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RESEARCH ARTICLE

An Autonomous Underwater Vehicle Navigation Technique for Inspection and Data Acquisition in UWSNs

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ABSTRACT This article introduces an innovative approach to the navigation of autonomous underwater vehicles (AUVs) in inspection and data acquisition missions within underwater wireless sensor networks (UWSNs). We combine at least five underwater navigation techniques to accomplish this mission, adapted from related works. These five techniques are employed to address at least four main challenges identified in inspection and data acquisition missions in UWSNs involving the use of AUVs, namely: communication constraints, energy usage optimization, precise navigation, and effective data acquisition. Limited simulations conducted demonstrate the reliability of the proposed model. The model successfully navigates to the target point in 3D coordinates X Y Z, assuming the launch point as d0 (10 40 40), and reaches the q-goal target point (45 45 0) within 21 seconds, with the addition of uattractive and urepulsive (magnetic beacon attraction force and repulsion force as simulation of underwater current disturbance factor). Furthermore, in the inspection and data acquisition mission in UWSN simulated as node points (o) in pink, AUV (*) in blue effectively follows the predetermined points while acquiring data, as indicated by green lines (-) within just 5 seconds, achievable by increasing the value of α (angle of attack) of the target node to reduce delay time. The evaluation of the experimental simulations has raised issues and future research challenges, including the development of environmental simulation challenges that can closely resemble real conditions, the measurement of energy usage effectiveness to reach each target point, and the potential development of underwater recharging techniques. Furthermore, there is a need for advanced precise navigation and the advancement of effective data acquisition techniques.

INDEX TERMS Underwater wireless sensor network (UWSN), autonomous underwater vehicle (AUV), navigation techniques, data acquisition, constraints, optimization.

I. INTRODUCTION

Underwater wireless sensor network (UWSN) have garnered significant attention in various applications such as environmental monitoring [1], [2], [3], [4], underwater exploration [5], and infrastructure inspection [6]. These networks hold great potential for real-time data collection and remote monitoring in the underwater environment [7], [8]. With the ability to utilize multiple sensors over a wide area, UWSNs enable researchers and industries to gain valuable insights into the underwater ecosystem, study marine life, assess the health of underwater structures, and monitor

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environmental parameters [9]. The use of UWSNs has proven to be a crucial tool in enhancing our understanding of the underwater domain and facilitating efficient management and conservation efforts [10].

Effective navigation in AUVs is crucial for the successful execution of missions in UWSNs [9], [10], [11]. AUVs play a vital role in performing various tasks such as underwater surveys, data collection, and maintenance operations in UWSNs [12]. With the ability to operate autonomously, AUVs need to have strong navigation capabilities to navigate through complex underwater environments and achieve mission objectives [13], [14]. Accurate and reliable navigation ensures optimal path planning, efficient resource utilization, and precise data acquisition [15]. By leveraging advanced navigation techniques, AUVs can move safely, adapt to changes in underwater conditions, and effectively contribute to the overall success of UWSN missions [16].

This paper focuses on proposing advanced navigation techniques for AUVs with the aim of enhancing inspection capabilities and enabling efficient data acquisition in UWSNs [17], [18]. By developing and implementing cutting-edge navigation algorithms and strategies, AUVs can effectively navigate and explore underwater environments, facilitating in-depth inspection and data collection [17]. These advanced techniques aim to optimize AUV path planning, improve localization accuracy, enable obstacle avoidance, and simplify the data collection process. The integration of advanced navigation techniques from previous research empowers AUVs to perform complex tasks, ensuring precise inspection and efficient data acquisition, thereby enhancing the overall performance and effectiveness of UWSNs [18].

Furthermore, our paper also provides an in-depth analysis of challenges and requirements in underwater navigation [15], considering factors such as communication limitations [19], underwater topography, and energy constraints [20]. Navigation in underwater environments poses unique challenges due to signal attenuation and distortion, limited visibility, and complex topography [21]. Communication limitations require careful consideration to ensure reliable data transmission and efficient command execution [22]. Understanding and adapting to underwater topography are crucial for safe and efficient navigation [23], considering movement across various depths, currents, and obstacles [24]. Additionally, energy constraints [20] play a vital role in designing navigation strategies [25] that optimize power consumption and maximize the duration of underwater vehicle missions [26]. By addressing these challenges and requirements, this paper aims to provide valuable insights and solutions to enhance the effectiveness and reliability of underwater navigation system.

Several navigation techniques [27], including path planning [28], sensor fusion-based localization [29], simultaneous localization and mapping (SLAM) [30], neural network-assisted SLAM (NN-SLAM) [31], cooperative localization [32], and obstacle avoidance strategies [9], have been explored. Additionally, we review data collection strategies specifically designed for applications in UWSN and the underwater Internet of Things (IoUT) [33], [34], where path planning involves determining the most optimal route for AUVs, considering factors such as efficiency [27], security, and mission objectives [28].

Advanced localization techniques enable AUVs to accurately determine their positions in the underwater environment [29], [30], [31], facilitating precise navigation and effective data collection [9], [32]. This includes obstacle avoidance algorithms, crucial to ensuring AUVs can navigate underwater obstacles, reducing the risk of collisions, and maintaining mission continuity [35]. Additionally, data collection strategies are developed to enable AUVs to efficiently collect and transmit sensor data [33], considering factors such as data relevance, storage capacity, and communication limitations [34].

In general, this research aims to provide a comprehensive understanding of how to enhance the efficiency, accuracy, and reliability of AUV navigation in complex underwater environments. It reviews and outlines various navigation techniques developed for routine data collection missions in UWSNs, while investigating the potential applications of these navigation techniques in real-world environments using mathematical approaches and simulations. Additionally, we conduct experiments to evaluate and validate the effectiveness of the proposed techniques, demonstrating their potential to improve AUV-based inspection performance and data collection in UWSNs. The overall contributions of this paper are summarized in the following points:

- We conduct a survey on AUV navigation techniques and categorized them based on underwater mission requirements
- We present a comparative analysis of several AUV navigation techniques
- We propose specific navigation techniques for inspection and data acquisition missions in UWSNs by evaluating various techniques and adapting them based on mission requirements
- We use mathematical approaches and simulations to validate the effectiveness of the proposed techniques

The rest of this paper is organized as follows. Section II highlights various relevant studies, categorizing them based on their strengths, particularly focusing on precise navigation techniques and effective data acquisition. Section III explains the reference architecture, which is adapted to develop new forms of navigation techniques, effective data acquisition, and overall mission planning. Then, in Section IV we present the problem formulation, which identifies and categorizes common issues, aligning them with the needs of navigation and effective data acquisition missions in UWSN. Next, in Section V we explain the proposed scheme, which includes technical proposals and designs aimed at addressing the formulated problems. Next, we present performance evaluation in Section VI, which demonstrates the effectiveness of the proposed technical solutions through simulations and discussions on model performance results. Section VII presents Open Issues and Research Challenges, which reveals findings from the evaluation of model performance tests, indicating open issues and opportunities for further development of the tested model. Finally, Section VIII draws the conclusion.

II. RELATED WORK

Several studies related to navigation for inspection and data acquisition in UWSNs, based on our review, are divided into two major groups: those specifically addressing AUV navigation techniques and those addressing sensor-based data collection techniques.

The first group focuses on AUV navigation techniques. In their research, Maurelli et al. [11] employed a machine-learning (ML) regression approach based on ultra-short-base-line (USBL) sensor outputs, Nad et al. [13] utilized a computer-vision (CV) approach for companion AUV missions with divers, Thompson et al. [14] introduced the cooperative simultaneous-localization-and-mapping (C-SLAM) localization method, Salavasidis et al. [15] employed a random process root-mean-square-error (RMSE) approach as the core algorithm for AUV navigation through complex underwater environments, Hernandez et al. [16] used adaptive algorithms and real-time online movement planning to control and monitor AUV missions, Claus et al. [17] applied ML regression for closed-loop odometry navigation, similarly Wang et al. [18], Zhuo et al. [20] used ML regression for path planning navigation, adaptive algorithms by Ferri et al. [26] and Zhang et al. [27], deep-learning with convolutional-neural-network (DL-CNN) by Sun et al. [28], Bucci et al. [29], Yuan et al. [35], and reinforcement-learning (RL) by Khan et al. [34].

Furthermore, Vagale et al. [36] conducted a review on route planning and collision avoidance for autonomous-surface-vehicles (ASVs), another form of AUV distinguished by its operation on the water surface. Li et al. [37] carried out comprehensive research on AUV control using trajectory tracking strategies. Hou et al. [31] conducted a literature study on underwater localization and mapping using artificial neural network algorithms. Salavasidis et al. [38] developed a navigation method utilizing information about the seafloor topography or morphology. In another work, Salavasidis et al. [39] developed a navigation method utilizing underwater topography information with a coarse-resolution map to support crossing in the Arctic latitudinal valleys. Keane et al. [40] developed a navigation method enabling AUVs to accurately navigate to a target using only inter-beacon distance information. Panda et al. [41] conducted a comprehensive review of various path planning algorithms used by AUVs. Gallimore et al. [42] surveyed the use of magnetic beacons and automatic target discovery using scalar magnetometers on small AUVs. Fortuna et al. [43] conducted a comprehensive review of unmanned underwater robotics, covering various aspects including structural design, materials, sensors, actuators, and navigation control. Kepper et al. [44] developed navigation solutions for AUVs using micro-electro-mechanical systems (MEMS) technology based on inertial measurement units (IMUs) with position estimation model-based mathematical calculations and one-way acoustic signal travel time measurements. King et al. [45] developed a method enabling AUVs to follow previously taught paths. Matsuda et al. [46] developed navigation methods based on parent-child relationships to coordinate multiple AUVs in autonomous underwater surveys. In another work, Matsuda et al. [47] developed a navigation method allowing multiple AUVs to conduct extensive seafloor surveys using alternating marker-based navigation. To facilitate identification, we summarized the initial identification of the above research in Table 1.

Furthermore, references discussing data acquisition techniques in UWSNs are directly summarized in Table 2 for easy content identification in each paper. This facilitates a straightforward comparison and selection of methods that align with mission requirements.

III. REFERENCE ARCHITECTURE

A. MISSION PLANNING

Based on the aforementioned related research, especially those focusing on navigation techniques, some of them are considered suitable for implementation in missions in UWSN involving inspection and data acquisition. These navigation techniques have the potential to enhance the navigation capabilities of AUVs, enabling them to move efficiently and accurately in the underwater environment.

By integrating these techniques, AUVs can optimize path planning, avoid collisions, and enhance overall navigation performance, thereby improving the success and effectiveness of inspection and data acquisition missions in UWSN.

Adopting Vagale et al. [36] who utilized vehicle dynamics calculations and algorithms to find collision-free routes. There are at least three autonomous vehicle dynamics modes, namely:

Definition 1: Fully Activated System: If instantaneous acceleration can be achieved in any direction v, then the system is considered a fully activated system. This can also mean that the rank $R(v) = dim(v)$.

Definition 2: Less Activated System: If instantaneous acceleration cannot be achieved in every direction v, then the system is considered a less activated system. This can also mean that the rank $R(v)<dim(v)$.

Definition 3: Degree of Less Activation: The degree of less activation is the number of configurations that cannot be directly controlled. Expressed as: rank $dim(v) - R(v)$.

By neglecting the environmental disturbance factor, we employ the local compact form dynamic linearization (local-CFDL) approach to control the initial movement of the AUV towards the designated starting point in the UWSN

TABLE 1. Comparison of several AUV control algorithms that can be considered, taking into account mission requirements and data collection optimization in UWSNs.

Research	Control Scheme	ML Technique	Developed Navigation Technique
[11]	Autonomous	Regression	Utilize Ultra-short-base-line (USBL)
[13]	Autonomous	Computer-vision (CV), Convolutional-neural-network (CNN)	Develop Cognitive-autonomous-diving-buddy (CADDY)
[14]	Autonomous	Deep Learning (DL)	Develop Cooperative Simultaneous-localization-and-mapping (C-SLAM)
[15]	Autonomous	Linear Regression	Develop Terrain-aided-navigation (TAN) algorithm
[16]	Autonomous	Reinforcement learning (RL)	Develop Online motion planning based on adaptive-control (AC) navigation
[17]	Autonomous	Regression	Develop Close-loop-odometry (CLO) navigation
[18]	Autonomous	Regression	Develop Artificial-potential-field (AFP) navigation
[20]	Autonomous	Regression	Develop Path planning navigation
[20]	Autonomous	Regression	Develop AUV-Aided-energy-efficient-data-collection (AEEDCO) navigation
[26]	Autonomous	RL	Develop Target tracking based on AC navigation
[27]	Autonomous	RL	Develop Path planning navigation based on topographic information and underwater terrain characteristics
[28]	Autonomous	Deep-learning (DL), CNN	Develop Hierarchical-deep-Q-network-path-planning (HDQN) navigation
[29]	Autonomous	Neural-network (NN), Gaussian-processes (GPs)	Develop Unscented-Kalman-filter (UKF) navigation based on Fusion-sensor
[35]	Autonomous	CNN, Deep-reinforcement-learning (DRL)	Develop Double Depp-Q-network (D-DQN) algorithm
[34]	Autonomous	RL	Develop Cluster-head (CH) navigation
[36]	Autonomous	RL, DL, Genetic Algorithm	Develop Autonomous-surface-vehicle (ASV) Path planning collision avoidance navigation
[37]	Autonomous	RL, NN, AC, GPs, Ensemble methods	AUV Trajectory tracking navigation
[31]	Autonomous	NN	SLAM Online algorithm navigation
[41]	Autonomous	RL,GPs Regression, CNN, Support-vector-machine (SVM)	Path planning navigation assisted by terrain information
[40]	Autonomous	SVM	Single range only beacon navigation
[44]	Autonomous	DL	Utilize Microelectromechanical-system (MEMS) and Inertia-measurement-unit (IMU) navigation
[45]	Autonomous	RL	Develop Teach and repeat method Machine-learning (ML) navigation
[46]	Autonomous	RL	Develop Parent child ML method navigation
[47]	Autonomous	RL	Develop Alternating landmark navigation

TABLE 2. Comparison of several data acquisition techniques in related UWSN studies.

Research	Data Acquisition Focused
[48], [49]	Develop Efficient sensor node placement strategies
[50]	Develop Optimization strategy of computing processes
[51], [52], [53], [54], [55], [56], [57], [58]	Develop Output from specific sensors and interpreting process
[59]	Develop Routing strategies for power consumption efficiency
[60], [61]	Develop Data transmission speed enhancement for efficient data acquisition
[62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72]	Develop Optimization strategies for ML, DL, RL, and specific algorithms
[73], [74], [75], [76], [77], [78]	Develop Optimal network resource management
[79], [80], [81]	Develop Integration of diverse sensors (Fusion), interpretation, and optimization strategies
[82], [83], [84], [85], [86], [87], [88], [89]	Develop RL model for optimizing interpretation Passive/Active Sound-navigation-and-ranging (SONAR)
[90]	Develop Efficient routing design for data acquisition optimization
[91]	Developing strategies for detecting and preventing attacks on UWSN

(node-1) in the equation:

$$\Delta y(t+1) = \varnothing(t)\Delta u(t) + \xi(t), \tag{1}$$

where t, represents the operational time of the AUV, $\Delta y(t+1) = y(t+1) - y(t)$, indicates the increase in output at the next time step, $\Delta u(t) = u(t) - u(t-1)$, represents the increase in current input, $\varnothing(t)$, denotes the partial derivative of the unknown nonlinear scalar function $f(\cdot)$, with respect to the control input, while $\xi(t)$, represents the nonlinear uncertainty residue from the modified linear data model and

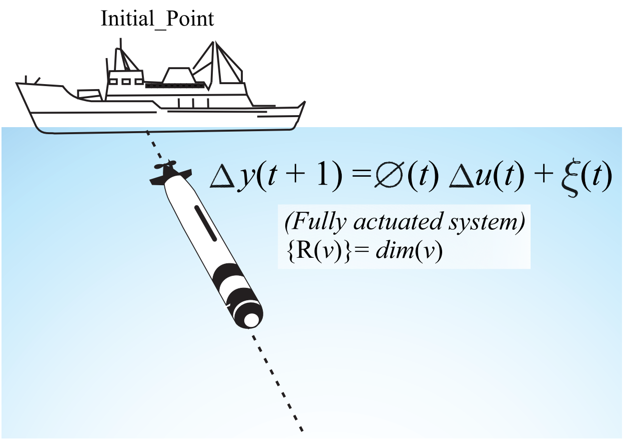

FIGURE 1. The stage of launching AUV from the vessel to UWSNs.

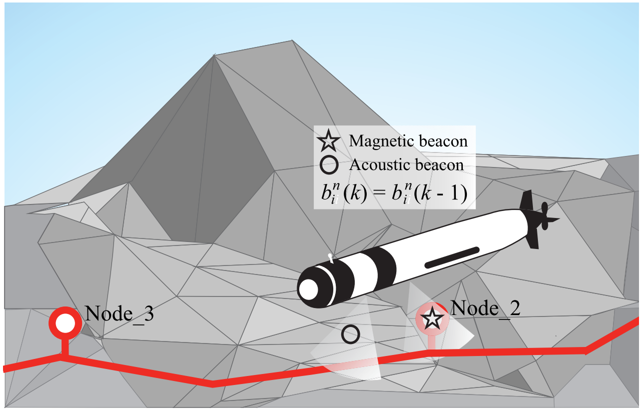

FIGURE 2. The combination of AC navigation and AMB-SLAM localization.

will be estimated collectively in the next control design process.

The illustration and approach in the AUV launching stage from the vessel to UWSNs are depicted in Figure 1.

Furthermore, in advanced algorithms, machine learning (ML) is used to model the surrounding environment of autonomous vehicles, including objects, other vehicles, and potential obstacles. Data obtained from sensors mounted on the vehicle can be used to train a model that can understand the environment. ML is also employed to assist autonomous vehicles in making complex decisions.

The orientation-based approach refers to a method that focuses on the direction or orientation of autonomous vehicles in route planning and collision avoidance. The orientation-based approach includes techniques such as speed constraints, directional control, and histogram vector fields.

After the AUV reaches the first node in the UWSN, we adopt the approach used by Li et al. in [37], which employs a tracking navigation strategy. This approach considers five tracking-based control algorithms, including proportional-integral-derivative (PID), model-predictive-control (MPC), sliding-mode-control (SMC), adaptive-control (AC), and artificial-neural-network-control (ANN-control).

Among the five available algorithms, we consider using AC based on navigation goals and the nature of the environment faced. This is because AC is a control approach capable of adapting control parameters dynamically to changes in the environment around the AUV.

To enhance the precision of our AUV in tracking trajectories and address potential uncertainties, we combine our AC with sensor node-based localization, as applied by Hou et al. in [31]. They introduced an acoustic-magnetic-beacon system for simultaneous-localization-and-mapping (AMB-SLAM) in controlled AUV navigation. An illustration of the combined AC navigation and AMB-SLAM localization can be seen in Figure 2.

Assuming that each node in the UWSN serves as a landmark that needs to be marked by the AUV using a magnetic beacon. Node 1 is considered as the starting point, where the vehicle's position is at (0, 0, 0). Furthermore, with the assistance of AMB-SLAM sensing, position information is continuously updated and observed using the extended Kalman filter (EKF) algorithm. Mathematically, the starting point of the magnetic beacon scan to node i can be written as:

$$b_i^n(k) = b_i^n(k-1), \tag{2}$$

where $b_i^n(k)$, represents the location of the i-th node at time k. After extracting sensor data and performing data association, the AMB-SLAM algorithm goes through three stages. First, the state when the AUV predicts using the output values from the sensors. Second, the estimated state is updated based on the landmark positions. Third, when the AUV's kinematic model is known, the relative vehicle position can be determined, and estimates for the next trajectory can be made. The relative vehicle position is weighted based on the three inputs using the EKF filter, where the angle positions and local coordinates of the AUV are described using the equations:

$$X_v(k) = [p_v(k) \quad \phi_v(k)]^T, \tag{3}$$

where P_v, represents the covariance matrix:

$$P_v = \begin{bmatrix} \sigma^2_{x_v x_v} & \sigma^2_{x_v y_v} & \sigma^2_{x_v \phi_v} \\ \sigma^2_{x_v y_v} & \sigma^2_{y_v y_v} & \sigma^2_{y_v \phi_v} \\ \sigma^2_{x_v \phi_v} & \sigma^2_{y_v \phi_v} & \sigma^2_{\phi_\phi x_v} \end{bmatrix}, \tag{4}$$

In these equations, $X_v(k)$, represents the state of AUV motion at time k, where $p_v(k)$, is the position of AUV, and $\phi_v(k)$, is the direction angle of AUV at time k.

Furthermore, $p_v(k) = [x_v(k) \quad y_v(k)]$, is assumed as the coordinates of the n-th feature, denoted as $x_m(k) = (x_b(k), y_b(k))^T$. This allows the neighboring landmark beacons to be expressed in the equation:

$$X_m(k) = [x_b(a), y_b(1) \ldots, x_b(k), y_b(k)]^T, \tag{5}$$

Adding the covariance matrix P_m, the equation becomes:

$$P_m = \begin{bmatrix} \sigma^2_{x_1x_1} & \sigma^2_{x_1y_1} & \cdots & \sigma^2_{x_1x_k} & \sigma^2_{x_1y_k} \\ \sigma^2_{x_1y_1} & \sigma^2_{y_1y_1} & \cdots & \sigma^2_{y_1x_k} & \sigma^2_{y_1y_k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \sigma^2_{x_1x_k} & \sigma^2_{y_1x_n} & \cdots & \sigma^2_{x_kx_k} & \sigma^2_{x_ky_k} \\ \sigma^2_{x_1y_k} & \sigma^2_{y_1y_k} & \cdots & \sigma^2_{x_ky_k} & \sigma^2_{y_ky_k} \end{bmatrix}, \quad (6)$$

The equation P_m, represents the diagonal elements of the covariance matrix, indicating the interconnection information among landmarks. Assuming that the node positions remain constant and unchanged allows for the re-observation of landmarks. Consequently, the construction of a trajectory based on landmarks can be expressed in the equation:

$$X_a(k) = [X_v(k) \quad X_m(k)]^T . \quad (7)$$

If changes in the AUVs state are represented by consecutive directional changes, the changes in the horizontal and vertical path directions can be written as $\Delta X = [\Delta x \quad \Delta y \quad \Delta\phi]^T$. The relative position of the AUV can be found using the calculation:

$$\begin{aligned} X(k) &= \begin{bmatrix} x_v(k) \\ x_b(k) \end{bmatrix} \\ &= \begin{bmatrix} x(k) & y(k) & \phi(k) & x_b(k) \end{bmatrix}^T \\ &= \begin{bmatrix} x(k-1) + \Delta x \cdot \cos(\phi(k-1)) \\ x(k-1) + \Delta x \cdot \sin(\phi(k-1)) \\ \phi(k-1) + \Delta\phi \\ x_b(k-1) \end{bmatrix}. \end{aligned} \quad (8)$$

From the above equation and by adding the Jacobian matrix, the formula can be represented as:

$$F = \begin{bmatrix} 1 & 0 & -\Delta x \cdot \sin(\phi(k-1)) & 0 \\ 0 & 1 & \Delta y \cdot \cos(\phi(k-1)) & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad (9)$$

where the observation values are the relative position of the AUV to the node. If the characteristics of the observed quantities and state variables are defined, then (x_{bi}, y_{bi}), represents the relative position of the AUV. Then, based on the estimated AUV position obtained by detecting beacons from node bi, we can estimate the observation values using the equation:

$$\hat{Z} = h(X(k)) = \begin{bmatrix} \sqrt{(X_{bi} - x(k))^2 + (y_{bi} - y(k))^2} \\ \arctan(\frac{y_{bi}-y(k)}{x_{bi}-x(k)}) - \phi(k)) \end{bmatrix}. \quad (10)$$

In addition to magnetic beacons, acoustic beacons are also added to the AUV frame. Acoustic beacons are used to observe the distance and angle between the AUV and the next node in the UWSN. To achieve this, the Jacobian matrix is used, and the equation can be written as:

$$H = \begin{bmatrix} \frac{x(k)-x_{bi}}{r} & \frac{y(k)-y_{bi}}{r} & 0 & \frac{x(k)-x_{bi}}{r} & \frac{y(k)-y_{bi}}{r} \\ \frac{y(k)-x_{bi}}{r^2} & \frac{x(k)-x_{bi}}{r^2} & 0 & \frac{y(k)-y_{bi}}{r^2} & \frac{x(k)-x_{bi}}{r^2} \end{bmatrix}. \quad (11)$$

where $r^2 = [x_{bi} - x(k)]^2 + [y_{bi} - y(k)]^2$, and r, represents the distance between the node and AUV. As the position of random magnetic signals can vary due to environmental influences, one of the standard nonlinear filtering problems, the Jacobian matrix and Kalman filter are employed in the AUV state measurement equation.

In its movement process, where the AUV continuously explores new environments and discovers new nodes, the automatic update of existing beacon positions is crucial. Therefore, a method is needed to expand the state variable dimensions, add new nodes to the previous landmark mapping, estimate the next nodes, and map the traversed nodes to build an accurate mapping. Assuming the correct size $z = [r \quad \phi]^T$, of the new feature, (x, y) representing the AUV position, and r, ϕ representing the relative position and angle between the AUV and the new node, the position of the new node can be expressed in the equation:

$$X_b = u(X, z) = \begin{bmatrix} x + r\cos(\phi + \varphi 0) \\ y + r\sin(\phi + \varphi 0) \end{bmatrix}. \quad (12)$$

Following these steps, a path mapping is created, with nodes functioning as landmarks or markers. In subsequent mission operations, this can be used as a guide for AUV navigation using path tracking algorithms.

Faced with an unpredictable underwater environment and limited mapping results, we adapted the method developed by Salavasidis et al. in [38]. They devised a navigation method using information about the topography or morphology of the seafloor to support AUV navigation in a changing environment with minimal mapping. They employed side-scan sonar and the doppler-velocity-log (DVL) approach to measure distances based on wave reflection time.

Measurement results heavily depend on the sonar used. For instance, measurements above the ship could be a scalar value r_k when only one basic distance measurement is available at a given time or a vector containing distances up to N_r, $r_k = \left[r_{k,1} \ldots r_{k,N_r}\right]^T$. To compensate for the vehicle's attitude and the sonar beam's orientation, the basic distance measurement $r_{k,i}$ can be projected into 3D space using the equation:

$$X^{NED}_{r_k,i} = \begin{bmatrix} X^N \\ X^E \\ X^D \end{bmatrix}_{r_k i} = \Re(\psi_k, \phi_k, \theta_k) \cdot \hat{q}r_i \cdot r_{k,i}, \quad (13)$$

where $\Re(\psi_k, \phi_k, \theta_k)$ represents the rotation matrix parameters at time k, $\hat{q}r_i$ is the unit vector in the i-beam direction, $X^{NED}r_k, i$ is the 3-Dimensional location where the i-beam intersects with the object, rk, i is expressed in meters, and $X^{NED}_{r_k,i}$ is also expressed in meters. With this additional

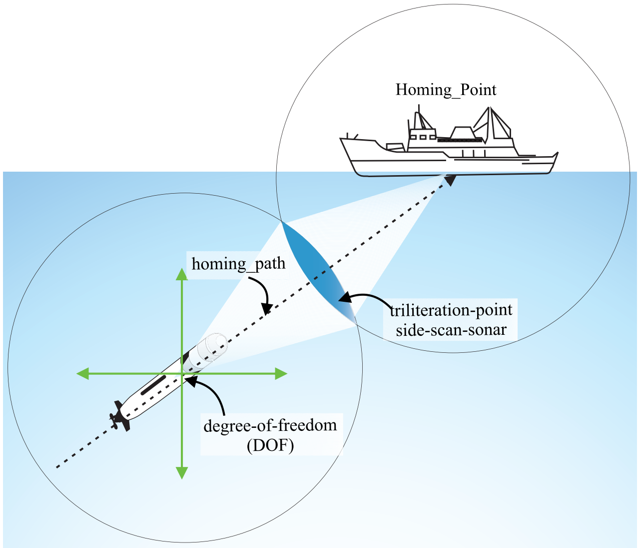

FIGURE 3. The homing technique employs circle trilateration based on side-scan sonar.

technique, the AUV can avoid collisions with underwater objects along the UWSN path.

After executing an inspection mission and data collection in the UWSN, the AUV is designed to return to the surface placement ship for data retrieval and recharging. We adopted the method developed by Keane et al. in [40], allowing the AUV to accurately navigate towards a target location using distance and orientation information from nodes. This method works by applying the principles of the Pythagorean theorem, trilateration, and median filtering.

By applying the Pythagorean theorem and the depth vector to create a virtual 2D flat geometry, the formation of a circle with the vehicle's location as the center of mass and the reported distance as the circle's radius is possible. This approach simplifies the solution from a 3D sphere to a 2D circle, utilizing accurate depth measurements from the AUV and known sonar depth information. A two-dimensional trilateration method is used to estimate the beacon's position based on the intersection of three or more distance circles, with the AUV's position as the center and the reported distance as the circle radius. Through brute-force iteration, a search is conducted for as many intersections as possible that meet the requirements, and the results are considered a Gaussian distribution representing the localization outcome. The median of the x and y coordinates is taken separately as the filtering result to select the most likely beacon location. The Homing technique we developed, which utilizes circle intersection theory based on side-scan sonar, is illustrated in Figure 3.

B. DATA COLLECTION

In UWSN, data collection techniques play a crucial role due to the unique challenges posed by the underwater environment [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64]. One such technique involves the use of autonomous underwater vehicles (AUVs) equipped with sensors to gather data from distant underwater nodes [54]. These AUVs navigate the network [55], following predefined paths using adaptive algorithms [56], to collect data from various locations [57]. This data collection technique ensures comprehensive coverage and timely data acquisition in UWSN.

Data collection in UWSN using adaptive algorithms aims to optimize the process of gathering data from various sensors [65]. Adaptive algorithms ensure efficient resource utilization by selecting the most valuable data packets based on mission requirements [66]. This approach minimizes energy consumption and maximizes the overall network throughput [65], [66], [67].

In some cases, to achieve reliable and efficient data collection in UWSN, especially in situations where nodes are damaged or unreliable, sophisticated data collection algorithms can be employed [68]. These algorithms use redundancy and error correction methods to overcome node failures and ensure accurate data collection. By dynamically adapting to changes in network conditions and avoiding problematic nodes, these algorithms enhance the reliability and efficiency of data collection throughout UWSN [69].

Distributed data collection systems in UWSN leverage the collaborative capabilities [70] of various sensors to collect and process data [71]. These systems consist of distributed sensor networks, where each sensor collects data from its environment and collaborates with neighboring sensors to exchange and gather the collected data [72]. This collaborative approach enables efficient data collection [73], improves network scalability, and enhances overall system performance [74].

We assume that the positions of sensors, previously identified in the deployment mission, are mapped as reference points that will be sequentially traversed by the AUV when conducting data retrieval missions in UWSN, ultimately returning to the surface ship (return point). The AUV must be capable of determining the route based on considerations of which sensors will collect data. For a clearer understanding, please refer to the illustration below adapted from the research by Wei et al. [51].

Adapting from Wei et al. [51], the adaptive intelligent power collection scheme considers factors such as sensor locations, distances, and data importance levels to determine the optimal route for the AUV. By utilizing intelligent decision-making techniques, the AUV can choose a route that minimizes energy consumption and maximizes data collection efficiency.

Additionally, the alternating-anchor-nodes-selection-and-flow-routing (AANSFR) algorithm [51] is employed. This algorithm is considered effective for route planning if it can maximize the number of nodes obtained by the AUV while minimizing energy usage. The AANSFR algorithm can be expressed using the following equation:

$$\max\min_{j\in\mathcal{N}} \ (E_j - \rho_j), \tag{14a}$$

$$\text{s.t.} \sum_{j\in\mathcal{N}} f_{ij} = (1-x_i)\left(\sum_{k\in\mathcal{N}} f_{ki} + g_i\right) + x_i m_i \quad \forall i \in \mathcal{N}, \tag{14b}$$

$$\rho_j = (\mu_j x_j + \gamma_j)\sum_{i\in\mathcal{N}} f_{ij} + g_j\mu_j x_j + \sum_{k\in\mathcal{N}} f_{jk}\epsilon_{jk}, \tag{14c}$$

$$\rho_j \leq E_j \quad \forall j \in \mathcal{N}, \tag{14d}$$

$$x_i \in \{0,1\} \quad \forall i \in \mathcal{N}, \tag{14e}$$

$$f_{ij} \geq 0 \quad \forall i,j \in \mathcal{N}, \tag{14f}$$

$$\sum_{i\in\mathcal{N}} x_i = k. \tag{14g}$$

where x_j represents the selection of Anchor-Nodes (AN), $x_j = 1$ & means node j is chosen as an AN, k is the total number of ANs predetermined, m_i is the MI data flow from node i, $x_i f_{ij}$ is constraint (14b), and $x_i m_i$ is constraint (14c).

Furthermore, using the optimization function, the above equations can be written as follows:

$$\max z, \tag{15a}$$

$$\text{s.t.}\ m_i \geq 0 \quad \forall i \in \mathcal{N}, \tag{15b}$$

$$m_i \leq x_i C_{MI} \quad \forall i \in \mathcal{N}, \tag{15c}$$

$$f_{ij} \geq 0 \quad \forall i,j \in \mathcal{N}, \tag{15d}$$

$$f_{ij} \leq C_{ij}(1-x_i) \quad \forall i,j \in \mathcal{N}, \tag{15e}$$

$$\sum_{j\in\mathcal{N}} f_{ij} + m_i = \sum_{k\in\mathcal{N}} f_{ki} + g_i \quad \forall i \in \mathcal{N}, \tag{15f}$$

$$\rho_j = \sum_{i\in\mathcal{N}} f_{ij}\gamma_{ij} + \mu x_j + \sum_{k\in\mathcal{N}} f_{jk}\epsilon_{jk} \quad \forall j \in \mathcal{N}, \tag{15g}$$

$$z \leq E_j - \rho_j \quad \forall j \in \mathcal{N}, \tag{15h}$$

$$x_i \in \{0,1\} \quad \forall i \in \mathcal{N} \tag{15i}$$

$$\sum_{i\in\mathcal{N}} x_i = k. \tag{15j}$$

where C_{MI} is the MI channel capacity, and C_{ij} is the acoustic channel capacity between node i and j.

Discussion about sensor basics, data acquisition fundamentals, and related terminology is a crucial component of data acquisition systems [75]. Understanding sensor technology and data acquisition techniques is key to designing and implementing an efficient data acquisition system. This involves knowledge of various types of sensors, operational principles of sensors, and techniques used to collect, process, and transmit data from these sensors. Accurate data acquisition relies on a strong understanding of these fundamentals and the application of appropriate data acquisition techniques [76].

Wireless sensors play a vital role in data acquisition systems, enabling them to collect data from various environments without the need for physical cable connections [77]. Equipped with internal communication capabilities, these sensors can autonomously collect data and wirelessly transmit it to central processing units or data storage devices. This wireless data acquisition approach eliminates the need for physical cable installations, reduces costs, and allows for flexible sensor deployment in various applications [78].

Data fusion in wireless sensor networks involves integrating and processing data from various sensors to obtain more accurate and comprehensive information about the environment [79]. By combining data from various sensors, redundant information can be eliminated, and the reliability and accuracy of the generated data can be improved [80]. Data fusion techniques in wireless sensor networks assist in decision-making, anomaly detection, and enhancing the overall performance of data acquisition systems [81].

Machine Learning (ML) techniques have proven to significantly enhance data analysis in various fields, including data obtained from wireless sensor networks. ML techniques enable the extraction of valuable insights from large datasets, aiding in identifying patterns, making predictions, and optimizing system performance [82], [83], [84], [85], [86], [87], [88], [89], [90], [91].

Based on the literature review we conducted, we can outline the mission to be carried out by an AUV in autonomously navigating for inspection and data acquisition in an UWSN. An illustration of this mission can be seen in Figure 4. The mission involves a series of tasks, including the movement of the AUV to reach specified locations, conducting inspections, and collecting necessary data in the context of the underwater environment.

IV. PROBLEM FORMULATION

The navigation of AUVs in UWSNs poses significant challenges due to the complex underwater environment. The main goal is to develop effective navigation techniques to enable AUVs to autonomously inspect and acquire data in UWSNs. Key challenges involve addressing communication constraints, optimizing energy usage, and ensuring accurate navigation under various underwater conditions.

Additionally, the formulation must consider the need for robust data acquisition methods and the impact of varied environmental factors on AUV navigation. The objective is to create a comprehensive framework to enhance autonomy, efficiency, and reliability in AUV navigation within UWSNs for inspection and data acquisition purposes.

V. PROPOSED SCHEME

In the previous section, at least four main problems were mentioned that require contributions to their resolution, namely:

Constraint 1. *Communication Constraint*: Considering the underwater environment with signal-absorbing properties, we propose that the entire communication process be carried out entirely on the surface environment while the AUV is still on the carrier ship. Before deployment, it is ensured that the mission commands are precise. It is assumed that the operator has exact information about the UWSN, and

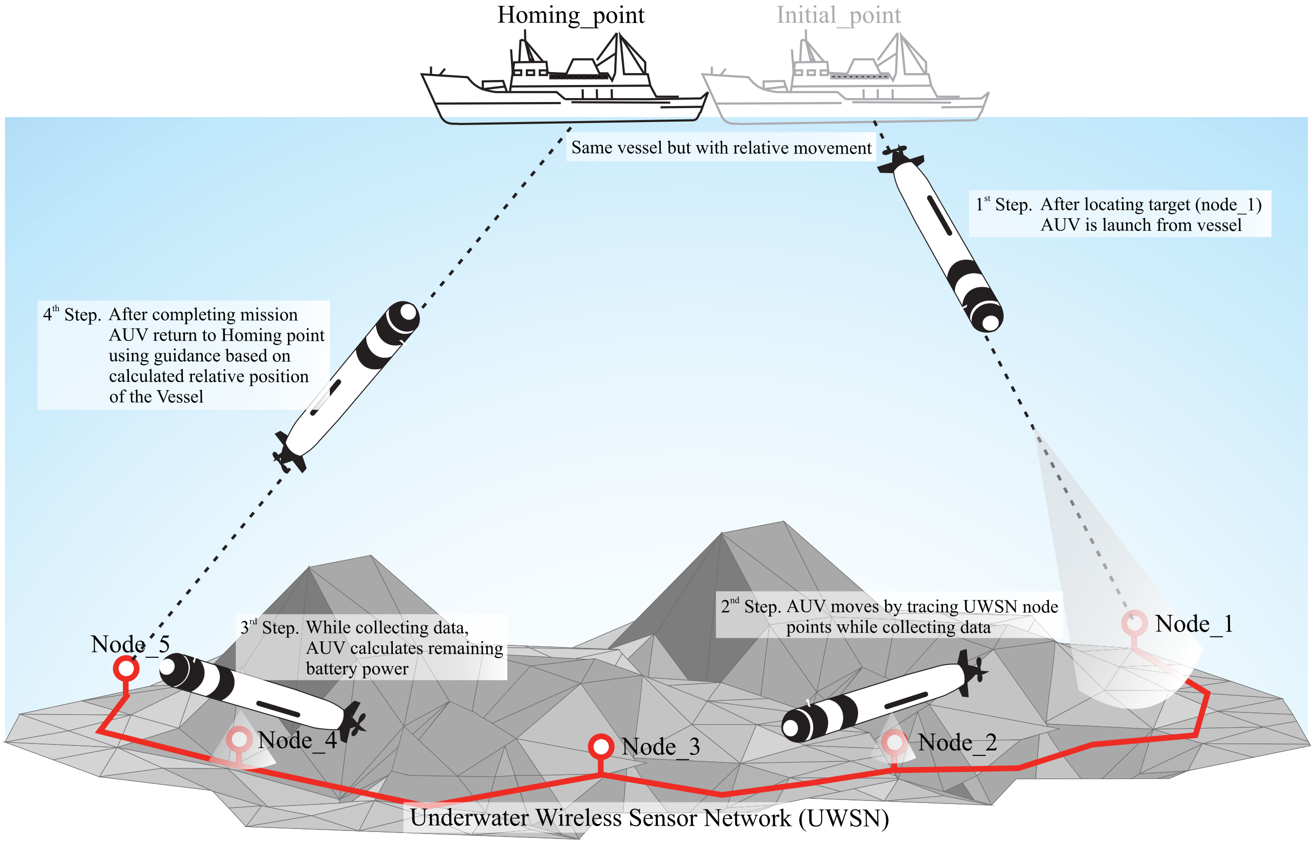

FIGURE 4. AUV mission planning for inspection and data acquisition in UWSNs.

by neglecting the environmental disturbance factor, the AUV is given a mission to reach the initial target point (See (1) and (2)).

Constraint 2. *Energy Usage Optimization*: After the AUV reaches the first node in the UWSN, the AC and AMB-SLAM navigation techniques are employed, assisted by magnetic beacons and acoustic beacons (See (3), (4) and (5)). Some studies indicate that this method is the most effective for power and data transfer due to minimal power loss.

Using a potential field-based control algorithm, where the potential field is employed to regulate the movement of the robot or object in a specific environment based on attractive (pulling) and repulsive (pushing) potentials. In this context, the attractive potential is generated by the desired goal (q-goal), while the repulsive potential is generated by surrounding objects (o-d) (See Algorithm 1).

Constraint 3. *Accurate Navigation*: We assume that the positions of all nodes have been mapped, and we design precise navigation tailored to the positions and distances between nodes. We implement the Homing (concentration) control algorithm using a motion method toward specific points. This algorithm works by moving the object sequentially toward each goal with control parameters determined by variables (alpha) and (dt). The object is attracted to each goal using attractive potential (alpha), and the position displacement occurs at time intervals dt. This process is

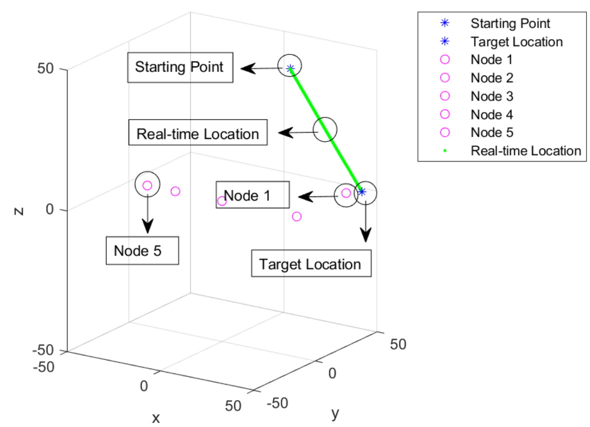

FIGURE 5. The launch of the AUV to the target (node-1) with the starting point at coordinates (10 40 40) and the target location at coordinates (45 45 0), was achieved in a relative time of 21 seconds.

repeated until the object reaches the specified goal (See Algorithm 2).

Constraint 4. *Effective Data Acquisition*: By implementing the Homing control algorithm to dynamically direct the movement of AUV towards specific points based on the level of information importance at each point, the effectiveness of data acquisition will be enhanced (See (14g) and (15j)).

As a whole, the implementation of this dynamic Homing control algorithm can bring significant benefits in the context of AUV for data acquisition. Directing AUV movement

Algorithm 1 Potential Field-Based Adaptive-Control (AC) Navigation

initialize:
$(q_{goal}, dsg, qoi, \zeta, \eta, \alpha)$
$(d0, o_d, u_{att}, u_r, u, d_{att}, u_{repulsive})$
parameters:
$q_{goal} \leftarrow [5, 5, 40]$
$dsg \leftarrow 10$
$qoi \leftarrow 25$
$\zeta \leftarrow 0.5$
$\eta \leftarrow 5$
$\alpha \leftarrow 0.05$
main loop:
while Plane did not reach the target:
    Compute u_{att} (attractive potential) from (2∼3)
    Compute u_r (repulsive potential)
    Compute u (total potential)
    Determine $d0$ (changes)
    Update $d0$
    Compute u_{att}
    Compute d_{att}
    if Distance $\leq$ safe distance: **then**
        Compute u_{att} (with the potential gradient)
        if Distance $\geq$ safedistance : **then**
            Compute u_{att} (with the potential gradient)
            Compute u_r
            if Distance $\leq$ influencedistance : **then**
                Compute u_r
                show result
            end If

Algorithm 2 Homing Control Using Motion Towards Specific Points Method

initialize:
$(q_{goal}, dsg, qoi, \zeta, \eta, \alpha)$
$(d0, o_d, u_{att}, u_r, u, d_{att}, u_{repulsive})$
parameters:
$q_{goal} \leftarrow [0, 0, 50]$
$dsg \leftarrow 5$
$qoi \leftarrow 15$
$\zeta \leftarrow 1$
$\eta \leftarrow 1$
$\alpha \leftarrow 0.2$
$dt \leftarrow 0.005$
Compute u_{att} from (2∼3)
main loop:
while Current goal index $\leq$ size(od, 1) **do**
    while $\|d0 -$ Current goal$\| > 0.1$ **do**
        Compute $d0_x = d0_x - \alpha$ (current goal x)
        Compute $d0_y = d0_y - \alpha$ (current goal y)
        Compute $d0_z = d0_z - \alpha$ (current goal z)
    end while
    Current goal index = Current goal index + 1
end while
movement toward final goal q_{goal}**:**
while $\|d0 - q_{goal}\| > 0.1$ **do**
    Compute $d0_x = d0_x - \alpha$ (final goal x)
    Compute $d0_y = d0_y - \alpha$ (final goal y)
    Compute $d0_z = d0_z - \alpha$ (final goal z)
    show result
end while=()

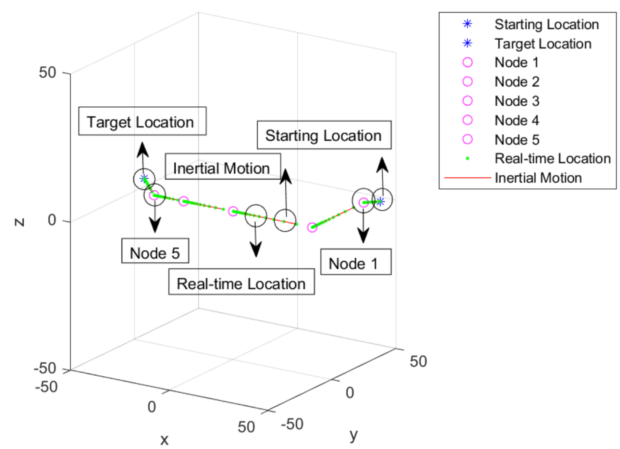

FIGURE 6. In the localization and data acquisition mission on UWSN the nodes are denoted as (o) pink, adapting the AMB-SLAM technique we add uattractive and urepulsive (as attractive and repulsive forces of magnetic beacons). It can be seen that the displacement of the aircraft in (*) blue is very precise with the moment of inertia notation (-) in green.

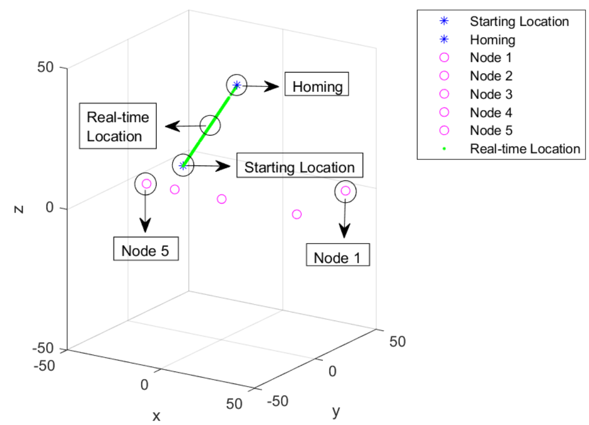

FIGURE 7. Assumed vessel position (Homing point) at (5 5 40) obtained from SONAR Triliteration, and AUV location at (−40 30 0), with travel time of 26 seconds.

based on the level of information importance at each point not only enhances observation accuracy but also optimizes the time and power used, ensuring that the collected data has maximum value according to mission or research objectives.

VI. PERFORMANCE EVALUATION

Next, we simulated the proposed AUV navigation technique based on node tracking in UWSN (See Algorithm 1), assuming the operator already has the coordinates of the destination point, allowing the initial coordinates of the AUV to be expressed in the order X Y Z (0, 0, 0).

In this simulation, we observed how the AUV could reach the target with minimal delay time. By calculating constant

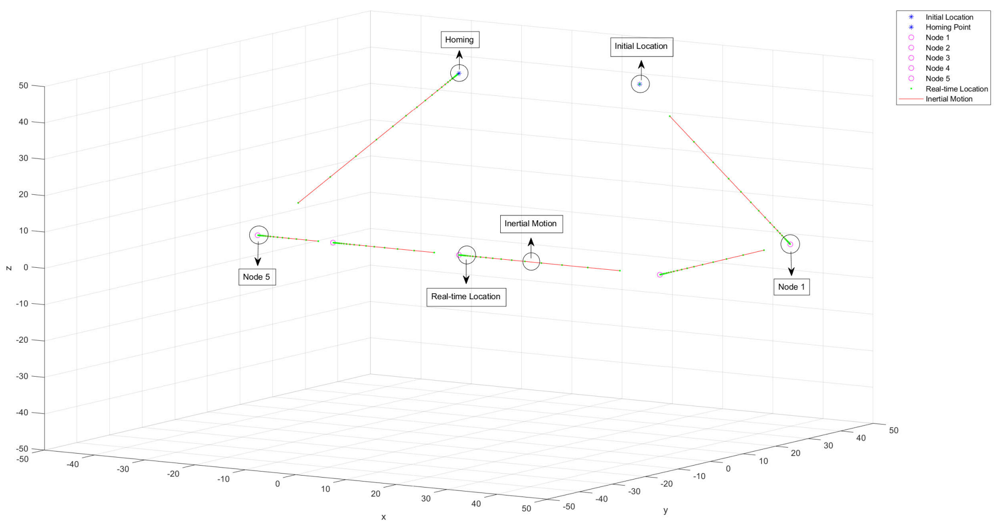

FIGURE 8. **The AUV performed continuous data acquisition indicated by the red (-) notation with data acquisition greater than the number of pink (o) notation nodes traversed, it is possible that the AUV also collected aircraft inertial and angle-of-attack data.**

speed and the time needed to reach the target, the relative distance between the launch location and the target can be estimated, disregarding the launch angle. The simulation results are presented in Figure 5.

Considering the efficiency of energy use, in the next simulation corresponding to the AUV mission to collect data on UWSN nodes, we mark the vehicle with (*) in blue, UWSN node points (o) in pink, and the trajectory occurs as the AUV moves from one node to another with (-) in green. Refer to the simulation in Figure 6.

At the same time, simulation 6 addresses Constraint 3 (Accurate Navigation), where it is evident that the aircraft is able to move from one node to the next without unnecessary maneuvers. Furthermore, through simulation 7, we aim to demonstrate the effectiveness and accuracy of the homing technique using the trilateration SONAR approach (See Figure 3). If the Homing coordinates are known, the aircraft will be able to effectively return to the mothership; see the simulation in Figure 7.

Finally, to address Constraint 4 (regarding Effective Data Acquisition), we implemented (Algorithm 2), as indicated by the notation (-) in red with data acquisition notations ranging from 1 to n from nodes 1 to 5 or more, depending on the number of nodes in the UWSN. This means that the AUV continuously and effectively performs data acquisition throughout the journey from the deployment point to the Homing point.

VII. OPEN ISSUES AND RESEARCH CHALLENGES

From the experiments we conducted, there are several open issues and future research challenges that we encountered, with at least four main issues including:

1) Environmental Challenges: In this study, we ignored the dynamic underwater environmental factors. Therefore, in future research, the development of dynamic simulation environments adapted to the actual operating environment is expected. This way, the created simulations can approach real scenarios.
2) Measurement of Energy Usage Effectiveness and Recharging: In Simulation 6, we did not measure the power required to reach each target point. We only globally demonstrated the effectiveness of the navigation system, assuming that with effective navigation, energy efficiency can be achieved. Based on this discussion, there is an opportunity for future development to simulate effective power usage and even simultaneous recharging during power acquisition operations in UWSN. This is considering that the use of magnetic beacons allows power transfer during operations in the underwater environment with an induction system.
3) Advanced Development of Precise Navigation: In the mission scenario we conducted, we ignored obstacles and collision avoidance schemes with underwater objects. Therefore, we hope for further development of precise navigation involving a reinforcement learning approach to the precise navigation system. This involves simulating training and testing for data collection mission scenarios in UWSN, incorporating obstacle avoidance elements, and autonomous system adaptation based on repeated training.
4) Advanced Development of Effective Data Acquisition: In this mission scenario, we did not involve the use of Fusion sensors on the AUV. In the future, we hope for further development and research in effective data acquisition in UWSN, also involving the use of Fusion sensors (such as MEMS and IMU). This way, during missions, diverse data about the AUV's experiences (such as movement, attack angle, pressure at each depth, light intensity received at each depth degree, and other useful data in the fields of underwater vehicle research, navigation, and data acquisition in underwater communication networks) can be obtained simultaneously.

VIII. CONCLUSION

From the overall research stages that were conducted, several conclusions can be drawn regarding the development of navigation techniques for inspection and data acquisition in UWSN designed for AUVs. One of the key findings is the necessity to develop a dynamic simulation environment capable of depicting actual operational conditions underwater. Moreover, the system's effectiveness requires detailed enhancement, and it is essential to develop mission scenarios by introducing obstacle elements based on real conditions in the environment. The reduction of human involvement as mission controllers through the incorporation of reinforcement learning into the system is also deemed crucial, enabling the navigation system to dynamically adapt to mission requirements. Considering the future, the involvement of Fusion sensors should be taken into account to enrich acquired data, enabling its utilization for training the developed model. Despite this, the overall research stages have provided valuable insights, emphasizing the importance of mission planning, optimization of energy usage, precise navigation, and effective data acquisition in UWSN. These insights contribute significantly to the potential development of similar research in the future.

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