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Evaluating the Impact of Ranging Error in Underwater Localization Using SAR Satellite Data

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Abstract— **The study evaluated the impact of ranging error in underwater localization processes using SAR satellite data within the framework of Underwater Wireless Sensor Networks (UWSN). By integrating a pre-trained ArcGIS deep learning model with SAR imagery, the study identifies static ships as reference nodes in a Scottish harbour, enabling precise localization of underwater nodes through range-based multilateration techniques in the Unetstack simulation environment. The study explores the impact of ranging errors on localization accuracy and optimizes node positioning to minimize the impact of these errors, demonstrating substantial improvements in the reliability of underwater node localization. This paper not only highlights the application of SAR data in enhancing underwater exploration but also sets a benchmark for future advancements in UWSN.**

Keywords— Underwater Localization, SAR Satellite Data, Optimization, Deep Learning, Unetstack, Multilateration, Underwater Wireless Sensor Networks (UWSN).

I. INTRODUCTION

While 71% of the Earth's surface is covered by water, only 5% of the ocean has been explored. Conventional exploration uses Remotely Operated Vehicles (ROVs) and Automated Underwater Vehicles (AUVs), yet these methods encounter difficulties such as inaccurate positioning due to the challenging underwater environment, limitations in speed, and constraints from tethers [1]. Particularly, ROVs are limited by their movement and range, complicating their depth capacity and increasing the risk of cable tangling [1]. To address these issues, subsea nodes are utilized as crucial communication hubs and data collectors in underwater settings. They support real-time data sharing, facilitate precise localization through acoustic signals, and enhance the efficiency and scope of underwater exploration and monitoring. Subsea nodes are instrumental in deepening our comprehension of oceanic ecosystems and bolster various sectors including oil, gas, marine research, and environmental surveillance. The localization of these nodes is crucial for underwater operations. Underwater localization is the process of determining a node's position relative to a known reference point [2].

Underwater localization predominantly depends on slow-moving acoustic signals since conventional signals like radio and optical are heavily attenuated in water [2]. Acoustic communication is favoured for mid to long-range underwater communication despite the delay in signal propagation [3, 4]. Underwater acoustic localization encounters several obstacles including the complex travel of acoustic waves influenced by temperature, pressure, salinity, sensor drift, and multipath effects [5], which lead to inaccurate range measurements and consequently imprecise localization. Power constraint is a challenge for Underwater Wireless Sensor Networks (UWSN) as limited battery life severely impacts the longevity, communication range, and overall performance of underwater sensor nodes [6]. The major challenge remains to accurately localize a network of mobile nodes within a specific area and constraint. To establish a 3D network of mobile nodes in a particular region, a fixed reference node is required. Synthetic Aperture Radar (SAR) data, which is extensively utilized for monitoring oceans and detecting targets, shows that there are around 100,000 oceangoing ships worldwide, distributed over an ocean area of about 360 million km² according to the United Nations Conference on Trade and Development (UNCTAD) [7]. This results in an average density of about one ship per 3600 km². Analysis of SAR data indicates that some of these ships are stationary in the North Sea. The positions of these stationary ships can be matched with the location of the area of interest, and the closest ones can be employed as reference nodes in an active network of subsea nodes. The key contributions of this paper are summarized as follows.

- The use of a pretrained ArcGIS deep learning model to identify static ships via SAR satellite imagery in the specified study area (the Scottish harbour). The static ships in our area of interest will function as reference nodes for the localization of subsea node.
- The simulation conducted in Unetstack leverages the position of these reference nodes to localize subsea floating nodes in the vicinity. Traditional methods such as acoustic range-based estimation and multilateration are utilized to accurately localize the underwater nodes.
- We investigated the impact of ranging errors on underwater node localization and optimized the localization process to determine the optimal position of an underwater node.

The rest of this article is structured into four sections. Section II explores advancements in subsea localization methods, and Section III covers the proposed technique. Section IV details the results and discussion. Finally, Section V provides the conclusions of the study.

II. UNDERWATER LOCALIZATION

Underwater localization continues to be a demanding area, requiring ongoing improvements to fulfil the needs of exploration, surveillance, and environmental monitoring in aquatic settings. This section delivers an exhaustive review of recent developments, ranging from centralized to distributed localization techniques.

A. Centralized Localization

Centralized localization involves processing and decision-making at a central node or unit [8]. Within this framework, techniques are categorized into estimation-based and prediction-based approaches.

i. Centralized Estimation Localization

This method focuses on accurately determining object positions by aggregating and analysing sensor data. Various centralized estimation-based methods have been proposed for underwater target localization, including wideband Direction of Arrival (DoA) estimation [9], sensor fusion using Kalman filtering [10], and optimized anchor node selection for Unmanned Underwater Vehicle (UUV) localization [11]. These techniques strive to improve accuracy and reduce energy usage through centralized processes. Other methods, such as underwater localization in Visible Light Communication (VLC) systems, have also been introduced [12]. However, centralized estimation-based localization encounters scalability and communication overhead challenges, potentially impacting efficiency in larger networks.

ii. Centralized Prediction Localization

This approach uses predictive algorithms to determine node positions based on location data or models [13]. Techniques include collaborative localization for underwater drifters, optimizing configurations to reduce position estimation errors [13]. Despite achieving significant performance improvements, prediction-based methods share similar scalability and communication issues as estimation-based approaches.

B. Distributed Localization

Distributed localization involves individual nodes calculating their positions independently without central processing [13]. This method is also divided into estimation-based and prediction-based types.

i. Distributed Estimation Localization

Here, each network node independently estimates its position using data from nearby or beacon nodes. Techniques include using geometrical relationships to determine target node coordinates without exact reference node positions, which can decrease computational complexity but potentially at the cost of accuracy [14]. Other researchers have introduced virtual node-assisted algorithms to improve accuracy, although these are vulnerable to environmental conditions and ranging errors [15]. Improved range-based estimation techniques have been developed to enhance accuracy, error variance, and coverage [16]. A hybrid optimization technique incorporating anchor node hops, Time of Arrival (ToA), and range estimation errors aids in achieving precise localization [2]. Further developments include improving node mobility models and introducing frequency-based anchor node prediction algorithms [17], and a hybrid approach using Doppler Shift and Angle of Arrival (AoA) for mobile underwater nodes [18]. Another model achieves extensive coverage using dive and rise mobile beacons, though it increases energy consumption [19].

ii. Distributed Prediction Localization

In this method, nodes predict their future positions based on mobility patterns or models, collaborating in a decentralized manner to estimate locations using predicted positions and shared information [20]. A node motion model based on tidal mobility predicts and updates positions, facilitating precise localization in large-scale, mobile networks [21].

In summary, while distributed localization (both estimation and prediction-based or a hybrid of the two) offers scalability, robustness, and energy efficiency without centralized coordination, accurately localizing subsea nodes under the effect of ranging error remains an intricate challenge that demands further refinement in localization techniques.

C. Medium and Node Motion

The motion of the underwater node in the Unetstack environment is influenced by the complex dynamics of the underwater medium, where the node navigates through a fluid environment shaped by currents, pressure variations, and other hydrodynamic forces. This environment drives the node's movement, which is mathematically described by differential equations that capture the interplay of heading, speed, turn rate, and dive rate. The node's position vector evolves over time according to the velocity components determined by

$$r\,(t) = [x(t), y(t), z(t) \tag{1}$$

where $x(t), y(t), z(t)$ represents the coordinates in time (t) in each direction. The node's horizontal position evolves according to

$$\frac{dx(t)}{dt} = s(t)\cos\big(\theta(t)\big) \tag{2}$$

$$\frac{dy(t)}{dt} = s(t)\sin\big(\theta(t)\big) \tag{3}$$

where $s(t)$ is the speed affected by underwater currents, $\theta(t)$ is the heading influenced by the turn rate $\omega(t)$. The vertical movement, crucial in the underwater medium, is defined by

$$\frac{dz(t)}{dt} = \partial(t) \tag{4}$$

where $\partial(t)$ is the dive rate.

The heading changes over time according to

$$\frac{d\theta(t)}{dt} = \omega(t) \tag{5}$$

where $\omega(t)$ is the turn rate affected by wind direction.

The speed of sound underwater, approximately 1500 m/s, is influenced by the medium's density, pressure, temperature, and salinity, all of which affect how sound waves propagate. Water’s higher density compared to air facilitates faster sound transmission, as molecules are closer together, enhancing the transfer of acoustic energy. The speed is defined by [22]

$$c = 1448.9 + 4.591T - 0.05304T^2 + 0.0002374T^3 + 1.34(S - 35) + 0.0163P \tag{6}$$

where c is the speed of sound in m/s, T is the temperature in degrees Celsius, S is the salinity in PSU, and P is the pressure in decibars.

D. Ranging and Localization

Range estimation utilizes acoustic energy to determine the distance between nodes by transmitting an acoustic signal from one node to another and measuring the signal's travel time [21]. Despite delays in signal propagation, acoustic signals are preferred for medium to long-range underwater transmissions due to their effectiveness compared to optical and radio frequency signals, which are significantly attenuated underwater [2, 3, 4]. Traditional range-based localization techniques are favoured over range-free methods because they provide a more accurate and dependable estimation of a node's location [23]. Conversely, range-free localization relies on the proximity of nodes and only offers a probable area where a node might be located [24].

In this study, three ships were designated as reference nodes positioned above water in the Unetstack simulation environment [24], and a sensor was placed below the fourth ship at a depth of 20 meters to assist in estimating the depth of the target node, as illustrated in Fig. 5. Unetstack two-way acoustic ranging between the reference and target nodes was conducted to ascertain the range to the target node, and this is the node whose position needs to be determined, using (7).

$$r = 0.5(v_s * T_f) \tag{7}$$

where r is the range to the target node, v_s is the speed of sound underwater (approx. 1500m/s), T_f is the time of flight of the signal.

Despite the best efforts to accurately estimate the true range of a target node in underwater localization, several factors can introduce significant errors. These include sensor drift, environmental variations such as temperature, salinity, and water currents, as well as multipath effects where the signal reflects off surfaces and objects [22]. These errors are often non-negligible and must be accounted for in the localization process to improve accuracy.

In our approach, we address the localization problem using multilateration with four known reference nodes and one target node whose location is to be determined. The coordinates of the reference nodes are $A\,(X_a,\ Y_a,\ Z_a)$, $B\,(X_b,\ Y_b,\ Z_b)$, $C\,(X_c,\ Y_c,\ Z_c)$, $D\,(X_d,\ Y_d,\ Z_d)$. The estimated ranges from each reference node to the target node are (R_a, R_b, R_c, R_d) respectively. These ranges include measurement errors due to the aforementioned factors.

To find the optimal position (X, Y, Z) of the target node, we minimize the sum of the squared differences between the estimated ranges and the actual distances calculated from the target node to each reference node. The optimization problem is formulated as follows:

$$J\,(X, Y, Z) = \textstyle\sum_{i\in\{a,b,c,d\}}(\,R_i\ -\ R_a\,)^2 \tag{8a}$$

where R_i is the estimated range from the i-th reference node to the target node, R_a is the actual range to the target node. R_a is defined as [22]

$$R_a\ = \sqrt{(X\ -\ X_i)^2 + (Y\ -\ Y_i)^2 + (Z\ -\ Z_i)^2)^2} \tag{8b}$$

$(X_i,\ Y_i,\ Z_i)$ are the coordinates of the i-th reference node, (X, Y, Z) is the coordinate of the target node.

We can approach this optimization problem as Nonlinear Least Squares Optimization (NLSO) and solve it using the Gradient descent method as follows:

i. Initial Guess

$$(X_0,\ Y_0,\ Z_0)\ =\ (0{,}0{,}0) \tag{9}$$

$(X_0,\ Y_0,\ Z_0)$ are the coordinates of target node at position (0,0,0).

ii. Range estimation with initial guess can be performed with (10)-(11)

$$R_a\ =\ \sqrt{{X_a}^2 + {Y_a}^2 + {Z_a}^2} \tag{10a}$$

$$R_b\ =\ \sqrt{{X_b}^2 + {Y_b}^2 + {Z_b}^2} \tag{10b}$$

$$R_c\ =\ \sqrt{{X_c}^2 + {Y_c}^2 + {Z_c}^2} \tag{10c}$$

$$R_c\ =\ \sqrt{{X_d}^2 + {Y_d}^2 + {Z_d}^2} \tag{10d}$$

The ranging error is estimated using as follows

$$E_a\ =\ R_a\ -\ \sqrt{{X_a}^2 + {Y_a}^2 + {Z_a}^2} \tag{11a}$$
$$E_b\ =\ R_b\ -\ \sqrt{{X_b}^2 + {Y_b}^2 + {Z_b}^2} \tag{11b}$$
$$E_c\ =\ R_c\ -\ \sqrt{{X_c}^2 + {Y_c}^2 + {Z_c}^2} \tag{11c}$$
$$E_d\ =\ R_c\ -\ \sqrt{{X_d}^2 + {Y_d}^2 + {Z_d}^2} \tag{11d}$$

where E_a, E_b, E_c, E_d are respectively the ranging errors with respect to node A, B, C and D.

The gradient can be computed as partial derivatives of $J\,(X, Y, Z)$ in (12)

$$\frac{\partial J}{\partial X} =\ -2\left(\frac{R_a - \sqrt{{X_a}^2+{Y_a}^2+{Z_a}^2}}{\sqrt{{X_a}^2+{Y_a}^2+{Z_a}^2}}X_a + \frac{R_b - \sqrt{{X_b}^2+{Y_b}^2+{Z_b}^2}}{\sqrt{{X_b}^2+{Y_b}^2+{Z_b}^2}}X_b\right) \tag{12}$$

By iteratively evaluating the estimated position using these steps, we can evaluate the impact of the measurement errors on localization technique.

III. PROPOSED TECHNIQUE

Sentinel-1 SAR imagery covering the Scottish harbour (Fig. 1) was utilized, acquired in single-polarimetric (VV), Ground Range Detected (GRD) format, using the interferometric wide (IW) swath imaging mode from October 1 to 22, 2023, sourced from the Copernicus Data Hub. The images were processed using ArcGIS Pro software with a pre-trained deep learning model to identify static ships over a three-week period. The model successfully detected several ships, and four ships with confidence values exceeding 80% were chosen, with their coordinates documented. The confidence value reflects the model's certainty in the detection. The area of interest is marked by a yellow polygon in Fig. 1, while the red and yellow polygons represent the satellite imagery coverage for the selected area.

A. Ship Detection

The deep learning model effectively pinpointed ships in the target area, marking them with rectangular bounding boxes and assigning confidence values that reflect the accuracy of detection. Three ships, each with confidence values of 84% or higher, were chosen as reference nodes because they maintained consistent positions over a week, as illustrated in Fig 2.

The study continued with systematic ship detection repeated in the second and third weeks, with each iteration yielding consistent results, as depicted in Fig 3 and 4. The analysis confirms that the ships within the designated harbour area remained stationary throughout the observation period, affirming their appropriateness as reference nodes.

Fig. 1: Designated Study Area in Scotland.

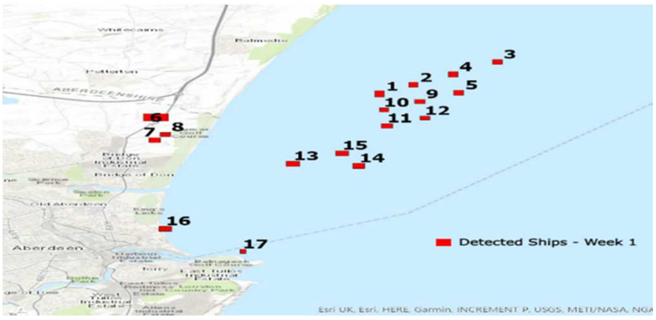

Fig. 2: Detected Ships in the first week of study

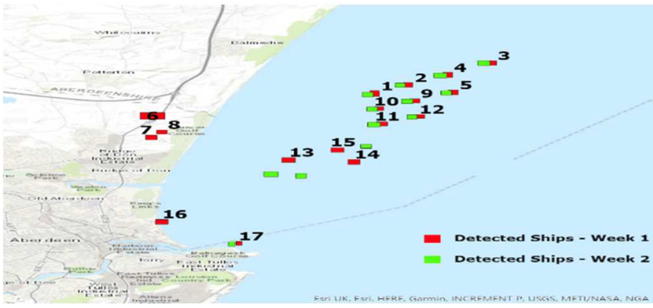

Fig. 3: Detected Ships in the Second week of study

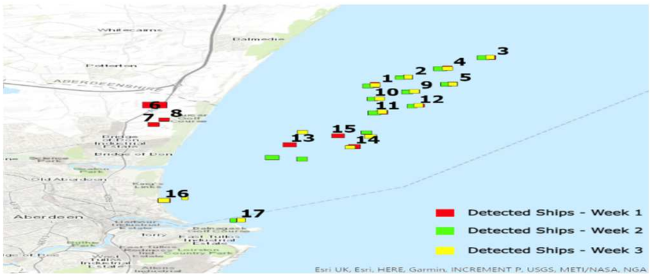

Fig. 4: Detected Ships in the Third week of study

The consistent positioning of the vessels, along with the high confidence values provided by the deep learning model, confirms their reliability as reference nodes over the three-week period. This demonstration of satellite imagery and ArcGIS Pro usage highlights their effectiveness in monitoring maritime dynamics and establishing stable reference points for navigation and research.

B. Reference Node Selection

Using identified stable ships as reference nodes, ships numbered 1, 2, and 9 from Fig 2-4 were selected to form three surface reference nodes. These nodes, equipped to utilize GPS for self-localization, were chosen based on factors like stability, geographic location, cost, and signal accessibility. Additionally, a fourth reference node was placed 20 meters underwater as depicted in Fig 2-4. This arrangement ensures the nodes are non-coplanar, improving the accuracy of the localization system. These four nodes cover the area for the target node, enabling precise localization using a combination of surface and underwater reference points. The position of the reference nodes can also be sent via a multimodal communication method as shown in [25].

For clarity in identification, ships 1, 2, 9, and 10 are labelled as nodes A, B, C, and D, respectively, with Node A as the origin (0,0,0). The target node, labeled E, is positioned 400 meters east and 700 meters south of the origin at a depth of 15 meters. This labeling system streamlines the coordination and calculation processes, facilitating effective localization through a well-organized reference point system.

These reference nodes are crucial for the ranging and localization of subsea nodes. The extracted data is then passed to Unetstack, an underwater network simulation framework. Within Unetstack, the reference nodes derived from the SAR data facilitate the computation of range measurements to the target subsea nodes. By using these range measurements, Unetstack performs multilateration to accurately determine the positions of the subsea nodes.

C. Nodes arrangement in the study area

Fig. 5 illustrates a 3D layout of the node placement within the study area. Reference nodes A, B, and C are positioned on the water's surface, while node D is 20m below the surface, and node E is located at a depth of 15m, as specified in Fig. 5.

To determine the location of target node E, the study applied multilateration, which relies on the principle of intersecting spheres. This method involved measuring the distance between target node E and each of the four reference nodes (A, B, C, and D) using two-way acoustic signal ranging within the Unetstack simulation environment. With the known coordinates of each reference node, the position of node E was estimated based on these distances. Additionally, the GPS coordinates of the reference nodes were converted into local Cartesian coordinates.

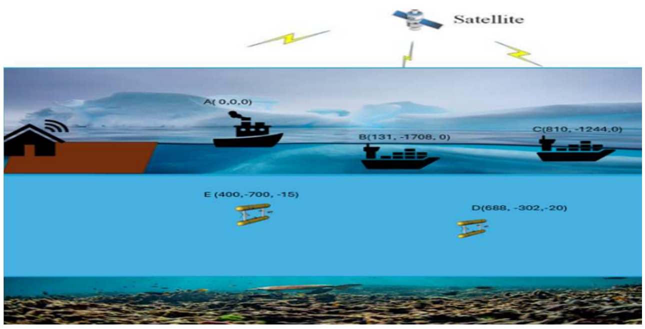

Fig. 5: Nodes arrangement in the study area

IV. RESULTS AND DISCUSSION

In this research, we maintained a constant depth for the target node and focused on evaluating the impact of ranging error, which directly influences localization accuracy. We operated under the assumption that the actual location of the target node E is known while. Fig 6 presents the outcomes of mobile target node localization at various error thresholds. This is critical to determine the maximum allowable ranging error for optimal localization.

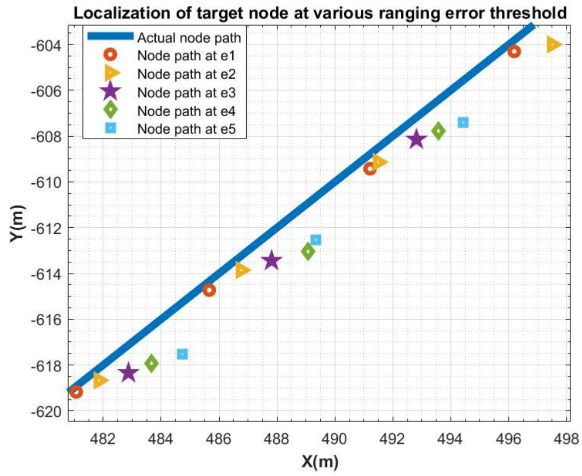

Fig. 6: Node path for various ranging error threshold

The study assumed a random normal distribution for errors in range estimation. The error categories were defined as follows: e1 represents errors from 0 to 1 meter, e2 from 1 to 2 meters, e3 from 2 to 3 meters, e4 from 3 to 4 meters, e5 from 4 to 5 meters, and e6 from 5 to 6 meters. It was observed that e1, with the smallest error range, resulted in the least localization error, adhering to the assumed maximum acceptable error of 2 meters. Fig 7 illustrates the localization error associated with each ranging error threshold, highlighting that a threshold of 1 meter provides the most accurate estimations. Fig 8 displays the relationship between node position and average ranging error, further supporting that the optimal error threshold should be kept below 1 meter for effective range estimation.

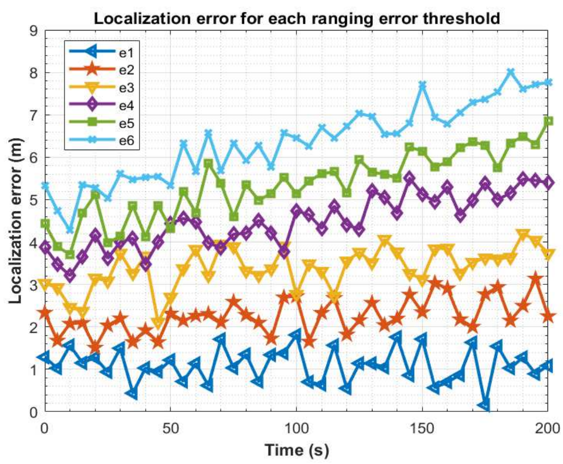

Fig. 7: Distribution of Localization error for various ranging error threshold

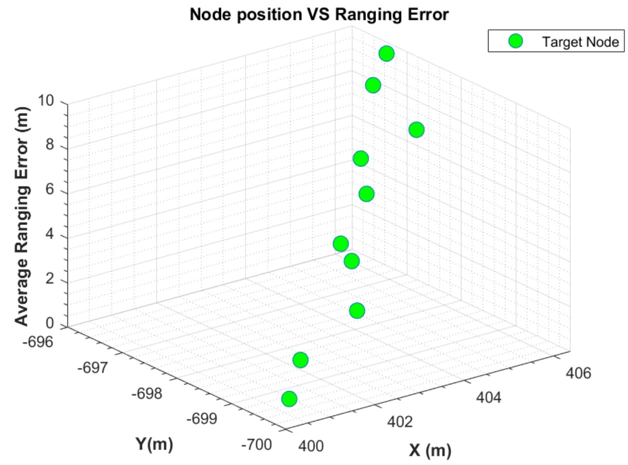

Fig. 8: Node position vs Ranging Error

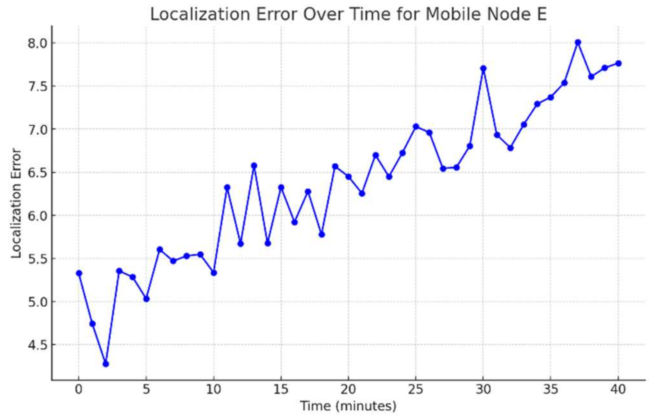

Fig. 9: Localization Error Over Time

Fig 9 shows the localization error of the mobile node E over time as it moves under the influence of simulated random ocean currents. Initially, the localization error fluctuates between 4.3m and 6.0m, indicating minor variations in the node's position accuracy. As time progresses, the error generally increases, reaching values above 7.5 towards the 35th minute, with occasional dips and rises. This trend suggests that the node's localization becomes increasingly less accurate over time, due to the compounding effects of ocean current influences, and positional drift. The oscillation in the error demonstrates the dynamic challenges of maintaining accurate localization in underwater environments.

V. CONCLUSION AND FUTURE WORK

In conclusion, this study evaluated the impact of ranging errors on underwater localization using SAR satellite data within the framework UWSN. By integrating SAR data and employing range-based multilateration techniques, we identified that maintaining ranging errors below 1m significantly enhances the localization accuracy of underwater nodes. The study establishes an acceptable error threshold of approximately 1m, optimizing node positioning to minimize localization errors. Future work will allow some degree of movement in the reference nodes to evaluate the impact of reference node mobility on localization accuracy, further enhancing the robustness of underwater localization strategies.

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