceedings of the 2021 IEEE 24th International Conference on Information Fusion (FUSION); 2021 Nov 1–4; Sun City, South Africa. p. 1–8. doi:10.23919/FUSION49465.2021.9626893.
11. Ding P, Cheng X. A new contour-based combined matching algorithm for underwater terrain-aided strapdown inertial navigation system. *Measurement*. 2022;202(2):111870. doi:10.1016/j.measurement.2022.111870.
12. Wang B, Ma Z, Huang L, Deng Z, Fu M. A filtered-marine map-based matching method for gravity-aided navigation of underwater vehicles. *IEEE/ASME Trans Mechatron*. 2022;27(6):4507–17. doi:10.1109/TMECH.2022.3159596.
13. Ai W, Zhong S, Leng Y, Wang S. A real-time autonomous gravity measurement method for underwater gravity-aided navigation. *IEEE Access*. 2023;11:135728–37. doi:10.1109/ACCESS.2023.3338537.
14. Chen X, Kong X, Zhou R, Zhang S. Fusion of altimetry-derived model and ship-borne data in preparation of high-resolution marine gravity determination. *Geophys J Int*. 2024;236(3):1262–74. doi:10.1093/gji/ggad471.
15. Li J, Li Z, Wu L, Bao L, Guo J. Enhancing bathymetric prediction by integrating gravity and gravity gradient data with deep learning. *Front Mar Sci*. 2024;11:1520401. doi:10.3389/fmars.2024.1520401.
16. Quan S, Zhou Y, Zhao S, Wang Z, Yang G, Hu H. An inertial constraint-aided geomagnetic matching algorithm for underwater navigation. *Measurement*. 2025;256(5):118156. doi:10.1016/j.measurement.2025.118156.
17. Zhang W, Yan J, Li F. An improved coastal marine gravity field based on the mean sea surface height constraint factor method. *Remote Sens*. 2022;14(16):4125. doi:10.3390/rs14164125.
18. He H, Li T, Zhang R. Joint inversion of 3D gravity and magnetic data under undulating terrain based on combined hexahedral grid. *Remote Sens*. 2022;14(18):4651. doi:10.3390/rs14184651.
19. Dai T, Miao L, Shao H. A robust underwater navigation method fusing data of gravity anomaly and magnetic anomaly. *Int J Syst Sci*. 2019;50(4):679–93. doi:10.1080/00207721.2019.1567866.
20. Zhao S, Zheng W, Li Z, Zhu H, Xu A. Improving matching efficiency and out-of-domain reliability of underwater gravity matching navigation based on a novel soft-margin local semicircular-domain re-searching model. *Remote Sens*. 2022;14(9):2129. doi:10.3390/rs14092129.
21. Lee W, Yoo YM, Yun S, Park CG. Weighting logic design of hybrid database referenced navigation algorithm using multiple geophysical information. *IFAC Proc*. 2014;47(3):3407–12. doi:10.3182/20140824-6-ZA-1003.01471.
22. Liu M, Chang G. Gravity matching aided inertial navigation technique based on marginal robust unscented Kalman filter. *Math Probl Eng*. 2015;2015:592480. doi:10.1155/2015/592480.
23. Saltus RW, Chulliat A, Meyer B, Bates M, Sirohey A. Magnetic anomaly grid and associated uncertainty from marine trackline data: the Caribbean alternative navigation reference experiment (CANREx). *Earth Space Sci*. 2023;10(11):e2023EA002958. doi:10.1029/2023EA002958.
24. Xiao C, Guo J, Zhu C, Li H, Liu S, Liu X. Refining satellite altimetry-derived gravity anomaly model with shipborne gravity using multilayer perceptron neural networks. *Sci Rep*. 2025;15(1):19467. doi:10.1038/s41598-025-04619-8.
25. Wang S, Zheng W, Li Z. Optimizing matching area for underwater gravity-aided inertial navigation based on the convolution slop parameter-support vector machine combined method. *Remote Sens*. 2021;13(19):3940. doi:10.3390/rs13193940.
26. Zhao X, Zheng W, Xu K, Zhang H. Optimizing the matching area for underwater gravity matching navigation based on a new gravity field feature parameters selection method. *Remote Sens*. 2024;16(12):2202. doi:10.3390/rs16122202.
27. Zou J, Cai T, Zhao S. Gravity-aided navigation underwater positioning confidence study based on Bayesian estimation of the interquartile range method. *Remote Sens*. 2025;17(13):2137. doi:10.3390/rs17132137.
28. Ramos JH, Shin J, Volle K, Buzaud P, Brink K, Ganesh P. Information-aware guidance for magnetic anomaly based navigation. In: Proceedings of the 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2022 Oct 23–27; Kyoto, Japan. p. 6347–54. doi:10.1109/IROS47612.2022.9981709.
29. Moradi M, Zhai ZM, Nielsen A, Lai YC. Random forests for detecting weak signals and extracting physical information: a case study of magnetic navigation. *APL Mach Learn*. 2024;2(1):016118. doi:10.1063/5.0189564.
30. Wang B, Li T, Deng Z, Fu M. Comprehensive image matching algorithm based on local GLCM for gravity-gradient-aided navigation. *IEEE/ASME Trans Mechatron*. 2023;28(5):2728–37. doi:10.1109/TMECH.2023.3242232.

31. Ma T, Ding S, Li Y, Fan J. A review of terrain aided navigation for underwater vehicles. *Ocean Eng.* 2023;281(33):114779. doi:10.1016/j.oceaneng.2023.114779.
32. Merveille FFR, Jia B, Xu Z, Fred B. Advancements in sensor fusion for underwater SLAM: a review on enhanced navigation and environmental perception. *Sensors.* 2024;24(23):7490. doi:10.3390/s24237490.
33. Heshmat M, Saad Saoud L, Abujabal M, Sultan A, Elmezain M, Seneviratne L. et al. Underwater SLAM meets deep learning: challenges, multi-sensor integration, and future directions. *Sensors.* 2025;25(11):3258. doi:10.3390/s25113258.
34. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ.* 2021;372:n71. doi:10.1136/bmj.n71.
35. Page MJ, Moher D, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. *BMJ.* 2021;372:n160. doi:10.1136/bmj.n160.
36. Bai Y, Dong D, Wu S, Liu Z, Zhang G, Xu K. A wavelet transformation approach for multi-source gravity fusion: applications and uncertainty tests. *J Appl Geophys.* 2016;128:18–30. doi:10.1016/j.jappgeo.2016.03.003.
37. Weatherall P, Marks KM, Jakobsson M, Schmitt T, Tani S, Arndt JE, et al. A new digital bathymetric model of the world's oceans. *Earth Space Sci.* 2015;2(8):331–45. doi:10.1002/2015EA000107.
38. Tozer B, Sandwell DT, Smith WHF, Olson C, Beale JR, Wessel P. Global bathymetry and topography at 15 arc sec: SRTM15+. *Earth Space Sci.* 2019;6(10):1847–64. doi:10.1029/2019EA000658.
39. GEBCO. GEBCO gridded bathymetry data. [cited 2026 Aug 2]. Available from: <https://www.gebco.net/data-products/gridded-bathymetry-data>.
40. Mao N, Li A, Xu J, Qin F. A multi-resolution sequence method with strong constraints for marine gravity matching navigation. *J Mar Sci Eng.* 2025;13(3):542. doi:10.3390/jmse13030542.
41. Ma L, Song H, Bai Y, Yan Q. Gravity data fusion using wavelet transform and window weighting: a case study in the Ross Sea of Antarctica. *Acta Geophysica.* 2025;73(1):187–201. doi:10.1007/s11600-024-01366-8.
42. Alken P, Thébaud E, Beggan CD, Amit H, Aubert J, Baerenzung J, et al. International geomagnetic reference field: the thirteenth generation. *Earth Planets Space.* 2021;73(1):49. doi:10.1186/s40623-020-01288-x.
43. Chulliat A, Brown W, Alken P, Beggan C, Nair M, Cox G, et al. The US/UK world magnetic model for 2020–2025 [Technical Report]. Washington, DC, USA: NOAA; 2020. doi:10.25923/ytkl-yx35.
44. NOAA/NCEI. World magnetic model 2025 and WMMHR2025. [cited 2026 Aug 2]. Available from: <https://www.ncei.noaa.gov/products/world-magnetic-model>.
45. Saltus R, Alken P, Balmes A, Boneh N, Califf S, Chulliat A, et al. Magnetic maps and models for alternative navigation. In: *Proceedings of the 2023 IEEE/ION Position, Location and Navigation Symposium (PLANS); 2023 Apr 24–27; Monterey, CA, USA.* p. 805–13.
46. Oehler JE, Rouxel D, Lequentrec-Lalancette MF. Comparison of global geomagnetic field models and evaluation using marine datasets in the north-eastern Atlantic Ocean and western Mediterranean Sea. *Earth Planets Space.* 2018;70:99. doi:10.1186/s40623-018-0862-6.
47. Pavlis NK, Holmes SA, Kenyon SC, Factor JK. The development and evaluation of the earth gravitational model 2008 (EGM2008). *J Geophys Res Solid Earth.* 2012;117(B4):B04406. doi:10.1029/2011JB008916.
48. Sandwell DT, Smith WHF. Global marine gravity from retracked Geosat and ERS-1 altimetry: ridge segmentation versus spreading rate. *J Geophys Res Solid Earth.* 2009;114(B1):B01411. doi:10.1029/2008JB006008.
49. Sandwell DT, Müller RD, Smith WHF, Garcia E, Francis R. New global marine gravity model from CryoSat-2 and Jason-1 reveals buried tectonic structure. *Science.* 2014;346(6205):65–7. doi:10.1126/science.1258213.
50. Zhu C, Guo J, Yuan J, Li Z, Liu X, Gao J. SDUST2021GRA: global marine gravity anomaly model recovered from Ka-band and Ku-band satellite altimeter data. *Earth Syst Sci Data.* 2022;14(10):4589–606. doi:10.5194/essd-14-4589-2022.
51. Li Z, Guo J, Zhu C, Liu X, Hwang C, Lebedev S, et al. The SDUST2022GRA global marine gravity anomalies recovered from radar and laser altimeter data: contribution of ICESat-2 laser altimetry. *Earth Syst Sci Data.* 2024;16(9):4119–35. doi:10.5194/essd-16-4119-2024.

52. Guo J, Wei X, Li Z, Jia Y, Chang X, Liu X. SDUST2023GRA_MSS: the new global marine gravity anomaly model determined from mean sea surface model. *Sci Data*. 2025;12(1):108. doi:10.1038/s41597-025-04394-1.
53. Zhang J, Zhan J, Li H, Rao Z. Research and application progress of underwater terrain-assisted navigation technology. *J Nat Univ Defense Technol*. 2015;37(3):8. (In Chinese). doi:10.11887/j.cn.201503021.
54. Khalilabadi MR. Underwater terrain and gravity aided inertial navigation based on Kalman filter. *Int J Coastal, Offshore Environ Eng*. 2020;5(3):15–21. doi:10.22034/ijcoe.2020.149349.
55. Zong J, Bian S, Tong Y, Ji B, Li H, Xi M. Classification of gravity matching areas using PSO-BP neural networks based on PCA and satellite altimetry data over the western Pacific. *Sensors*. 2022;22(24):9892. doi:10.3390/s22249892.
56. Meyer B, Chulliat A, Saltus R. Derivation and error analysis of the earth magnetic anomaly grid at 2 arc min resolution. *Geochem Geophys Geosyst*. 2017;18(12):4522–36. doi:10.1002/2017GC007280.
57. Lesur V, Hamoudi M, Choi Y, Dymont J, Thébaud E. Building the second version of the world digital magnetic anomaly map. *Earth Planets Space*. 2016;68(1):27. doi:10.1186/s40623-016-0404-6.
58. Zheng H, Wang H, Wu L, Chai H, Wang Y. Simulation research on gravity-geomagnetism combined aided underwater navigation. *J Navig*. 2013;66(1):83–98. doi:10.1017/S0373463312000388.
59. Li H, Chen S, Zhuang J, Zhang B, Lu H. Bayesian fusion algorithm for multi-source Bouguer gravity anomaly data and its application in Sichuan–Yunnan region. *Chin J Geophys*. 2021;64(9):3340–53. (In Chinese). doi:10.6038/cjg202100291.
60. Ma X, Liu X, Li C, Che S. Multi-source information fusion based on factor graph in autonomous underwater vehicles navigation systems. *Assem Autom*. 2021;41(5):536–45. doi:10.1108/AA-05-2020-0070.
61. Ma X, Zhou P, He X. Advances in multi-source navigation data fusion processing methods. *Mathematics*. 2025;13(9):1485. doi:10.3390/math13091485.
62. Wu M, Weng Y. Neural network-aided adaptive UKF for integrated underwater navigation. In: *Proceedings of the 22nd International Conference on Neural Information Processing (ICONIP 2015)*; 2015 Nov 9–12; Istanbul, Turkey. p. 301–10. doi:10.1007/978-3-319-26535-3_35.
63. Li Q, Zhai Z, Bao L, Wang Y, Wu L, Mao G, et al. A convolutional neural network to optimize multi-mission satellite altimeter fusion for improving the marine gravity field. *Earth Planets Space*. 2024;76(1):129. doi:10.1186/s40623-024-02070-z.
64. Yuan J, Liu H, Chen J, Yang C. PSO-optimized dual-channel BP neural network for bathymetric prediction using multisource marine geodetic data: a case study of the Gulf of Mexico. *Sci Remote Sens*. 2025;12(9):100274. doi:10.1016/j.srs.2025.100274.
65. Gao B, Hu Z, Li D, Du J. Application of the multi-level equivalent source method in the fusion of ground and aeromagnetic anomaly data. *Earth Sci*. 2021;46(5):1881–95. (In Chinese). doi:10.3799/dqkx.2020.134.
66. Li Y, Oldenburg DW. 3-D inversion of gravity data. *Geophysics*. 1998;63(1):109–19. doi:10.1190/1.1444302.
67. Fregoso E, Gallardo LA. Cross-gradients joint 3D inversion with applications to gravity and magnetic data. *Geophysics*. 2009;74(4):L31–42. doi:10.1190/1.3119263.
68. Del Razo Gonzalez A, Yutsis V. Robust 3D joint inversion of gravity and magnetic data: a high-performance computing approach. *Appl Sci*. 2023;13(20):11292. doi:10.3390/app132011292.
69. Yang C, Strader J, Gu G. A scalable framework for map matching based cooperative localization. *Sensors*. 2021;21(19):6400. doi:10.3390/s21196400.
70. Haralick RM, Shanmugam K, Dinstein I. Textural features for image classification. *IEEE Trans Syst Man Cybern*. 1973;3(6):610–21. doi:10.1109/TSMC.1973.4309314.
71. Ojala T, Pietikäinen M, Mäenpää T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Trans Pattern Anal Mach Intell*. 2002;24(7):971–87. doi:10.1109/TPAMI.2002.1017623.
72. Lowe DG. Distinctive image features from scale-invariant keypoints. *Int J Comput Vis*. 2004;60(2):91–110. doi:10.1023/B:VISI.0000029664.99615.94.
73. Bay H, Ess A, Tuytelaars T, Gool LV. Speeded-up robust features (SURF). *Comput Vis Image Underst*. 2008;110(3):346–59. doi:10.1016/j.cviu.2007.09.014.

74. Portes L, Pirot G, Nzikou MM, Giraud J, Lindsay M, Jessell M, et al. Feature fusion-enhanced t-SNE image atlas for geophysical features discovery. *Sci Rep*. 2025;15(1):17152. doi:10.1038/s41598-025-01333-3.
75. Prasad KND, Pham LT, Singh AP, Eldosouky AM, Abdelrahman K, Fnais MS, et al. A novel enhanced total gradient (ETG) for interpretation of magnetic data. *Minerals*. 2022;12(11):1468. doi:10.3390/min12111468.
76. Dwivedi D, Chamoli A, Rana SK. Wavelet entropy: a new tool for edge detection of potential field data. *Entropy*. 2023;25(2):240. doi:10.3390/e25020240.
77. Wang R, Wang J, Li Y, Ma T, Zhang X. Research advances and prospects of underwater terrain-aided navigation. *Remote Sens*. 2024;16(14):2560. doi:10.3390/rs16142560.
78. Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, et al. MobileNets: efficient convolutional neural networks for mobile vision applications. *arXiv:1704.04861*. 2017.
79. Hu J, Shen L, Sun G. Squeeze-and-excitation networks. In: *Proceedings of the 2018 IEEE Conference on Computer Vision and Pattern Recognition*; 2018 Jun 18–22; Salt Lake City, UT, USA. p. 7132–41.
80. Woo S, Park J, Lee JY, Kweon IS. CBAM: convolutional block attention module. In: *Proceedings of the 15th European Conference on Computer Vision*; 2018 Sep 8–14; Munich, Germany. p. 3–19.
81. Tan M, Le Q. EfficientNet: rethinking model scaling for convolutional neural networks. In: *Proceedings of the 36th International Conference on Machine Learning*; 2019 Jun 9–15; Long Beach, CA, USA. p. 6105–14.
82. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention is all you need. In: *Advances in neural information processing systems*. Red Hook, NY, USA: Curran Associates, Inc.; 2017. p. 5998–6008.
83. Chen C, Li H, Zhang Y, Jin X, Liu J. Three-dimensional gravity inversion based on attention feature fusion. *Sensors*. 2024;24(17):5697. doi:10.3390/s24175697.
84. Kukreja V, Abraham A, Kalaiselvi K, Thilak KD, Hariharan S, Chen SY. Machine learning for data fusion: a fuzzy AHP approach for open issues. *Comput Mater Contin*. 2023;77(3):2899–2914. doi:10.32604/cmc.2023.045136.
85. Mustafa HT, Shamsolmoali P, Lee IH. TGF: multiscale transformer graph attention network for multi-sensor image fusion. *Expert Syst Appl*. 2024;238(12):121789. doi:10.1016/j.eswa.2023.121789.
86. Zhou T, Peng D, Xu C, Zhang W, Shen J. An adaptive particle filter based on Kullback–Leibler distance for underwater terrain aided navigation with multi-beam sonar. *IET Radar, Sonar Navig*. 2018;12(4):433–41. doi:10.1049/iet-rsn.2017.0239.
87. Lee J, Bang H. A robust terrain aided navigation using the Rao-Blackwellized particle filter trained by long short-term memory networks. *Sensors*. 2018;18(9):2886. doi:10.3390/s18092886.
88. Zhang J, Zhang T, Liu S. An outlier-robust Rao-Blackwellized particle filter for underwater terrain-aided navigation. *Ocean Eng*. 2023;288:116006. doi:10.1016/j.oceaneng.2023.116006.
89. Yousuf S, Kadri MB. Improving the position accuracy and computational efficiency of UAV terrain aided navigation using a two-stage hybrid fuzzy particle filtering method. *Comput Mater Contin*. 2025;82(1):1193–210. doi:10.32604/cmc.2024.054587.
90. Wang X, Gilliam C, Kealy A, Close J, Moran B. Probabilistic map matching for robust inertial navigation aiding. *NAVIGATION: J Inst Navig*. 2023;70(2):navi.583. doi:10.33012/navi.583.
91. Wang X, Li W, Moran B. Quantum diamond magnetometry for navigation in GNSS denied environments. In: *Reference frames for applications in geosciences*. Cham, Switzerland: Springer; 2023. p. 87–92. doi:10.1007/1345_2023_218.
92. Dellaert F, Kaess M. Factor graphs for robot perception. *Found Trends Rob*. 2017;6(1–2):1–139. doi:10.1561/23000000043.
93. Zeng Q, Chen W, Liu J, Wang H. An improved multi-sensor fusion navigation algorithm based on the factor graph. *Sensors*. 2017;17(3):641. doi:10.3390/s17030641.
94. Song J, Li W, Liu R, Zhu X. FGO-ILNS: tightly coupled multi-sensor integrated navigation system based on factor graph optimization for autonomous underwater vehicle. *arXiv:2310.14163*. 2023.
95. Ma X, Li C, Liu X. Research on multi-source information fusion based on sliding window-factor graph for autonomous underwater vehicle. *Trans Inst Meas Contr*. 2025;47(14):2930–9. doi:10.1177/01423312241274573.

96. Zhang B, Yin H, Liu S, Zhang F, Xu W. VIMS: a visual-inertial-magnetic-sonar SLAM system in underwater environments. In: Proceedings of the 2025 IEEE/RSJ International Conference on Intelligent Robots and Systems; 2025 Oct 19–25; Hangzhou, China. p. 7065–72. doi:10.1109/IROS60139.2025.11247569.
97. Wang D, Liu L, Ben Y, Cao L, Dong Z. A novel algorithm for enhancing terrain-aided navigation in autonomous underwater vehicles. *Information*. 2024;15(9):532. doi:10.3390/info15090532.
98. Xu N, Wang L, Wu T, Yao Z. An innovative PSO-ICCP matching algorithm for geomagnetic navigation. *Measurement*. 2022;193(7):110958. doi:10.1016/j.measurement.2022.110958.
99. Huang J, Hu Z, Yi W. Complex environmental geomagnetic matching-assisted navigation algorithm based on improved extreme learning machine. *Sensors*. 2025;25(14):4310. doi:10.3390/s25144310.
100. Lin YH, Chuang PC, Huang JYT. Simultaneous depth and heading control for autonomous underwater vehicle docking maneuvers using deep reinforcement learning within a digital twin system. *Comput Mater Contin*. 2025;84(3):4907–48. doi:10.32604/cmc.2025.065995.
101. Blakely B, Nielsen A, Duff P. Comparative analysis of different magnetic anomaly datasets using navigation performance with flight test data. In: Proceedings of the 38th International Technical Meeting of the Satellite Division of the Institute of Navigation (ION GNSS+ 2025); 2025 Sep 8–12; Baltimore, MD, USA. p. 1647–63. doi:10.33012/2025.20278.