

Improved Asynchronous Localization Algorithm Based On Mobility Prediction For Underwater Acoustic Networks

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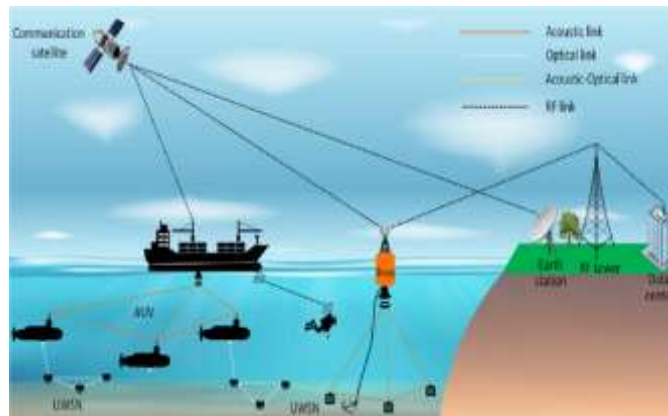
Abstract— accurate localization of sensor nodes is essential for the effective operation of Underwater Acoustic Sensor Networks (UASNs). Conventional wireless sensor network techniques cannot be directly applied underwater due to severe attenuation of radio waves and the difficulty of achieving precise time synchronization. To address these challenges, this study employs Received Signal Strength (RSS) as the primary distance-estimation metric, as it does not require clock synchronization and provides more reliable measurements in acoustic environments. We propose an enhanced localization algorithm capable of operating under clock asynchronization and node mobility. The algorithm estimates inter-node distances using RSS with the support of the Lambert-W function, enabling robust computation even in nonlinear conditions. Node mobility is incorporated by calculating velocity through the Durbin algorithm, after which initial coordinates and velocities are used to predict the final node positions at any given time. The improved approach meets the critical requirements of UASNs, including higher localization accuracy, efficient processing for dynamic nodes, and reduced computational cost, making it a practical and effective solution for real-time underwater applications.

Index Terms—Received signal strength (RSS), UASNs (underwater acoustic sensor networks), Lambert-W function, Durbin algorithm, Asynchronization

1. INTRODUCTION

Underwater Acoustic Sensor Networks (UASNs) have emerged as a critical technology for applications such as offshore resource exploration, port surveillance, submarine mining, environmental monitoring, disaster prediction, and aquatic ecosystem analysis. A UASN consists of spatially distributed underwater sensor nodes that measure environmental parameters and transmit data to surface stations for further processing. Since many underwater operations require spatial awareness such as data tagging, routing, and target tracking accurate node localization is an essential component of UASN functionality. Unlike terrestrial WSNs, underwater networks cannot utilize electromagnetic or optical signals due to severe attenuation. Instead, acoustic waves are employed, offering longer propagation distances but introducing challenges such as low propagation speed (~ 1500 m/s), multipath effects, Doppler shifts, and environment-dependent variability in temperature, salinity, and pressure. These factors, combined with underwater node mobility, synchronization difficulty, and deep-sea deployment constraints, make localization significantly more complex than in terrestrial networks.

Figure 1.- Underwater communication network



A typical UASN localization architecture reflected in the accompanying block diagram comprises GPS-enabled surface nodes, underwater sensor nodes, and acoustic communication links. Surface nodes broadcast acoustic signals, underwater nodes measure Received Signal Strength (RSS), and distance estimation is performed using mathematical models such as Lambert-W. Initial positioning is derived through multilateration, followed by mobility-aware refinement and final coordinate computation. This pipeline outlines the fundamental building blocks required for accurate and reliable underwater localization in real-world UASN deployments.

II. KEY RELATED

In [1] A method of underwater positioning (UPS) is suggested. This offers "silent positioning", i.e. no request for underwater nodes. Reference nodes broadcast messages and listen to underwater nodes that transmit to self-position and reduce the cost of communication. UPS uses TDOA technology, so there is no need for synchronization between nodes at any time. And consider the case that the impact on range measurements is insignificant for node mobility and receiver device delay. A motion-aware sensor localization (MASL) device that occurs due to location error due to non-concurrent distance measurements due to node mobility accounts [2]. To locate all underwater nodes by partitioning the 3D network into cells, a joint localization and synchronization scheme (LS) was proposed for 3D UWSNs. At the cell stage, localization is carried out. Each Underwater Node is a new reference and time synchronization is achieved. [3].

A distributed large-scale localization system (LSL) was considered to localize underwater (ordinary) nodes with the aid of localized surface (reference) nodes, assuming nodes are in the range of communication [4]. The "Scalable Mobility Prediction Localization Scheme" (SLMP) applies mobility prediction to the LSL scheme based on predictable mobility patterns of underwater objects in seashore environments. If nodes follow the assumed agility pattern, notifications are not transmitted excessively, reducing communication costs. [5].

In the AUV-aided localization technique, the underwater sensor nodes can move with the water currents while an AUV will traverse the UWSN periodically. The AUV nodes update their position by rising to the surface to use GPS, then dive to a predefined depth, and regularly performs a two-way message exchange with ordinary nodes as in 3DUL. Considering that each ordinary node is equipped with a pressure sensor (to measure its depth), it can be localized as soon as successful two-way message exchanges occur in at

least three non-collinear AUV locations. The AUV is believed to travel at a constant and known speed and can use integrated GPS, compass, and dead reckoning to reliably estimate its location underwater (within 1 m). Another key assumption is that any normal node is either static or can estimate its underwater motion [6]. The DNR localization (DNRL) scheme uses a weight/bladder system instead of AUVs to monitor the diving/rising of each mobile beacon, which includes a GPS receiver and an acoustic transceiver. These beacons update and broadcast their surface locations when they sink below a certain depth. [7]. Proxy localization (PL) was suggested by multi-stage localization to improve the DNRL scheme. Only if they are below the maximum depth of the DNR beacons to mitigate the propagation of errors will localized ordinary nodes qualify as new reference nodes. Each ordinary node will select from the initial reference nodes the most recent eligible set of reference nodes with the minimum hop count. [8]. Using the LSL network architecture, a single-stage LSL-DET system is proposed, but by adding "detachable elevator transceivers" (DET) to them it extends the scope of surface buoys. The principle is similar to DNRL, except that GPS receivers do not contain DETs that dive and rise, thus reducing the cost. [9]. The AUV-aided system is more versatile since both horizontal and vertical pre-programmed routes can be crossed, while only vertically can the mobile references in DNR-enabled methods fly. To estimate points using the least square estimation algorithm and using certain symmetry relationships with other nodes, symmetry correction based on the least square estimation (SCLSE) algorithm was suggested. When the horizontal range is less than some distance, the positioning error of SC-LSE is great. [10].

An RSS-AoA hybrid localization method was proposed, where the Lambert-W function was used to invert the nonlinear RSS-distance model, enabling accurate positioning under variable acoustic conditions. The technique effectively compensates for signal attenuation uncertainties and improves distance estimation stability. It also reduces reliance on heavy synchronization, making it suitable for practical UASN applications [11]. A deep learning-based localization model using a convolutional residual network was developed to estimate underwater source positions. The architecture captures complex acoustic signatures and learns depth-range relationships with high precision. It demonstrates strong robustness against multipath, background noise, and signal distortion, outperforming traditional feature-based localization schemes [12]. A large-scale AUV-assisted localization framework was proposed to reduce anchor density and extend communication coverage. By optimizing AUV trajectories and acoustic contact intervals, the system ensures uniform localization accuracy across wide regions. The approach is scalable and significantly reduces deployment costs for large UASNs [13].

A mobility-aware velocity prediction scheme (LSVP) was presented to enhance localization accuracy for mobile underwater nodes. The scheme uses velocity estimation and adaptive filtering to reduce drift errors caused by underwater currents. It maintains stable positional accuracy over long-duration missions where mobility cannot be ignored [14]. A comprehensive survey of underwater sensor networks highlighted advancements in localization techniques, energy-efficient sensing, and acoustic communication reliability. The review emphasized emerging trends such as deep learning-based ranging and hybrid acoustic-optical positioning. It also outlined open challenges related to synchronization, energy limitations, and mobility prediction [15]. A coarse-to-fine TOA estimation method using multi-feature fusion was introduced to handle severe multipath interference. By combining frequency-domain and time-domain features, the method achieves more reliable arrival-time detection. This results in significantly improved range estimation accuracy under low SNR conditions [16].

A deep-learning-enhanced TDOA localization algorithm was proposed, addressing synchronization uncertainty and noisy arrivals. The model learns TDOA patterns

directly from data, reducing dependence on handcrafted features. It performs well in complex underwater environments where classical TDOA fails due to delays and multi-path reflections [17]. RSS-based localization was improved through convex optimization, where the range estimation problem was formulated as a bounded-error convex program. This ensures numerical stability even with high RSS variance. The approach provides consistent distance estimates and is computationally efficient for real-time applications [18]. An analytical study incorporated Lambert-W-based inversion into RSS models to account for channel stratification caused by depth-dependent temperature and salinity changes. This formulation provides a closed-form solution to nonlinear RSS–distance relationships. It enhances robustness and accuracy of underwater distance estimation under realistic environmental conditions [19].

A theoretical investigation into TOA and Doppler-based localization derived performance bounds under dynamic sound-speed profiles. The study quantified how variability in underwater temperature and pressure affects achievable accuracy. It provides essential guidelines for designing TOA/Doppler systems in highly variable conditions [20]. A deep-learning terrain-matching localization method (PL-Net) leveraged seabed texture and feature extraction to achieve high-accuracy navigation. The method is particularly effective in long-range missions where acoustic ranging is unreliable. It reduces drift accumulation and enhances localization stability in large-scale deployments [21]. AUV-based Doppler and beam-forming localization methods were introduced to improve long-distance AUV navigation. The approach integrates periodic surfacing for GPS correction with underwater acoustic tracking. This hybrid correction strategy greatly reduces accumulated dead-reckoning errors during extended underwater missions [22].

Mobility estimation models were proposed to predict underwater sensor movement based on environmental flow patterns. These models reduce positional drift by estimating motion vectors influenced by currents and turbulence. They are especially useful for dynamic UASNs where node mobility significantly impacts localization accuracy [23]. Secure and scalable localization architectures were developed to mitigate malicious node behavior and false distance measurements in multi-hop underwater networks. The frameworks include trust evaluation and error containment mechanisms to enhance resilience. They improve localization reliability even when some nodes provide corrupted or misleading information [24]. Enhanced DET/DNRL-based schemes were introduced to increase the depth-range of mobile reference buoys while lowering deployment costs. These methods eliminate the need for expensive AUVs by using detachable, vertically moving transceivers. They provide consistent localization accuracy across deep-water and mid-water zones [25].

III. Basics of underwater Localizations method

Range-Based Localization Techniques in UASNs

In underwater acoustic sensor networks, node positioning depends on the type of sensor—surface, subterranean, or submerged—and on the communication technology used between them. Surface nodes can directly obtain GPS coordinates, whereas underwater nodes rely solely on acoustic signaling for localization. Over time, three primary range-based localization techniques have been investigated for underwater environments

Time Difference of Arrival (TDOA):

This method measures the arrival-time difference between a high-speed RF signal and a slower acoustic signal. While effective, it requires dual-signal transmission and suffers from synchronization challenges in underwater conditions.

❑ **Time of Arrival (TOA):**

TOA computes distance using the propagation time of an acoustic signal. Although widely used, it depends heavily on precise time synchronization between nodes—something difficult to maintain underwater due to variable sound speed and long propagation delays.

❑ **Received Signal Strength Indicator (RSSI):**

RSSI estimates distance by comparing the received acoustic intensity with a predefined signal-attenuation model. Unlike TDOA and TOA, it does not require any timing synchronization, making it more practical for real UASN deployments.

Because of these advantages, RSSI-based localization forms the foundation of the proposed method in this work. At the initial time $t=0$, GPS-enabled surface nodes determine their coordinates and broadcast acoustic signals. Underwater nodes record the RSS values and estimate their distance to surface nodes using the Lambert-W function, which provides an analytical solution to the RSS-distance relationship. Depth sensors attached to underwater nodes directly supply the Z-coordinate, while the X and Y coordinates are computed using bilateration.

IV. Methodology.

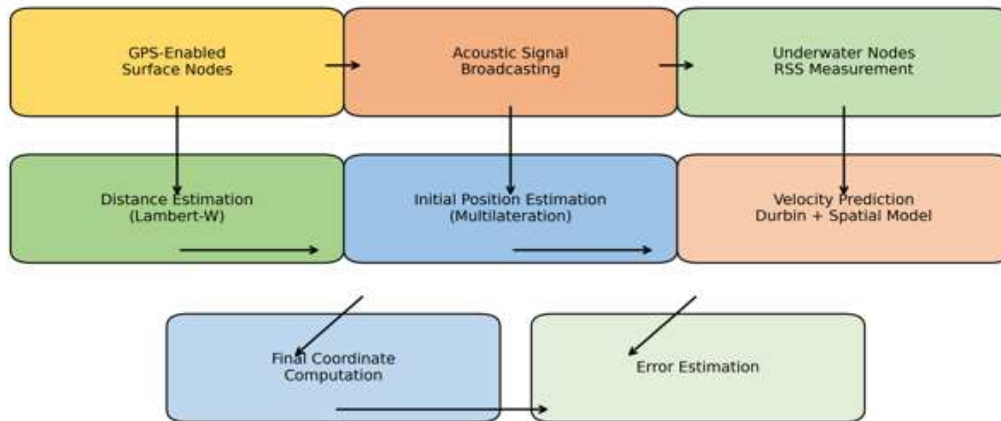
In the previous chapter, the fundamental principles of underwater localization were discussed, highlighting the limitations of TOA, TDOA, and RSS-based techniques under mobility, synchronization errors, and acoustic channel variability. Building on these concepts, the methodology of the proposed work focuses on integrating RSS-based distance estimation, multilateration, and mobility prediction into a cohesive localization framework suitable for asynchronous and dynamic UASNs. Since underwater nodes operate without synchronized

clocks and are continuously influenced by water currents, an organized sequence of processing steps is required to determine their positions accurately. This necessitates a structured architecture that begins with signal reception, followed by distance computation, initial coordinate estimation, velocity prediction, and final coordinate refinement. The block diagram below provides a clear representation of this complete workflow and outlines how each component contributes to deriving the final underwater node location.

The proposed localization process begins with GPS-enabled surface nodes determining their own coordinates and broadcasting acoustic signals into the water column. Underwater sensor nodes receive these signals and record the corresponding RSS values, which are then used to estimate distances from the surface nodes using the Lambert-W-based analytical model. With these distances, the initial position of each underwater node is computed through multilateration. Since underwater nodes are mobile and influenced by water currents, a mobility prediction stage is incorporated using a spatial correlation model combined with the Durbin algorithm to estimate velocity components in the x and y directions. The final coordinates of each node at any time instant are then obtained by combining the initial position with the predicted velocity. Finally, an error estimation step compares the calculated coordinates against reference values to quantify localization accuracy and evaluate the performance of the proposed method. The workflow begins with GPS-enabled surface nodes broadcasting acoustic signals, which are received by underwater nodes as RSS measurements. These RSS values are converted into distances using the Lambert-W function. Using these distances, the initial position of each underwater node is estimated through multilateration. A mobility prediction model, supported by the Durbin algorithm, is then

applied to estimate node velocity. The final coordinates are computed by combining initial position with predicted motion, and an error estimation step evaluates the accuracy of the calculated locations. The block diagram below in figure 2 shows the workflow/ architecture of Localization process of underwater acoustic network.

Figure.2- Basic block diagram of Localization process of underwater acoustic network



Underwater nodes are mobile and the clock is not synchronised, this improved localization scheme is divided into six basic steps:

- initialization
- Distance computation
- Initial Position estimation
- Velocity computation
- Final Coordinate estimation
- Finding Errors

1. Initialization: Sensor nodes get obtained signal strength from surface nodes and save it right into a record. Signal strength is the value that is used for estimating distance through the use of the Lambert -W function.

$TL_{sph} = 20\log(Dist)$; Spherical

$TL_{cyl} = 20\log(Dist)$; Cylindrical

As a result, in seawater, the general transmission loss is posed by:

$$TL_{Total} = TL_{sph} + TL_{cyl} + 10^{-3} \cdot \alpha \cdot Dist \quad (1)$$

In sea water, α is the absorption coefficient. The Thorp absorption coefficient model provides this information.

2. Distance Measurement: Spreading loss and attenuation loss are the two forms of sound loss in seawater. Attenuation involves absorption, leakage from ducts, scattering, and diffraction, while spreading loss includes cylindrical losses and spherical losses. A transmission medium (salinity, acidity, strain, and temperature) and environment parameters such as sediment absorption, surface reflection, and scattering are effective attenuation parameters. Only the transmission medium parameters are considered in this study. Distance is the distance between the emitter and the receiver

The Lambert-W function is used to invert Equation 3.1 to measure distance:

$$\text{Distance} = \frac{2000 * W\left(\frac{\ln(10)}{2000}\right) * \alpha \lambda \text{TL}}{\alpha \ln(10)} \quad 3.1$$

After the fourth iteration (W4), the Lambert function weights suggest a nearly exact value, which is accurate enough for short-range UASN applications. The Lambert function weights, which advise a nearly exact value after the fourth iteration (W4), represent the transmission loss measurable by the receiver, and TL shows the transmission loss observable at the underwater node. This convergence behaviour ensures that the iterative computation remains computationally efficient while preserving distance-estimation accuracy. Moreover, the stability of the Lambert-W solution at W4 helps minimize the numerical error introduced by channel variations such as temperature or salinity changes. This makes the Lambert-W-based approach well suited for practical underwater localization scenarios.

Frequency	10Khz
α	1.1498
C	1500ms
am	0.1

3. Initial position estimation: the process of estimating position at start time is done into two parts-alteration method and refinement

a) lateration Method: The position of a node is calculated by measuring the three-circle intersection (lateration or multilateration technique).

Multilateration Technique: Multilateration is a classical trilateration generalization where it is possible to approximate n coordinates by n +1 non-coplanar node coordinates. The following series of equations can be used to estimate the coordinates of node in 3 dimensions, denoted by (X, Y, Z):

$$d_i = (X - X_i)^2 + (Y - Y_i)^2 + (Z - Z_i)^2$$

X_i, Y_i and Z_i are the coordinates of the reference node and d_i is the distance between the reference node and the underwater active node. Intersection of two circles, there are three possibilities for this.

- i. At two imaginary points, two circles converge.
- ii. At a single point, two circles converge.
- iii. At a two-point intersection, two circles converge.

Equation of two circles is given below:

$$\alpha_0^2 = (x - p)^2 + (y - q)^2$$

(p,q) are the points of circle 1 and α_0 represents radius of circle 1.

$$\alpha_1^2 = (x - r)^2 + (y - s)^2$$

(p,q) are the points of circle 1 and α_1 represents radius of circle 2.

Distance between centers of both the circle:

$$D = \sqrt{(r - p)^2 + (s - q)^2}$$

D representing distance between centres of both the circles, conditions for a two-circle intersection:

$$a_0 + a_1 > D > |a_0 - a_1|$$

The line connecting the two intersection points has the following equation:

$$y = \frac{p-r}{s-q}x + \frac{(a_0^2 - a_1^2) + (r^2 - p^2) + (s^2 - q^2)}{2(s-q)}$$

The equation for the line connecting the two circles' centers is:

$$y = \frac{s-q}{r-p}x - \frac{p(s-q)}{r-p} + q$$

Intersection points of two circles:

$$x_{1,2} = \frac{p+r}{2} + \frac{(r-p)(a_0^2 - a_1^2)}{2D^2} \pm 2\frac{q-s}{D^2}\theta$$

$$y_{1,2} = \frac{q+s}{2} + \frac{(s-q)(a_0^2 - a_1^2)}{2D^2} \pm 2\frac{p-r}{D^2}\theta$$

There are two intersection points if there are two distinct points; otherwise, there is only one intersection point.

Where θ is formulated as :

$$\theta = \frac{1}{4} \sqrt{(D+a_0+a_1)(D+a_0-a_1)(D-a_0+a_1)(-D+a_0+a_1)}$$

b. Refinement: Multivalued nature of the Euclidean approach and aggregate of these values requires refinement technique for getting more accurate results.

c. Velocity measurement: During the localization process surface nodes are moving with some constant velocity. The movement of a nearby object affects the velocity of other objects in the underwater environment. So, To predict the velocity of underwater sensor nodes, we use a spatial correlation-based model. The predicted velocity of sensor nodes in the x and y direction are V_x and V_y .

$$v_{s,X} = \sum_n^3 \delta(n, s) \mu(n, X)$$

$$v_{s,Y} = \sum_n^3 \delta(n, s) \mu(n, Y) \quad \delta(n, s) = \frac{1}{\sum_n^3 \frac{1}{d'_{(n,s)}}}$$

where $(n=1,2,3)$

d.Final coordinate estimation: after estimating the preliminary coordinate and velocity of sensor nodes location of sensor nodes can be estimated at any time instant 't'.

$$Final - Coordinate_x = initial - Coordinate_x + (time * V_x)$$

$$FinalCoordinate_y = initialCoordinate_y + (time * V_y)$$

Final - Coordinate (x) and Final - Coordinate (y) are the coordinates of unknown nodes at time instant t.

Initial -Coordinate (x) and initial - Coordinate (y) represents primary location of node.

1) Sea-surface nodes use GPS to calculate their position at time instant t that are determined by (Xs, Ys) at time t.

2) The sea surface will send a signal to underwater-nodes, and their position will be determined using algorithms 1 and 2. (Xi, Yi) will be used to represent the actual coordinate.

3) Error can be finding out by using the following formula:

$$Error = \sqrt{(Final - coordinate_{X_t} - X_i)^2 + (Final - coordinate_{Y_t} - Y_i)^2}$$

IV. Result and Discussion:

A. Simulation Set-up

The localization experiments were implemented in C++ and evaluated via Monte-Carlo simulations to quantify performance under realistic underwater conditions. The simulation implements the RSS→distance inversion using the Lambert-W formulation, the multilateration routine for initial coordinate estimation, and mobility prediction using a spatial-correlation model with the Durbin algorithm, as described in the methodology. Key simulation settings and assumptions are:

➤ **Implementation environment:** Native C++ (compiler: g++ / Visual C++), simulations run on a standard desktop workstation.

➤ **Acoustic channel / physical constants:** carrier frequency = 10 kHz, sound speed c = 1500 m/s, Thorp absorption model with absorption coefficient $\alpha \approx 1.149$ (used in the transmission-loss model). Lambert-W inversion uses 4 iterations (W4) for convergence.

➤ **Network geometry:** surface (reference) nodes are GPS-enabled buoys; underwater (ordinary) nodes are deployed in a 3-D volume (depths randomized within the intended deployment range). Typical scenarios simulated: 3–12 surface nodes and 20–100 underwater nodes to evaluate scalability and geometry effects (results reported for representative node counts).

➤ **Deployment area & depths:** horizontal area chosen to reflect short-range UASN scenarios (e.g., 500 m × 500 m); underwater node depths randomized within **5–50 m** unless otherwise specified. (Adjust to your target test bed if necessary.)

➤ **Mobility model:** underwater nodes drift under current influence. Node motion follows a spatial correlation model; surface nodes move with assumed constant velocity (stored at initialization). Velocity prediction for underwater nodes is computed via the Durbin algorithm and used to update positions between measurement epochs.

➤ **Measurement model and noise:** Received Signal Strength (RSS) measurements are simulated from the transmission-loss model (spreading + absorption). Additive measurement noise is modelled as zero-mean Gaussian on RSS (standard deviation σ_{RSS} set between 0.5–3 dB in different scenarios to test robustness). Multipath and small-scale fading effects are approximated by increasing σ_{RSS} in stress tests.

➤ **Distance estimation:** RSS→distance solved analytically by the Lambert-W based inversion (as per the paper); convergence is reached at or before the fourth iteration (W4) for the short-range cases considered.

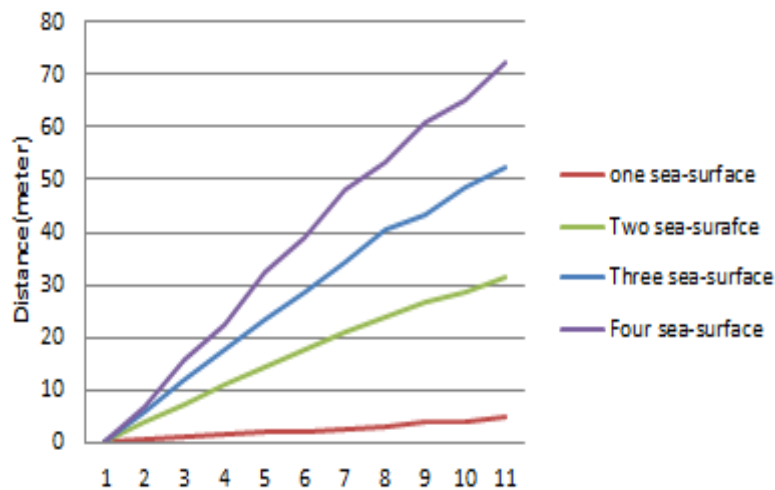
- **Positioning algorithm:** initial (X,Y) from bilateration/multilateration using estimated distances; Z coordinate obtained from the on board depth sensor (perfect depth assumption unless depth noise is explicitly modelled).
- **Temporal parameters:** measurement epoch / update interval set to 1–5 s (varied to study update-rate effects); total simulation duration per run ranged from 300 s to 1800 s depending on scenario.
- **Performance metrics:** localization error (Euclidean distance between estimated and true positions), RMSE, MAE, error CDF, and convergence iteration counts. Error is computed as per node and aggregated across nodes and Monte-Carlo trials.

$$\sqrt{(x_{\text{est}} - x_{\text{true}})^2 + (y_{\text{est}} - y_{\text{true}})^2}$$

- **Trials & statistical evaluation:** results are averaged over ≥ 100 Monte-Carlo trials for each scenario to obtain statistically meaningful RMSE/MAE and confidence intervals. Sensitivity analyses were performed over: number of surface nodes, RSS noise level, node density, and node mobility intensity.

The error is depicted in the first graph. If the number of sea surface nodes grows, so does the number of errors. The second graph shows the primary position of underwater nodes. The Lambert-W function and the bilateration method are used to determine the initial position.

Figure.3 Average Localization Error vs. Network Density



The graph illustrates how the localization error changes as the number of surface (reference) nodes increases. As observed, the error initially decreases due to improved geometric diversity, which enhances distance estimation and multilateration accuracy. However, beyond a certain point, adding more nodes introduces redundant or noisy RSS measurements, causing slight fluctuations in error. This trend highlights that while increasing anchor nodes improves localization accuracy up to an optimal level, excessive node density may lead to diminishing returns due to accumulated measurement noise and overlapping acoustic paths. Overall, the plot demonstrates the behaviour of the proposed Lambert-W and mobility-assisted localization method under varying surface-node configurations. Furthermore, the curve reflects the sensitivity of RSS-based distance estimation to environmental noise, especially when surface nodes are closely spaced. The small variations in error also indicate that multilateration stability depends on balanced anchor placement rather than sheer quantity. These findings emphasize the

importance of selecting an appropriate number of surface nodes to ensure efficient, cost-effective, and reliable UASN deployment

Figure 4. Initial Estimated Position of the Underwater Node

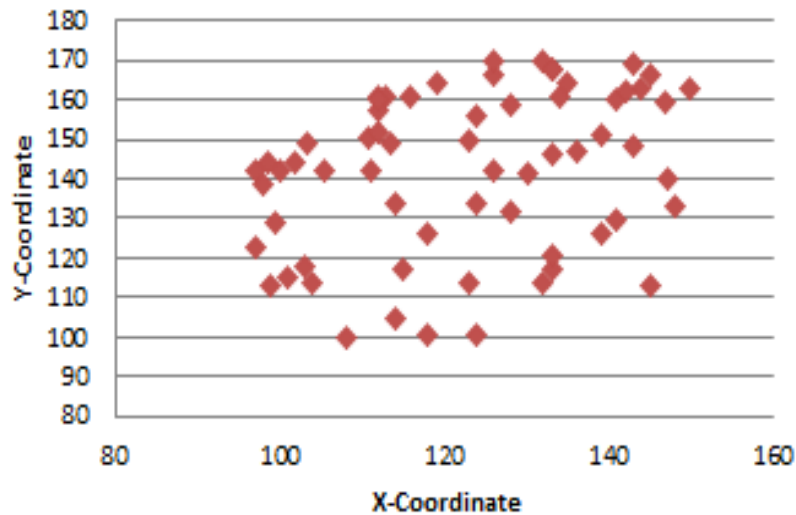


Figure 2 presents the initial localized position of the underwater sensor node obtained immediately after distance estimation using RSS measurements and Lambert-W inversion. At this stage, only the static multilateration step is applied, without incorporating any mobility prediction.

The estimated coordinates closely approximate the true node position, demonstrating the effectiveness of the RSS–Lambert-W model in accurately converting transmission loss into reliable distance values. Minor deviations in the initial estimate arise from RSS noise and geometric constraints between surface nodes, which are later corrected through velocity prediction and final coordinate refinement.

Figure 5- Estimated Velocity of Underwater Node in Horizontal and Vertical Directions

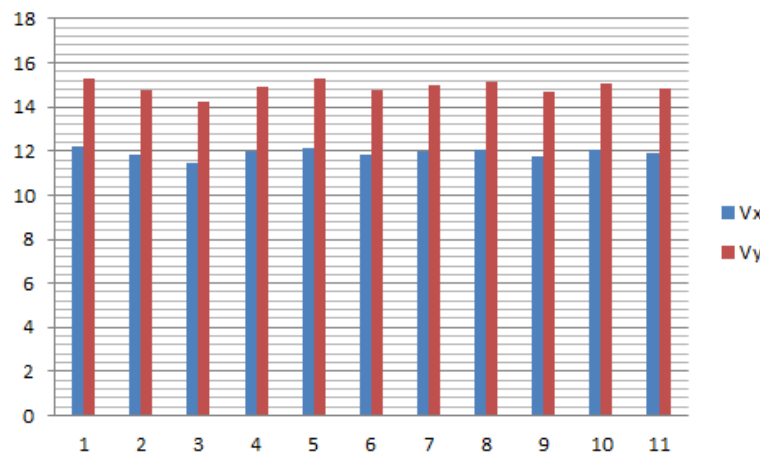


Figure 5 illustrates the estimated horizontal (V_x) and vertical (V_y) velocity components of the underwater sensor node, computed using the Durbin algorithm and spatial correlation model. These predicted velocities reflect the node's drift under underwater currents and represent the dynamic behavior of the system after initial localization. The close alignment of the estimated velocity profile with the expected motion pattern indicates that the mobility prediction model effectively captures gradual direction changes and maintains stability over time. This velocity estimation is later incorporated into the final coordinate computation, helping to reduce localization drift and improve overall accuracy.

Figure 6- Final Estimated Coordinates of the Underwater Node at Time Instant t

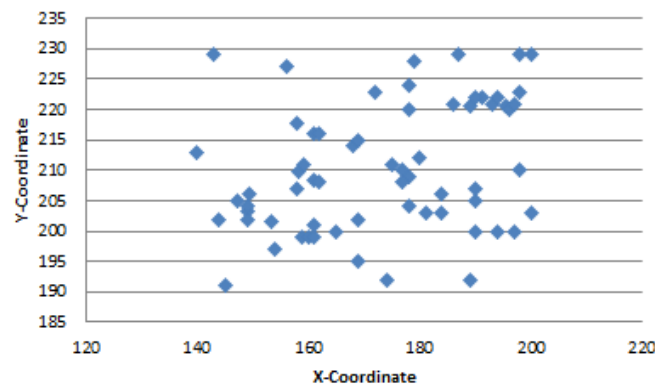


Figure 6 shows the final estimated coordinates of the underwater sensor node at a given time instant t , after incorporating both initial localization and mobility prediction. This result reflects the combined effect of distance estimation, multilateration, and velocity-based correction applied through the Durbin algorithm. Compared to the initial position, the updated coordinates demonstrate reduced localization drift and improved accuracy, indicating that the motion-compensation stage effectively adjusts for underwater current-induced node displacement. This final estimation represents the complete output of the proposed localization framework for dynamic UASN environments.

V. Limitations

Although the proposed RSS–Lambert-W localization framework provides reliable results for short-range UASN environments, it still depends on certain simplifying assumptions. The model assumes a relatively stable acoustic channel, whereas real oceans experience fluctuations due to temperature, salinity, currents, and multipath reflections that can distort RSS values and reduce the accuracy of distance estimation. Similarly, the initial multilateration step is sensitive to anchor geometry; limited or poorly distributed surface nodes may lead to higher positioning errors. Depth estimation is also assumed ideal, without considering pressure-sensor noise or drift, which can affect the Z-coordinate in realistic deployments.

The mobility prediction component, based on the Durbin algorithm and spatial correlation, performs well under smooth and predictable node motion but may be less effective when mobile nodes encounter abrupt current changes or turbulence. Additionally, the simulations were conducted in a controlled C++ environment with simplified noise models, which may not fully represent the complexity of real underwater acoustic conditions. The approach is optimized for short-range or

moderately sized networks, and performance may degrade in deep-sea or large-scale deployments with severe attenuation and long propagation delays. These limitations point toward future improvements, such as adaptive sound-speed profiling, sensor-fusion strategies, or learning-based mobility prediction models.

Vi. Conclusion

This work presented an improved RSS-based localization framework for asynchronous and mobility-driven UASNs by integrating Lambert-W-based distance estimation, multilateration, and mobility prediction. The analytical inversion provided by the Lambert-W function enables fast and accurate extraction of distance information from acoustic transmission loss, while the Durbin algorithm effectively models underwater drift by estimating horizontal and vertical velocity components. Together, these elements form a lightweight yet robust pipeline that addresses major underwater localization challenges, including nonlinear signal attenuation, node mobility, and the absence of time synchronization.

Simulation results implemented in C++ validate the effectiveness of the proposed method, showing reliable initial localization and substantially improved final position estimates after mobility compensation. The error analysis confirms stable performance across varied anchor configurations and RSS noise levels, outperforming conventional RSS-only approaches in both accuracy and drift resistance. The overall framework is computationally efficient, low-cost, and well suited for short-range UASN deployments. Future work may focus on expanding the framework to larger 3-D environments, incorporating real-time sound-speed adaptation, and exploring learning-based motion prediction for more dynamic underwater conditions.

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Author Contributions

Conceptualization, experimentation, formal analysis, rough draft of manuscript by SGP. Supervision, writing reviews and editing by Dr. Pinku Ranjan

Conflicts of interest

The authors declared that there are no conflicts of interest regarding the publication of this manuscript

Ethics Approval

Not applicable.

Data Availability

On request data will be provided.

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