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Underwater localization using SAR satellite data.

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Underwater Localization Using SAR Satellite Data

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***Abstract*—This study delves into the realm of Underwater Wireless Sensor Networks (UWSN) and explores contemporary methods of ocean exploration. It provides an extensive background on UWSN, detailing existing approaches to underwater localization. The study then introduces a novel contribution to this domain by leveraging advanced satellite technology. Employing a pre-trained deep learning model from ArcGIS, static ships within the study area are identified using C-band Synthetic Aperture Radar (SAR) satellite imagery. The identified ship locations serve as reference nodes for underwater localization. Utilizing range-based multilateration in the UnetStack environment, the study achieves precise localization of underwater nodes. The proposed approach demonstrates an error of less than 1% when compared to the actual positions of the underwater nodes, showcasing its effectiveness in enhancing the field of underwater exploration and localization.**

Keywords—Underwater Localization, SAR data, Dynamic underwater Localization.

I. INTRODUCTION

Despite water covering 71% of Earth's surface, only 5% of the ocean has been explored. Traditional exploration involves Remotely Operated Vehicles (ROVs) and Automated Underwater Vehicles (AUVs), but these technologies face limitations in precise positioning due to challenging underwater conditions, speed, and tether restrictions [1]. ROVs, in particular, are constrained in their movement and range, which limits their depth and increases the risk of cable entanglement [1]. Subsea nodes are essential in overcoming these challenges by serving as communication hubs and data collection points in underwater environments. They facilitate real-time data transmission, enable accurate positioning through acoustic signals, and expand the range and efficiency of underwater exploration and monitoring efforts. Subsea nodes play a vital role in enhancing our understanding of the ocean and its ecosystems, as well as supporting various industries such as oil and gas, marine research, and environmental monitoring. The localization of these underwater nodes is essential for various underwater applications. Underwater localization is the process by which the location of a node is obtained with respect to a known reference point [2].

Underwater localization currently relies on slow propagating acoustic signals as other conventional signals such as radio and optical are severely attenuated underwater [2]. Acoustic communication, despite propagation delays, is preferred for medium to long-range underwater transmission [3, 4]. Underwater acoustic localization faces many challenges which includes complex propagation of acoustic signals influenced by factors such as temperature, pressure, salinity, sensor drifting, and multipath effects [5] leading to inaccuracies in range measurements. These inaccurate range measurements produce inaccurate localization results. Despite diverse attempts to underwater localization, precise localization of a network of mobile nodes in specific area remains difficult. To set up a 3D network of mobile nodes in specific area, there is a need for fixes reference node. Synthetic Aperture Radar (SAR) data is widely used for ocean monitoring and target detection. Based on statistics from the United Nations Conference on Trade and Development (UNCTAD), there are roughly 100,000 oceangoing ships (100 gross tons and above) worldwide, spread across an ocean area of approximately 360 million km² [6]. This equates to an average density of approximately one ship per 3600 km². Analysis of SAR data over a period of time reveals that some of these ships remain stationary in North Sea. The location of these stationary ships can be compared to the location of the area of interest and the closes ones can be used as reference nodes for an active dynamic network of subsea nodes. The contribution of this paper is concluded as follows.

- The utilization of pretrained ArcGIS deep learning model to detect static ships using SAR satellite imagery around the local area of interest (in this case Scottish harbour) . The closes static items (in this case ships) to our area of interest will serve as reference nodes for localization of a network of dynamic nodes.
- The simulation in UnetStack uses the location of these reference node for localization of subsea floating nodes in that area. conventional acoustic range based estimation and multilateration will be employed to precisely localize the underwater nodes.

The remainder of this article is organized into four sections. Section II discusses advances in subsea localization techniques, while section III introduces ship detection using SAR data. In section IV, the proposed approach to enhance subsea localization accuracy is presented along with results while Section V concludes the study.

II. SUBSEA LOCALIZATION

Underwater localization remains a challenging frontier, necessitating continual advancements to meet the demands of exploration, surveillance, and environmental monitoring in the underwater environments. This section provides a comprehensive overview of recent advancements from Centralized Localization techniques to distributed techniques,

A. Centralized Localization

This refers to a localization approach where the processing and decision-making tasks are performed at a central node or a central processing unit [7]. In centralized localization, techniques are further classified into estimation-based and prediction-based techniques.

i. Estimation-Based Centralized Localization

This localization focuses on the precise determination of object positions through the aggregation and analysis of sensor-derived data. Researchers have proposed various centralized estimation-based methods for underwater target localization. These include wideband Direction of Arrival (DoA) estimation in [8], sensor fusion with Kalman filtering in [9], and optimized anchor node selection for Unmanned Underwater Vehicle (UUV) localization in [10]. These techniques aim to enhance accuracy and reduce energy consumption utilizing centralized estimation techniques. Additionally, other approaches such as underwater localization in Visible Light Communication (VLC) systems in [11] have also been proposed. Despite their effectiveness, centralized estimation-based localization faces challenges like scalability issues and communication overhead, which may hinder efficiency in large-scale networks.

ii. Prediction-Based Centralized Localization

Predictive-based centralized localization predict the positions of nodes based on location information or models [12]. The node entity uses predictive algorithms to estimate node positions, which can be affected by inaccuracies in the current model or variations in environmental conditions. In [12]the authors propose collaborative localization for underwater drifters, optimizing swarm configurations to minimize position estimation errors. The study achieved considerable performance gains; however, prediction-based centralized localization faces similar issues with estimation-based centralized localization.

B. Distributed Localization

Distributed localization refers to a localization technique where each node independently performs calculations without the need to send information to a central node for processing [12]. Distributed Localization is also divided into estimation-based and prediction-based.

i. Estimation-Based Distributed Localization

Estimation-based distributed localization refers to a localization approach where each node in a network independently estimates its own position based on available information from neighboring nodes or beacon nodes. In [13], estimation-based technique calculates the target node coordinates using geometrical relationship without needing the exact reference node positions, thus reducing computational complexity arguably at the expense of accuracy. Researchers in [14] introduces a virtual node-assisted algorithm which improves accuracy but susceptible to environmental conditions and range estimation errors. [15] focuses on range-based estimation technique, utilizing improved algorithms to enhance accuracy, error variance, and coverage. In [2], a hybrid optimization technique considers anchor node hops, Time of Arrival (ToA) and range estimation errors to aid precise localization. Additionally, [16] addresses challenges in underwater node localization by improving node mobility models and introducing a frequency-based anchor node prediction algorithm. [17] proposes a hybrid algorithm based on Doppler Shift and Angle of Arrival (AoA) for underwater mobile nodes, estimating positions and velocities of mobile nodes, while [18] presents a localization scheme using dive and rise mobile beacons, achieving high coverage at the expense of energy consumption.

ii. Prediction-Based Distributed Localization

This is a localization approach where nodes in a network predict their future positions based on mobility patterns or models. In this method, nodes collaborate with each other in a decentralized manner to estimate their locations using predicted future positions and information exchanged among neighboring nodes. The authors in [19] leveraged a node motion model based on tidal mobility, and predicts and updates node positions, enabling precise localization in large scale networks with mobility.

In conclusion, estimation-based distributed localization (or hybrid which combines prediction and estimation) offers scalability, robustness against failures, and energy efficiency by allowing nodes to autonomously estimate their locations without centralized coordination, making it a popular choice for large-scale deployments. Despite massive effort, accurate localization of mobile and static nodes remains a challenging task that requires advancement in localization technique.

C. Acoustic Range Estimation

Acoustic range estimation refers to the use of acoustic energy to estimate the distance between nodes by sending an acoustic signal from one node to the other [20], then measuring the time of travel of the signal. Despite propagation delays, acoustic signal is preferred for medium to long-range underwater transmission [3, 4]. This because other signals such as optical and radio frequency signal are highly attenuated underwater [2]. Conventional ranged-based localization techniques are considered superior to range-free localization techniques due to their ability to provide more precise and reliable estimation of a node's location[21] In contrast, range-free localization depends on node's proximity, and provides only a probable area where a node could be located. [22].

To estimate the range between reference node and target node, this study designated three ships as reference nodes above the water surface in Unetstack [22] simulation environment, and a sensor was placed beneath the fourth ship at a depth of 20m to aid depth estimation for target node as shown in Fig. 5. Unetstack two-way acoustic ranging between reference and target nodes was performed to determine the range to the target node according to (1). The target node is the node of interest whose position we need to determine.:

$$r = 0.5(v_s * T_f) \qquad (1)$$

Where r = range, T_f = two-way time of flight of the acoustic signal, v_s= velocity of sound.

Depending on the environment, the velocity of sound according to (2) is evaluated as 1500 m/s approximately.

$$c = 1449 + 4.6 * t + 0.055 * t^2 + 0.003 * t^3 + (1.39 - 0.012 * t)(s - 35) + 0.017 * d \quad (2)$$

Where c is the speed of sound in meters per second, t is the temperature in degree Celsius, s is the salinity in parts per thousand, d is the depth in meters.

D. Localization of Static Underwater Node

Having established the range of the target node, range based multilateration was conducted to calculate target node coordinates according to (3).

$$\sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} = r_i \quad (3)$$

Where x, y, and z are the cartesian coordinates of the target node, x_i , y_i , z_i are the cartesian coordinates of the i^{th} reference node, and r_i is the measured range between the target node and the reference node. Equation (3) enables the accurate determination of the underwater target node's position by solving the system of equations derived from the multilateration process.

i. Multilateration:

This is an extension of the trilateration technique, it employs multiple reference nodes to estimate the position of a target node. Trilateration estimates the position of a target node by measuring the distances from three reference nodes [23]. This involves intersecting circles whose center is each reference node and have equal radii. The point of intersection of these three circles provides an estimate of the probable location of the node being localized. Multilateration is preferred for its high precision in estimating the location of an object in a three-dimensional space.

E. Localization of MobileUnderwater Node

For mobile localization, the target node was set in motion at various speeds, at an angle θ which can be estimated by Pythagoras theorem using the range and horizontal distance information, assuming a constant depth of target node.

The target node is localized at intervals, and the horizontal distance traveled by the target node can be estimated using the relationship between two points in a straight line as shown in (4).

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (4)$$

Where $(x_1, \ y_1)$, and (x_2, y_2) are respectively the previous and current coordinates of target node E, and d is the distance travelled. Equation (4) assumes a constant depth for the target node.

This distance travelled and time can be used in estimating the velocity (v) of the node, using the relationship between distance, change in time (Δt), and velocity.

The x and y components of the velocity (U_x and U_y respectively) can be estimated from the overall velocity of the node, as shown in (5) and (6).

$$U_x = v cos\theta \quad (5)$$
$$U_y = v sin\theta \quad (6)$$

The next location of the target node (E) can then be estimated using (7) and (8) [24]:

$$X_c = X_p + \Delta t \text{ x } U_x(E) \quad (7)$$
$$Y_c = Y_p + \Delta t \text{ x } U_y(E) \quad (8)$$

Where X_c and Y_c are the current position of node E along x and y axis respectively. X_p and Y_p are the previous position of node E along x and y axis respectively, t is the localization time.

III. SHIP DETECTION USING SAR DATA

In this study, the Sentinel-1 SAR scenes over the Scottish harbour (Fig. 1) were used in single-polarimetric (VV), Ground Range Detected (GRD) product, interferometric wide (IW) swath imaging mode from October 1 to 22, 2023 from the Copernicus Data Hub. The image was processed with ArcGIS Pro software [25] with a pre-trained deep learning model to detect static ships over a three-week period. The deep learning model successfully detected multiple ships, and four ships with a confidence value exceeding 80% were selected and their coordinates recorded. The confidence value indicates the degree of certainty of detection by the deep learning model. The area of interest is highlighted by the yellow polygon in Fig. 1. The red and yellow polygons indicate the available satellite image for the chosen area.

A. Ship Detection Performance

The deep learning model successfully identifies ships within the target region, delineating them with rectangular bounding boxes and assigning confidence values indicative of detection accuracy. Three ships, each exhibiting confidence values of 84% and above, were selected as reference nodes due to their consistent positions over a one-week period as shown in Fig 2.

Continuing the study, the ship detection was systematically repeated for the second and third weeks, each iteration revealing consistent results as shown in Fig 3 and 4. The analysis demonstrates that the ships within the targeted harbor area remained stationary over the observed period, reinforcing their suitability as reference nodes.

Fig. 1: Designated Study Area in Scotland.

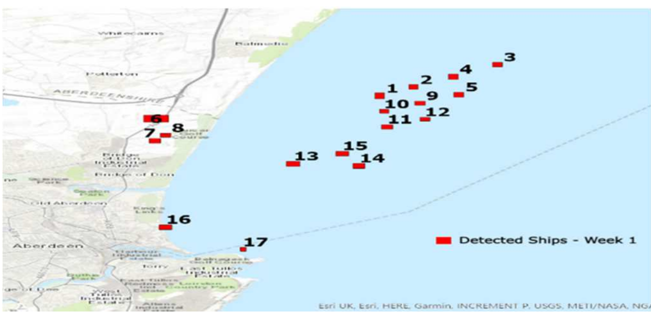

Fig. 2: Detected Ships in the first week of study

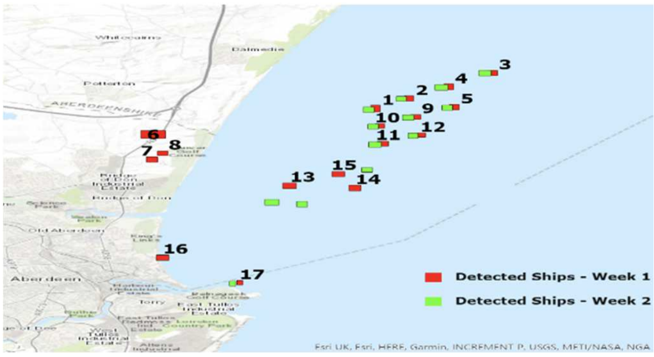

Fig. 3: Detected Ships in the Second week of study

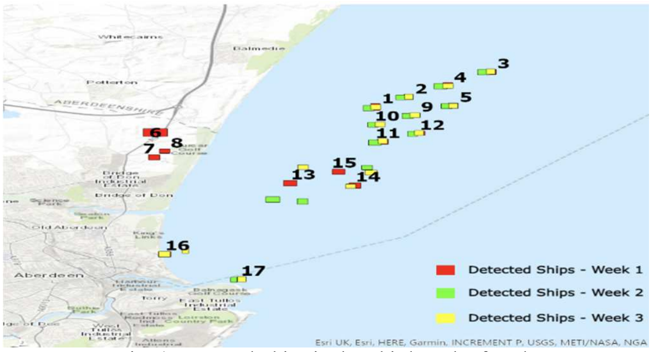

Fig. 4: Detected Ships in the Third week of study

This persistence in location, coupled with the robust confidence values obtained from the deep learning model, further solidifies the selection of these vessels as reliable reference nodes for the specified three-week duration. This detection showcases the practical application of satellite imagery and ArcGIS Pro in monitoring maritime dynamics and establishing dependable reference points for navigational and research purposes.

B. Reference Node Selection

Leveraging the identified stable ships as reference nodes, the coordinates of ships numbered 1, 2, and 9 as shown in Fig 2-4 were chosen to establish the three surface reference nodes. These surface reference nodes are equipped to communicate with GPS signals for self-localization as GPS signal is available on the surface of the water. The criteria and factors including stability, geographic location, cost, and signal limitations, guided the reference node selection process.

In addition to these three nodes, a fourth reference node was strategically placed at a depth of 20m directly beneath ship number 10, as illustrated in Fig. 2-4. The deliberate arrangement of these reference nodes ensures they are non-coplanar, enhancing the accuracy of the localization system. With these reference nodes in place, the target node to be localized is positioned within the geographical coverage of the four reference nodes, facilitating precise localization through the integration of both surface and underwater reference points.

To facilitate the identification of reference nodes, ships 1, 2, 9, and 10 are assigned labels A, B, C, and D, respectively. Node A is designated as the origin (0,0,0). The target node, denoted as E, is positioned 400 meters east and 700 meters south of the origin at a depth of 15 meters. This labeling and positioning system simplifies the coordination and calculation processes, streamlining the localization efforts through a clear and structured reference point system.

IV. PROPOSED APPROACH

Fig. 5 shows a 3D representation of the nodes placement in the study area. While reference node A, B, C are on the surface of the water, node D is located 20m below the water surface, and node E is located at a depth of 15m at the stated coordinates in fig. 5.

To localize the target node E, our study implemented the concept of multilateration, a technique based on the intersecting spheres principle. In this approach, the range between the target node E and each of the four reference nodes (A, B, C, and D) was measured utilizing the two-way ranging of acoustic signal in Unetstack simulation environment. Given that the coordinates of each reference node are known, the position of the target node was estimated using the calculated ranges, by employing (3). In localizing the target node E, the GPS coordinates of the reference nodes (A, B, C, and D) were transformed into local Cartesian coordinates, as outlined in Table 1. The measured range from each of the reference nodes to the target node was estimated using the two-way acoustic ranging technique, with the results presented in Table 1 as well.

TABLE 1: RANGE BETWEEN TARGET NODE AND REFERENCE NODES

Node	X (m)	Y (m)	Z (m)	Range to E (m)
A	0	0	0	806
B	131	-1708	0	1043
C	810	-1244	0	681
D	688	-302	-20^{*}	491
E (actual)	400	-700	-15^{*}	0

(*The negative value in Z column indicates depth below sea level, and while X and Y Column shows local coordinates with respect to node A.)

The estimated location of the target node E using the above (3) was determined to be: X = 399.99m, Y = 700m, Z = -14.97m.

Notably, this solution demonstrated an estimation error of less than 1%, underscoring the high accuracy achieved in the localization process. These findings affirm the reliability of the approach, showcasing its effectiveness in accurately determining the underwater position of the target node.

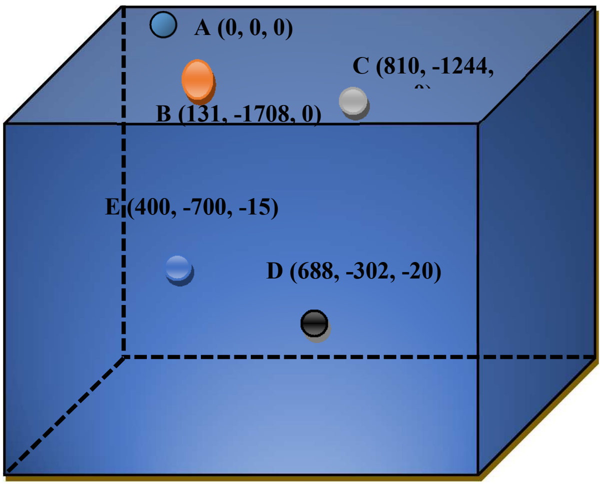

Fig. 5: Nodes Placement in the Study Area

A. Mobile Target Localization

Assuming a scenario where the target node is allowed to freely drifts underwater only in the x and y direction and is localized at intervals of time (t), the study set the target node E in motion at a constant velocity of 0.1m/s at -60.25° towards reference node A. The target node was localized every 60 seconds, and the result is shown in fig. 6.
It should be noted that multiple studies [26] [27] have placed the mean velocity of normal underwater current between 0.02 to 0.73 m/s, and this informed the choice of velocity for the simulations in this study.

Fig. 6 shows the predicted and the actual path of target node E moving at a speed of $0.1m/s$, and the prediction is nearly identical to the actual path with average location error of 0.3m. Localization error is defined as the Euclidean distance between the actual and predicted location [28] of the node. Fig. 7 shows a plot of the localization error at each instance of localization. At this velocity of 0.1 m/s, this method achieved nearly accurate localization with an error of less than 0.6 meters. Fig. 8 shows the localization error when the node speed is 0.2m/s. The localization error increased significantly at speed of 0.2m/s as shown in fig. 8, with errors reaching 200m. The speed of the node was further increased to 0.5m/s and the result is shown in fig 9.

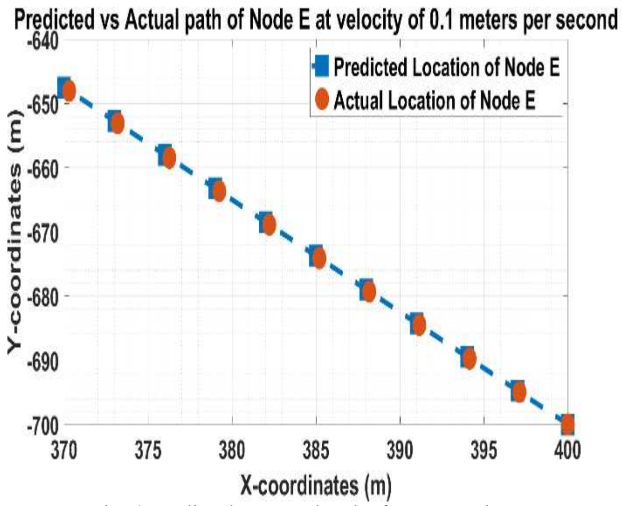

Fig. 6: Predicted vs Actual Path of Target Node E

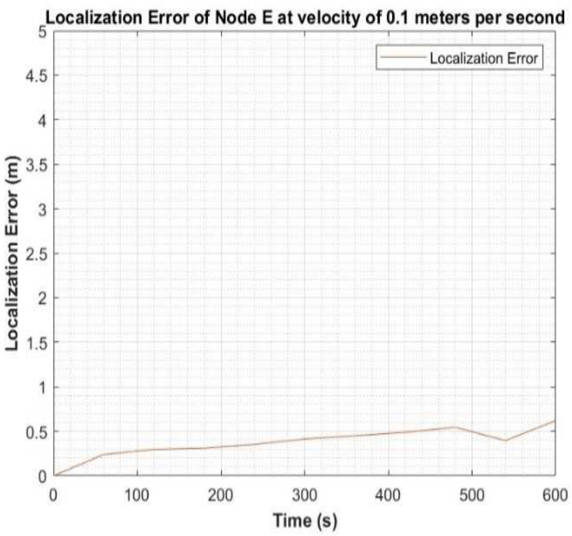

Fig. 7: Localization error per unit time at velocity of 0.1 m/s

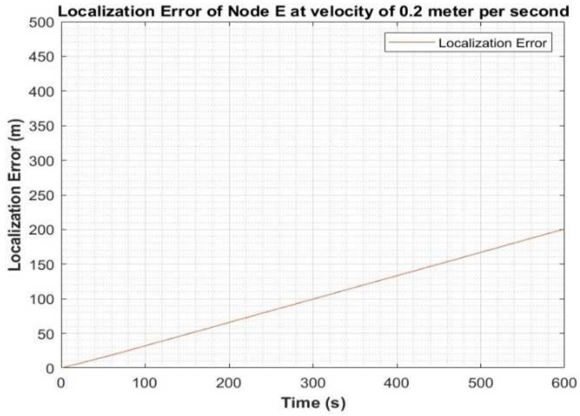

Fig. 8: Localization error per unit time at velocity of 0.2 m/s

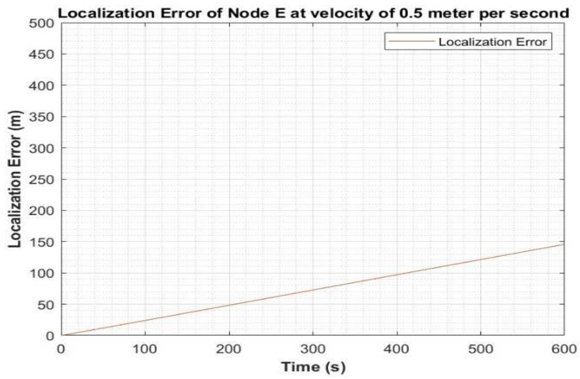

Fig. 9: Localization error per unit time at velocity of 0.5 m/s

The result showed a significant increase in error, with peak error reaching 145m.
This study has demonstrated promising results in the localization of underwater nodes, achieving nearly accurate predictions at node speed of 0.1m/s. However, it is crucial to acknowledge the challenges encountered when operating at higher speeds, where the algorithm faced an increased level of location error. While our current findings highlight the effectiveness of the algorithm within a specific speed range, future research endeavors could delve into the optimization and adaptation of the algorithm to address challenges posed by higher speeds.

V. CONCLUSION

The integration of satellite imagery analysis, ArcGIS deep learning model, and acoustic multilateration presents a comprehensive and effective approach to underwater localization. Leveraging stable ships as reference nodes, we successfully demonstrated the accuracy of this methodology in pinpointing the location of a target node in an underwater environment. The careful selection of reference nodes, along with the systematic application of multilateration principles, allowed for precise localization of the target node in both stationary and mobile state.

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