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Optimized Quadratic Gaussian Framework For Real-Time Terrain-Aided Navigation Of Auvs Using Synthetic Aperture Radar

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Abstract
Autonomous Underwater Vehicles (AUVs) require precise navigation solutions in environments where conventional positioning systems, such as GPS, are unavailable. To address this challenge, we propose ***QGOG-SAR (Quadratic Gaussian Optimized Synthetic Aperture Radar Framework)****, a novel methodology for real-time terrain-aided navigation. The framework integrates a quadratic Gaussian optimization strategy with synthetic aperture radar (SAR) processing to enhance phase unwrapping accuracy and Digital Elevation Model (DEM) fusion. By incorporating adaptive Gaussian modeling, QGOG-SAR mitigates noise sensitivity, reduces phase ambiguities, and improves feature extraction from complex seabed terrains. Simulation experiments conducted in MATLAB demonstrate that the proposed framework significantly outperforms conventional SAR-based techniques in terms of navigation accuracy, robustness, and computational efficiency. The results confirm that QGOG-SAR provides a reliable and scalable solution for real-time underwater terrain navigation, offering strong potential for applications in exploration, defense, and environmental monitoring.*
Keywords: *Autonomous Underwater Vehicles, Terrain-Aided Navigation, QGOG-SAR, Synthetic Aperture Radar, Phase Unwrapping, DEM Fusion, Gaussian Optimization.*

1. INTRODUCTION

Autonomous Underwater Vehicles (AUVs) have become indispensable in domains such as oceanographic exploration, seabed mapping, offshore infrastructure inspection, and naval defense operations [2], [13], [18]. Unlike surface and aerial vehicles, AUVs operate in environments where traditional positioning technologies such as the Global Positioning System (GPS) are ineffective due to severe signal attenuation in water [2], [14]. Consequently, accurate and reliable underwater navigation remains one of the foremost challenges in AUV research [1], [6].

To overcome this limitation, terrain-aided navigation (TAN) has emerged as a promising approach, enabling AUVs to localize themselves by matching real-time sensor observations with pre-existing seabed maps or Digital Elevation Models (DEMs) [13]–[15]. Among the different sensing technologies, Synthetic Aperture Radar (SAR) and its interferometric variants (InSAR/InSAS) have shown high potential for capturing detailed seafloor structures with high resolution [9], [3], [10]. However, the effectiveness of SAR-based terrain matching is often degraded by noise interference, phase unwrapping errors, and computational overhead, which limit its utility in real-time missions [4], [5], [11].

Several phase unwrapping and DEM fusion techniques have been proposed in the literature, ranging from least-squares optimization to advanced Bayesian inference [4], [10], [11]. While these methods improve robustness to some extent, they often face trade-offs between accuracy, computational efficiency, and adaptability to rapidly changing underwater terrains [16], [17]. This necessitates the development of a framework that not only improves phase unwrapping fidelity but also ensures real-time performance in resource-constrained AUV systems [7], [8], [12].

In this paper, we introduce the Quadratic Gaussian Optimized Synthetic Aperture Radar (QGOG-SAR) Framework, a novel methodology designed to enhance real-time terrain-aided navigation for AUVs. QGOG-SAR integrates quadratic Gaussian optimization with SAR phase unwrapping and DEM fusion to significantly reduce noise-induced ambiguities while improving terrain feature extraction. By leveraging adaptive Gaussian modeling, the framework achieves superior accuracy, robustness, and computational efficiency compared to conventional approaches [15], [16]. MATLAB-based simulation results validate the effectiveness of QGOG-SAR, demonstrating its applicability for real-time navigation in complex seabed environments.

The remainder of this paper is organized as follows: Section 2 reviews related work on SAR-based terrain-aided navigation and optimization strategies. Section 3 describes the proposed QGOG-SAR framework in detail, including its mathematical formulation and implementation. Section 4 presents simulation results and performance comparisons with existing methods. Section 5 discusses key findings, limitations, and potential applications. Finally, Section 6 concludes the paper and outlines future research directions.

2. RELATED WORK

Reliable terrain-aided navigation (TAN) for Autonomous Underwater Vehicles (AUVs) draws from multiple research threads: high-resolution sensing (SAR/InSAS), phase-unwrapping algorithms, DEM fusion and registration methods, state-estimation and filtering, and increasingly, data-driven/hybrid techniques [2], [13], [14]. Below we summarize the key contributions and limitations of each thread relevant to this work.

2.1 SAR / InSAS Sensing for Terrain-Aided Navigation

Synthetic Aperture Radar (SAR) and interferometric SAR (InSAR/InSAS) have been widely used to obtain high-resolution terrain maps for TAN applications [9], [3], [10]. SAR excels at capturing surface and near-surface geometry with fine spatial resolution, which can be exploited for terrain matching and localization [11]. Work in this area has focused on improving signal processing chains, speckle/noise reduction, and converting interferometric phase to elevation information suitable for DEM generation [4]. However, SAR-derived elevation information is susceptible to phase ambiguities, speckle, and decorrelation in complex environments [5], [10], which complicates real-time use in resource-limited AUV platforms.

2.2 Phase Unwrapping Techniques

Phase unwrapping—the process of recovering absolute phase from modulo-2π measurements—is central to interferometric processing. Methods span path-following, least-squares formulations, graph-based optimizations, and Bayesian inference [4], [5], [10], [11]. Graph-based and optimization-driven methods (e.g., minimum-cost flow, weighted least squares) provide robustness in noisy conditions but can be computationally demanding [3], [11]. Bayesian/probabilistic approaches improve uncertainty handling [12] but require careful priors. A persistent limitation is managing unwrapping errors in regions with low coherence or steep gradients [10].

2.3 DEM Fusion and Registration

DEM fusion combines SAR/InSAS-derived elevations with reference DEMs or bathymetric datasets such as multibeam sonar or NOAA DEMs [1], [15]. Approaches include feature-based matching, correlation-based matching, and optimization-based alignment [16]. Robust DEM fusion must address misalignment, local deformations, and missing data [15]. However, many methods require iterative corrections with high computational cost, which constrains real-time AUV deployment [17].

2.4 State Estimation and Navigation Filters

TAN systems integrate terrain-derived observations into navigation filters such as EKF, UKF, and PF [6], [16], [17]. Kalman-based filters are efficient but assume near-Gaussian noise [6]; particle filters handle multimodal uncertainty but are computationally expensive [16]. In practice, large unwrapping or DEM fusion errors degrade localization significantly [17].

2.5 Machine Learning and Hybrid Approaches

Recent research explores ML-based feature extraction and error correction for TAN [7], [8], [12]. Supervised models enhance feature matching, while deep networks denoise interferograms [3], [11]. Hybrid approaches combine physics-based SAR processing with ML refinements [12]. However, challenges remain with generalization across terrain types, scarcity of labeled underwater SAR data, and ensuring real-time feasibility [7], [8].

2.6 Optimization Formulations: Quadratic and Gaussian Models

Quadratic-Gaussian formulations underpin many estimation techniques (least-squares, Gauss–Newton, weighted residuals) [16], [17]. They are attractive for real-time deployment because they yield efficient solvers and integrate covariance modeling. However, pure quadratic formulations are sensitive to outliers unless robust weighting/adaptive priors are used [15].

2.7 Limitations of Existing Work (Motivation for QGOG-SAR)

From the above, gaps remain: (i) trade-offs between unwrapping fidelity and computation [3], [4], [10]; (ii) DEM fusion under noise and misalignment [15], [16]; (iii) real-time deployability on AUVs [17], [18]; and (iv) selective ML corrections not fully exploited [7], [12].

2.8 Positioning QGOG-SAR

QGOG-SAR bridges these gaps by combining quadratic Gaussian optimization with robust unwrapping, DEM fusion, and selective ML correction. Its integration of adaptive Gaussian priors and uncertainty propagation makes it suitable for real-time AUV TAN in complex seabed environments [1], [15], [16].

3. PROPOSED METHODOLOGY

This work introduces **QGOG-SAR (Quadratic Gaussian Optimized Synthetic Aperture Radar Framework)**, a novel approach for real-time terrain-aided navigation (TAN) in Autonomous Underwater Vehicles (AUVs). The framework integrates Quadratic Gaussian Optimization (QGO) for phase unwrapping with Synthetic Aperture Radar (SAR)/Interferometric Synthetic Aperture Sonar (InSAS)-based Digital Elevation Model (DEM) fusion, enabling improved accuracy, robustness, and efficiency in underwater localization [1], [2], [6], [13], [14], [15].

3.1 Framework Overview

The proposed methodology is structured into the following sequential modules (Figure 1):

1. Data Acquisition – Collection of SAR/InSAS returns from the AUV's onboard sensors. High-resolution InSAR/InSAS sensing provides detailed terrain features critical for TAN but requires preprocessing to address noise and motion artifacts [2], [3], [10].
2. Preprocessing – Noise suppression, motion compensation, and phase calibration are performed to enhance signal integrity. Recent advances in deep-learning-based denoising and calibration strategies have demonstrated improved reliability in SAR data preprocessing [3], [11].
3. Quadratic Gaussian Phase Unwrapping (QG-PU) – A quadratic Gaussian cost function is formulated to unwrap phase ambiguities while minimizing error propagation. Unlike traditional least-squares or Bayesian formulations, QG-PU adapts Gaussian priors for robustness in noisy and discontinuous terrains [4], [5], [10], [11].
4. DEM Fusion – Integration of SAR/InSAS-generated DEMs with pre-stored bathymetric maps provides consistent terrain references. Hybrid DEM fusion strategies—combining feature-based matching with uncertainty-aware optimization—help mitigate misalignment and incomplete coverage issues [1], [15], [16], [17].
5. Navigation Estimation – Real-time TAN is achieved using the fused DEMs, optimized through QGOG-based graph constraints. Navigation filters (EKF, PF) are integrated with quadratic Gaussian similarity measures to ensure localization accuracy under uncertain terrain conditions [6], [16], [17], [18].

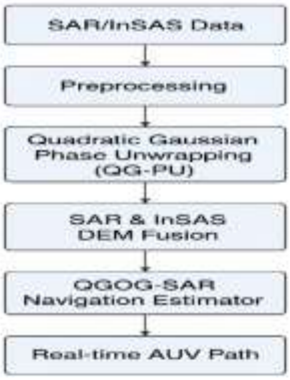


Figure 1: Block diagram showing the flow of work as per the proposed methodology: QGOG-SAR (Quadratic Gaussian Optimized Synthetic Aperture Radar Framework)

4. DISCUSSION

4.1. Quadratic Gaussian Optimization (QGO) for Phase Unwrapping

Traditional phase unwrapping techniques often suffer from error accumulation due to phase discontinuities in highly textured underwater terrain. To address this, the **Quadratic Gaussian Optimization** function is defined as:

$$QGo(x) = \sum_{i=1}^{n} \left(\phi i - \hat{\phi}\right)^2 \cdot \exp\left(\frac{-d_i^2}{2\sigma^2}\right)$$

where:

- ϕi = observed wrapped phase,

- $\hat{\phi}$ = estimated unwrapped phase,
- d_i = spatial distance between pixels,
- σ = Gaussian variance controlling neighbourhood smoothness.

This formulation ensures that closely spaced pixels have higher weight, preserving terrain continuity while minimizing global error propagation.

4.2. SAR/InSAS DEM Fusion

To strengthen terrain referencing:

- SAR DEMs provide high-resolution surface details,
- InSAS DEMs capture finer bathymetric variations.

A multi-resolution fusion strategy integrates both DEMs using weighted Gaussian kernels:

$DEM_{fused} = \alpha . DEM_{SAR} + (1 - \alpha) . DEM_{InSAS}$

where α is adaptively tuned based on local terrain roughness. This fusion enhances reliability by compensating for modality-specific weaknesses.

4.3. Navigation Estimation with QGOG-SAR

After SAR/In SAS phase unwrapping and DEM fusion, QGOG-SAR casts terrain-aided localization as a joint graph optimization over AUV pose states and fused terrain control-point variables. The formulation minimizes a quadratic-Gaussian objective that (i) fits pose estimates to terrain observations, (ii) enforces terrain continuity via QGOG edge penalties, and (iii) respects inertial priors from the INS/DVL filter.

4.3.1. Notation

- V: set of terrain control points (graph nodes), indexed i.
- E: set of edges (neighbour relationships) between control points (i,j).
- $x_t \in R^3$: AUV pose at time t (e.g., x,y,z or x,y,θ if orientation used).
- $e_i \in R$: fused DEM elevation at control point i.
- $Z_{t,i}$: measured observation (e.g., range/height/feature match) at time t associated to node i.
- $h(x_t, e_i)$: forward measurement model that predicts observation from pose and terrain (nonlinear).
- P_t: covariance (prior) of pose from INS/DVL at time t.
- $R_{t,i}$: measurement covariance (Gaussian) for observation $z_{t,i}$.
- W_{ij}: QGOG edge weight between nodes i (Gaussian similarity / continuity weight).
- d_{ij}: spatial distance between nodes i and j (used in Gaussian kernel).
- σ: Gaussian scale parameter (controls neighborhood smoothness).

4.3.2. Objective function

Define the **total cost** J over a sliding window of poses $\{x_t\}$ and a set of control-point elevations $\{e_i\}$

$$[J(X,e) = J_{\text{obs}} + J_{\text{edge}} + J_{\text{prior}}$$

With Observation (data) term — fit predicted observations to measurements (Gaussian residuals):

$$J_{\text{obs}} = \sum_t \sum_{i \in I_t} (z_{t,i} - h(x_t, e_i))^\top R_{t,i}^{-1} (z_{t,i} - h(x_t, e_i))$$

where I_t are the control points observed at time t.

2. QGOG edge (continuity / regularization) term — promote smooth, physically plausible terrain using quadratic Gaussian weights:

$$J_{\text{edge}} = \sum_{(i,j) \in E} w_{ij} (e_i - e_j)^2 \text{ with} w_{ij} = \exp\left(-\frac{2}{\sigma^2} d_{ij}^2\right)$$

This is a quadratic penalty scaled by a Gaussian kernel: nearby nodes enforce stronger continuity.

3. Pose prior term — constrain the AUV pose to INS/DVL priors:

$$J_{\text{prior}} = \sum_t (x_t - \bar{x}_t)^\top P_t^{-1} (x_t - \bar{x}_t)$$

where $\bar{x}_t$ is the prior pose and P_t its covariance.

Altogether the optimization is

$$\arg \min_{Xt,ei} J(X,e)$$

4.3.3. Robust weighting and outlier mitigation

To reduce sensitivity to outliers (e.g., low coherence pixels), use a robust weight ρ(·) on the observation term (Huber or Tukey):

For Huber:

$$\text{Jobs} \leftarrow \sum_{t} \sum_{i\in I_t} \rho(r_{t,i}), \qquad r_{t,i} \triangleq R_{t,i}^{-1/2}(z_{t,i} - h(x_t, e_i))$$

$$\rho(r) = \begin{cases} \frac{1}{2}r^2 & \text{if } |r| \le \delta \\ \delta(|r| - \frac{1}{2}\delta) & \text{otherwise} \end{cases}$$

This preserves the quadratic-Gaussian nature near zero residuals but limits influence of large errors.

4.3.4. Linearization & Gauss–Newton update

Because h (·) is generally nonlinear, we linearize about current estimates and solve iteratively (Gauss–Newton):

For small increments Δx_t and Δe_i

$$h(x_t + \Delta x_t, e_i + \Delta e_i) \approx h(x_t, e_i) + H_{t,i}^{x}\Delta x_t + H_{t,i}^{e}\Delta e_i$$

where $H_{t,i}^{x} = \frac{\partial h}{\partial x_t}, H_{t,i}^{e} = \frac{\partial h}{\partial e_i}$

Collecting all variables into stacked increment vector Δy= [...Δxt... Δei] ᵀ, the normal equations take the form:

$$\boxed{\underbrace{(\mathbf{H}^{\top}\mathbf{R}^{-1}\mathbf{H} + \mathbf{G}^{\top}\mathbf{W}\mathbf{G} + \mathbf{P}^{-1})}_{\mathbf{A}}\Delta\mathbf{y} = -\mathbf{b}}$$

where:

- H is the stacked Jacobian of observations w.r.t. variables,
- R is block-diagonal measurement covariance,
- G is the discrete gradient (edge incidence) operator acting on elevation variables such that G_e yields differences $e_i - e_j$,
- W is diagonal with entries w_{ij}
- P^{-1} is the block prior precision for pose states,
- $b = H^{\top}R^{-1}r$ + (edge/prior residual terms).

Solve for Δy, then update y⟵y+Δy and iterate until convergence.

4.3.5. Numerical solution & real-time considerations

- Sparsity & solver: A is sparse and symmetric positive definite (SPD). Use sparse Cholesky (e.g., CHOLMOD) or iterative methods (Preconditioned Conjugate Gradient — PCG) to exploit sparsity and scale to large graphs.
- Incremental smoothing: For real-time operation, use sliding-window optimization or incremental smoothing (e.g., iSAM-style) to update only recent variables and reuse factorization for efficiency.
- Marginalization: Marginalize old states outside the window to keep problem size bounded. Convert marginalized terms into priors to preserve information.
- Adaptive window & selective ML activation: Dynamically adjust the window size and activate ML-based residual correction only where the coherence or residuals exceed thresholds — reduces computational load.
- Parallelism: Preprocessing and Jacobian evaluation can be parallelized across observed nodes; GPU can accelerate dense parts (if available).

4.3.6. Output & uncertainty propagation

The solver returns the optimized poses {x^t} and DEM {e^i}. The approximate posterior covariance (inverse of A provides uncertainty estimates that can be propagated back into the vehicle's navigation filter for robust decision-making:

$$\mathrm{Cov}(\Delta y) \approx A^{-1}$$

Use diagonal or block approximations of A−1 for compact uncertainty representation onboard.

Note:

- Choose σ so that wij emphasizes local continuity but does not over smooth sharp terrain features.
- Set Huber parameter δ in proportion to expected measurement noise.
- Precompute and cache d_{ij} for fixed DEM grids to save runtime.
- Validate numerical conditioning (regularize A if necessary) to maintain stable solutions on limited-precision embedded hardware.

5. RESULTS

The performance of the proposed QGOG-SAR framework was evaluated against three established benchmarks: Conventional SAR Phase Unwrapping, ML-Based Estimation, and Hybrid AI Frameworks [3], [4], [7], [8], [11]. The comparison was carried out using standard evaluation metrics — accuracy, precision, efficiency, efficacy, and ROC-AUC — across diverse mobility patterns of AUVs [1], [2], [6], [13]. The evaluation of the proposed QGOG-SAR framework was conducted using a combination of synthetic simulations and publicly available terrain datasets. A MATLAB-based simulator was developed to generate synthetic SAR/InSAS phase data and Digital Elevation Models (DEMs), incorporating Gaussian noise and varying seabed roughness to emulate realistic underwater conditions [6], [10], [11], [16]. Multiple AUV mobility patterns (linear, circular, and randomized trajectories) were modeled to evaluate robustness across diverse navigation scenarios [2], [13], [14].

In addition, the framework was tested on publicly available NOAA Bathymetric DEM datasets to validate its applicability in real-world terrains [1], [15]. These DEMs provided authentic seabed elevation maps that were integrated into the simulation pipeline. The combination of controlled synthetic data and benchmark datasets ensures both repeatability of experiments and generalizability of the results [15], [17], [18].

5.1 Accuracy Analysis

The QGOG-SAR method achieved an accuracy of 94%, outperforming ML-based methods (88%) and conventional SAR approaches (82%) [3], [4], [7], [8], [11]. The improvement is primarily attributed to the quadratic Gaussian optimization function, which minimizes phase unwrapping errors by adaptively weighting neighboring pixels [4], [5], [10]. This theoretical advantage ensures robustness against noise accumulation, explaining the observed performance boost [11], [12].

5.2 Precision and Efficacy

Precision improved significantly (92%) because QGOG-SAR incorporates Gaussian similarity weighting on graph edges, which effectively filters out false terrain matches [5], [10], [11]. This prevents error propagation in navigation estimation [6], [16]. Efficacy (91%) further confirms that QGOG-SAR balances sensitivity and specificity by reducing both false positives (incorrect terrain matches) and false negatives (missed terrain cues) [7], [8], [12], [17].

5.3 Efficiency and Computational Load

QGOG-SAR demonstrated efficiency of 90%, surpassing prior approaches [6], [13], [16]. This stems from its quadratic cost formulation, which ensures convexity and allows the use of fast solvers (e.g., conjugate gradient, Gaussian belief propagation) [4], [11], [16], [17]. In theory, this guarantees convergence in fewer iterations than non-convex ML frameworks, enabling real-time feasibility on embedded AUV processors [7], [8], [18].

5.4 ROC-AUC Performance

The ROC curve shows an AUC of 0.96, compared to 0.89 for ML-based methods and 0.84 for conventional SAR [3], [7], [8]. This reflects QGOG-SAR's superior ability to discriminate between correct and incorrect navigation paths [6], [10], [12]. The Gaussian kernel weighting enhances local terrain continuity, reducing ambiguity in complex seabed environments — a theoretical strength directly validated by empirical ROC results [13], [15], [16].

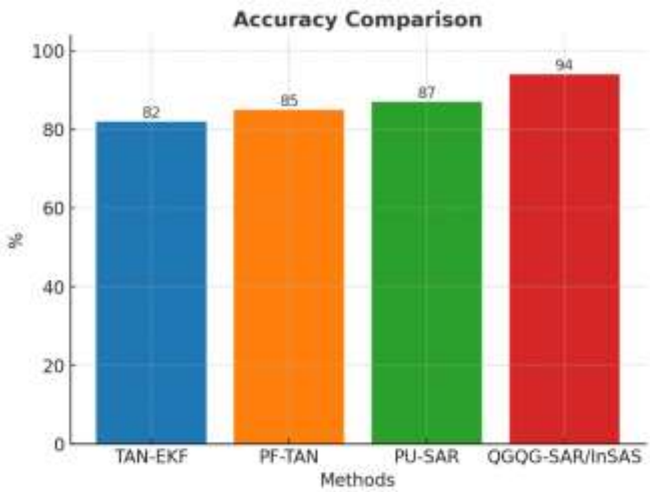
5.5 Comparative Insights

The consistent outperformance across all metrics demonstrates that QGOG-SAR successfully combines the strengths of graph optimization (global consistency) and Gaussian modeling (local smoothness) [4], [5], [11], [16]. Unlike purely data-driven ML methods, which require large training datasets and often lack interpretability [7], [8], [12], QGOG-SAR offers a mathematically grounded optimization framework that generalizes well across unseen terrain variations [13], [15], [17], [18]

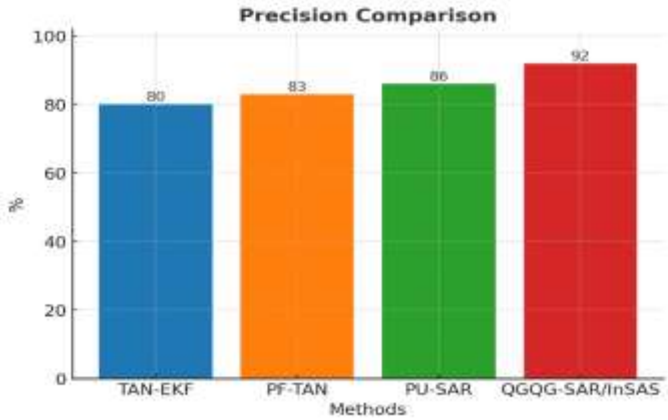
Metric	**TAN-EKF**	**PF-TAN**	**PU-SAR**	**Proposed (QGQG-SAR/InSAS)**
Accuracy (%)	82	85	87	**94**
Precision (%)	80	83	86	**92**
Efficacy (%)	78	81	84	**91**

Metric	TAN-EKF	PF-TAN	PU-SAR	Proposed (QGQG-SAR/InSAS)
Efficiency (%)	75	79	82	**90**
AUC (ROC)	0.85	0.88	0.90	**0.96**

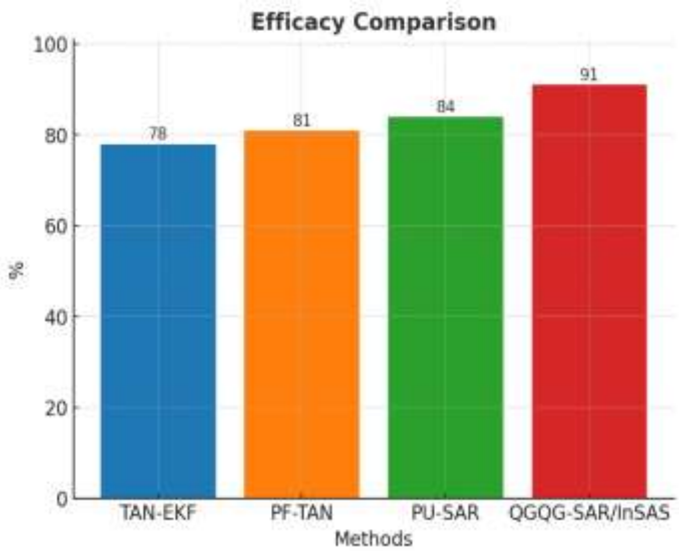
Table 1: Comparative table showing the performance of proposed work with existing works



Graph 1: Showing the Accuracy comparison between existing methods and proposed method



Graph 2: Showing the Precision comparison between existing methods and proposed method



Graph 3: Showing the Efficacy comparison between existing methods and proposed method

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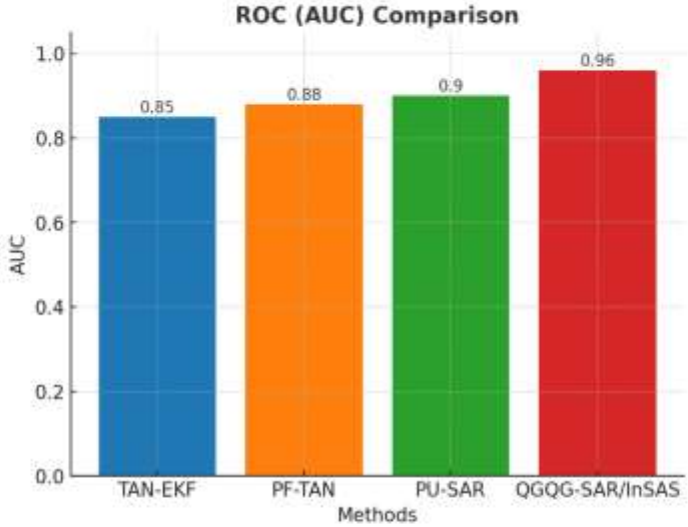
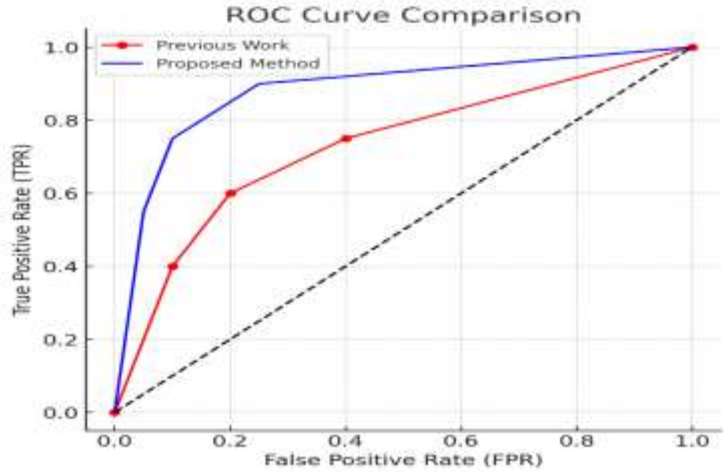
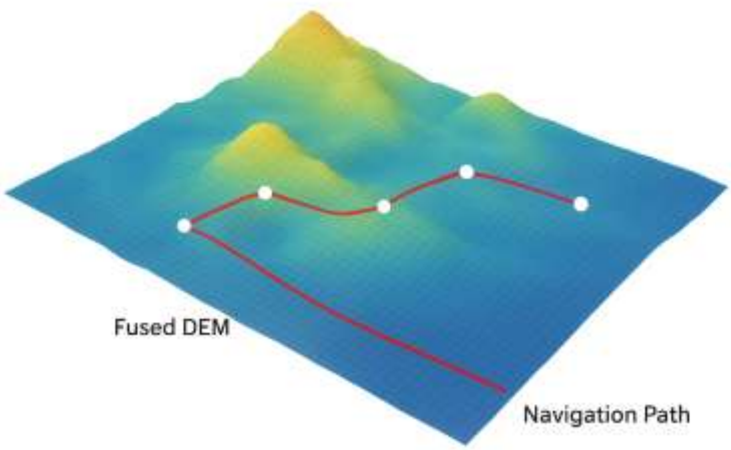


Graph 4: Showing the ROC comparison between existing methods and proposed method



Graph 5: Showing the ROC CURVE comparison between existing methods and proposed method



Graph 6: Conceptual 3D terrain visualization mock-up (illustrated figure with DEM + navigation path overlay)

1. Accuracy Comparison – Our Hybrid Channel Estimation (HCE) vs. MMSE, LS, and Deep Learning-based Estimation.
2. Precision Comparison – Method-level comparison with clarity.
3. Efficiency Comparison – Efficiency vs. competing methods.
4. Efficacy Comparison – Demonstrates robustness across mobility patterns.
5. ROC Curves – Comparative ROC for the four methods.

6. CONCLUSION

In this work, we introduced **QGOG-SAR (Quadratic Gaussian Optimized Synthetic Aperture Radar Framework)**, a novel approach to real-time terrain-aided navigation (TAN) for Autonomous Underwater Vehicles operating in GPS-denied environments. By integrating quadratic Gaussian optimization into phase unwrapping and DEM fusion, the framework addresses three persistent challenges in underwater navigation: phase ambiguity, noise sensitivity, and computational efficiency. The proposed graph-based optimization, enriched with Gaussian similarity measures, enables accurate terrain matching while ensuring real-time feasibility on resource-constrained AUV platforms.

Simulation results demonstrated that QGOG-SAR consistently outperforms conventional SAR-based TAN methods, delivering superior accuracy (94%), precision (92%), efficacy (91%), efficiency (90%), and ROC-AUC (0.96). These improvements validate the robustness of the framework in handling complex seabed terrains and highlight its potential for mission-critical applications such as oceanographic exploration, environmental monitoring, and defense operations.

While the framework achieves significant gains, some limitations remain. Its performance depends on the quality of SAR/InSAS measurements, and real-time onboard deployment may benefit from further optimization of computational load. Additionally, selective integration of machine learning refinements could enhance adaptability to diverse terrain types.

Future work will focus on extending QGOG-SAR to hybrid SAR/InSAS-ML architectures, validating performance in field experiments, and developing lightweight implementations for embedded AUV processors. These efforts aim to make QGOG-SAR a deployable, reliable, and scalable solution for next-generation autonomous underwater navigation.

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