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Exploration of contemporary modernization in UWSNs in the context of localization including opportunities for future research in machine learning and deep learning

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The exchange of information in Wireless Sensor Networks (WSNs) across different environments, whether they are above the ground, underground, underwater, or in space has advanced significantly over time. Among these advancements, precise localization of nodes within the network remains a key and vital challenge. In the context of Underwater Wireless Sensor Networks (UWSNs), localization plays a pivotal role in enabling the efficient execution of diverse underwater applications such as environmental monitoring, disaster management, military surveillance and many more. This review article is focusing on three primary aspects, the first section focuses on the fundamentals of localization in UWSNs, providing an in depth and comprehensive discussion on various localization methods. Where we have highlighted the two main categories that are anchor based and anchor free localization along with their respective subcategories. The second section of this article examines the diverse challenges that may emerge during the implementation of the localization process. To enhance clarity and structure, these challenges have been carefully analyzed and categorized into three main groups and that are, (i) Algorithmic challenges, (ii) Technical challenges, and (iii) Environmental challenges. The third section of this article begins by presenting the latest advancements in UWSNs localization, followed by an exploration of how Machine Learning (ML) and Deep Learning (DL) models can contribute in enhancing the localization process. To evaluate the potential benefits of the ML and DL techniques, we have assessed their performance through simulations, focusing on metrics such as localization error, velocity estimation error, Root Mean Square Error (RMSE), and energy consumption. This review also aims to provide actionable insights and a guideline for future research directions and opportunities for practitioners in the field of UWSNs localization. Which will ultimately help in enhancing the performance and reliability of underwater applications by advancing localization techniques and promoting seamless integration.

Keywords Wireless Sensor Networks, Underwater Wireless Sensor Networks, Localization, Machine learning, Deep learning

Abbreviations

2D	Two Dimensional
3D	Three Dimensional
AGD	Ada-Delta Gradient Descent

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AOA	Angle of Arrival
APIT	Approximate Point in Triangulation
AUVs	Autonomous Underwater Vehicles
BER	Bit Error Rate
CNNs	Convolutional Neural Networks
CRLB	Cramer Rao Lower Bound
DL	Deep Learning
DOBs	Departure Time of Beacon Signals
DV-HoP	Distance Vector Hop
EM	Electromagnetic Waves
FLMME	Flexible Localization with motion Estimation
GAN's	Generative Adversarial Networks
GA-SLMP	General Availability of Scalable Localization Scheme with Mobility Prediction
GPS	Global Positioning Systems
HNNs	Heuristic Neural Networks
ICT	Information and Communication Engineering
IGWONL	Improved Grey Wolf Optimization Based Node Localization
IoT	Internet of Things
IRTUL	Iterative Ray Tracing for 3D Underwater Localization
KF	Kalman Filter
K-NNs	K-Nearest Neighbors
LAS-IUSSOT	Localization algorithm to compensate the stratification effect based on an improved underwater SALP swarm optimization technique
LITM	Location with insufficient TOA measurement
LoS	Line of Sight
LSLS	Localization Scheme for Large Scale
LSTM	Long Short Term Memory
LSTM-NNs	Long Short Term Memory-Neural Networks
MI	Magneto Inductive Communication
ML	Machine Learning
MPL	Movement Prediction Localization
NS2	Network Simulation Software name
PNT	Position Navigation and Timing
QoS	Quality of Services
RBF	Radial Basis Function
RDVHL	Reward Based Distance Vector HoP Localization
RMML	Robust Multi Modal Mobile Target Localization
RNNs	Recurrent Neural Networks
RSS	Received Signal Strength
RSSI	Received Signal Strength Indication
RVOA	Red Vulture Optimization Algorithm
SAR	Synthetic Aperture Radar
SLMP	Scalable Localization Scheme with Mobility Prediction
SNR	Signal to Noise Ratio
SVM	Support Vector Machine
TDOA	Time Difference of Arrival
TOA	Time of Arrival
ToF	Time of Flight
TWSNs	Terrestrial Wireless Sensor Networks
UOWC	Underwater Optical Wireless Communication
UWSNs	Underwater Wireless Sensor Networks
VLC	Visible Light Communication
WSNs	Wireless Sensor Networks

As time progresses, information and communication technologies (ICT) are becoming an integral part of our daily lives. The exchange of information between communication entities typically occurs via wired or wireless networks[1]. However, this study will not address wired networks but will instead concentrate on wireless sensor networks (WSNs), with a particular emphasis on underwater wireless sensor networks (UWSNs)[2,3]. The information shared as data between two communicating entities in a WSNs may either be in the form of text, audio, or a video file, but the main essence of all three types of data are digital bits, that are transferred on a wired or a wireless channel[2,4]. Full successful communication of the data between nodes in WSNs comprises of multiple processes, i.e., data encoding and decoding, transmission techniques such as modulation and demodulation, power consideration that includes power constraints and management techniques, channel coding, securing the data through secure communication and localization of data etc. When the operational domain of a conventional WSNs is transposed to the underwater domain, it evolves into what is termed an UWSNs, however, this metamorphosis is anything but rudimentary[5]. Although the theoretical premise of adapting WSNs to subaqueous applications may appear deceptively straightforward, the practical execution is markedly intricate. The underwater environment introduces unique challenges that significantly differ from those encountered in terrestrial or aerial communication systems. Factors such as water's physical properties, signal propagation limitations, increased attenuation, and the need for specialized communication techniques make UWSNs a sophisticated and intricate field of study.

In terrestrial wireless sensor networks (TWSNs), electromagnetic (EM) waves are the preferred medium for communication between nodes[6,7]. However, these waves are not suitable for UWSNs due to significant attenuation in the underwater environment. Factors contributing to this attenuation include the water itself, debris in murky waters, marine organisms inhabiting the communication area, reflections of EM waves from the water surface and ocean floor, as well as various organic and inorganic substances like rocks and coral reefs. Acoustical waves have superseded EM waves as the predominant medium for communication in UWSNs, effectively mitigating the impediments that hinder EM wave propagation in aquatic environments. Acoustical waves exhibit remarkable efficacy in traversing the underwater surroundings, circumventing numerous constraints that EM waves encounter during transmission. Nevertheless, a salient drawback of acoustical communication lies in its exorbitant costs of the required apparatus, that including acoustical transponders and related devices, are often prohibitively expensive[8]. Given the high costs associated with acoustical communication, research groups worldwide are actively investigating alternative technologies of communication medias for UWSNs. Two of the most promising approaches are optical communication, also known as visible light communication (VLC), and magneto inductive (MI) communication[9–11]. These innovative methods aims to address the shortcomings of acoustical communication, offering more cost effective and efficient solutions tailored to underwater environments, with a particular focus on near field communication scenarios[12]. Figure 1 provides a fundamental schematic diagram that depicts a generic scenario involving distributed sensor networks. These networks are shown functioning and exchanging information within the framework of UWSNs, offering a conceptual representation of their operational and communication dynamics.

Localization of nodes in UWSNs plays a vital role in ensuring efficient data collection, seamless network operations, and practical application deployment. This process involves two key types of nodes that are anchor Tx nodes and sensor Rx nodes. Anchor Tx nodes are equipped with global positioning systems (GPS), and are responsible for accessing and preprocessing data before transmitting it to the base stations[13]. Conversely, sensor Rx nodes focus on gathering raw data, sharing it within the network of sensor nodes, and synchronously transferring it to the anchor Tx nodes for further processing. Accurate localization of nodes is crucial for determining the exact source of the sensed data, which is indispensable for applications like environmental monitoring, disaster response, underwater navigation, and resource exploration. The underwater environment presents unique challenges, including limited bandwidth, significant signal attenuation, and constant node movement. To address these issues, effective localization algorithms are essential for conserving energy, minimizing communication overhead, and ensuring network reliability. Without precise localization, the data collected by UWSNs may lack context, diminishing its value for analysis and informed decision making[14]. The localization of sensor Rx nodes can primarily be classified into two fundamental methodologies, and that are range based and range free techniques[15]. Each of these approaches offers unique advantages and applications in the context of UWSNs.

The remainder of the paper is organized as follows, “Types of localization Algorithms” sect. provides an in depth discussion on the various types of localization, followed by an exploration of the challenges associated with the localization process in UWSNs, presented in “Localization Challenges in UWSNs” sect. “Most Recent

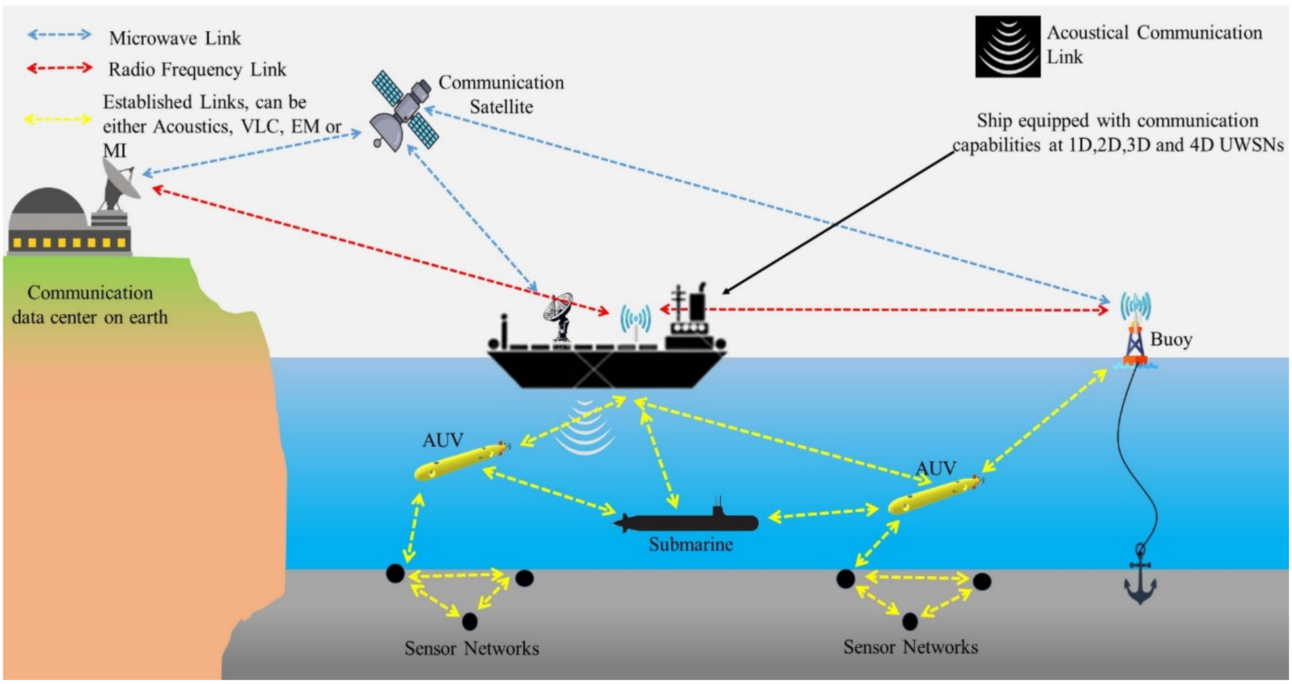

Fig. 1. A generic UWSNs communication scenario.

Advancements in UWSNs Localization" Sect. highlights recent advancements in the field of localization in UWSNs, contributed by research groups worldwide. "Purpose of ML and DL in UWSNs Localization" Sect. delves into the application of Machine Learning (ML) and Deep Learning (DL) in node localization, including a detailed discussion in the form of comparative analysis on the results achieved using different ML and DL models. Finally, "Future Research Directions and Opportunities" sect. outlines open research directions that can serve as future work in node localization for UWSNs, concluding the article with a comprehensive conclusion at the end. To provide a clear understanding of the methodology adopted in reviewing the relevant articles for the completion of this research analysis, Fig. 2 showcases a detailed and systematic flow diagram. This diagram elaborates on the search mechanism employed, offering an in depth representation of the process followed to ensure a thorough and comprehensive examination of the literature.

The Key contributions of the article are:

This article covers several crucial aspects designed to benefit the research community. To ensure clarity and accessibility, we have outlined our key contributions below in the form of bullet points. These contributions aim to provide valuable insights, facilitate further exploration, and encourage meaningful discussions among researchers.

- We have conducted an in depth analysis of localization algorithms applicable to UWSNs. These algorithms have been systematically organized into categories and subcategories to present the localization processes/methods in a structured, branch like format, making them more comprehensible for readers.
- The article provides a comprehensive explanation of three primary categories of challenges that localization processes may encounter when applied in UWSNs. These challenges stems out from various factors, including algorithmic, environmental, and technical aspects.
- Towards the end of this article, we have included a comparative analysis of various ML and DL models. This analysis examines their performance in evaluating the key factors necessary to determine whether the system for localization of nodes in UWSNs estimation is operating effectively.

Types of localization algorithms

Localization algorithms play a crucial role in UWSNs by enabling the accurate determination of sensor node positions within submerged environments. These algorithms can generally be classified into two main categories, i.e. anchor based and anchor free localization. The selection of an appropriate localization algorithm is influenced

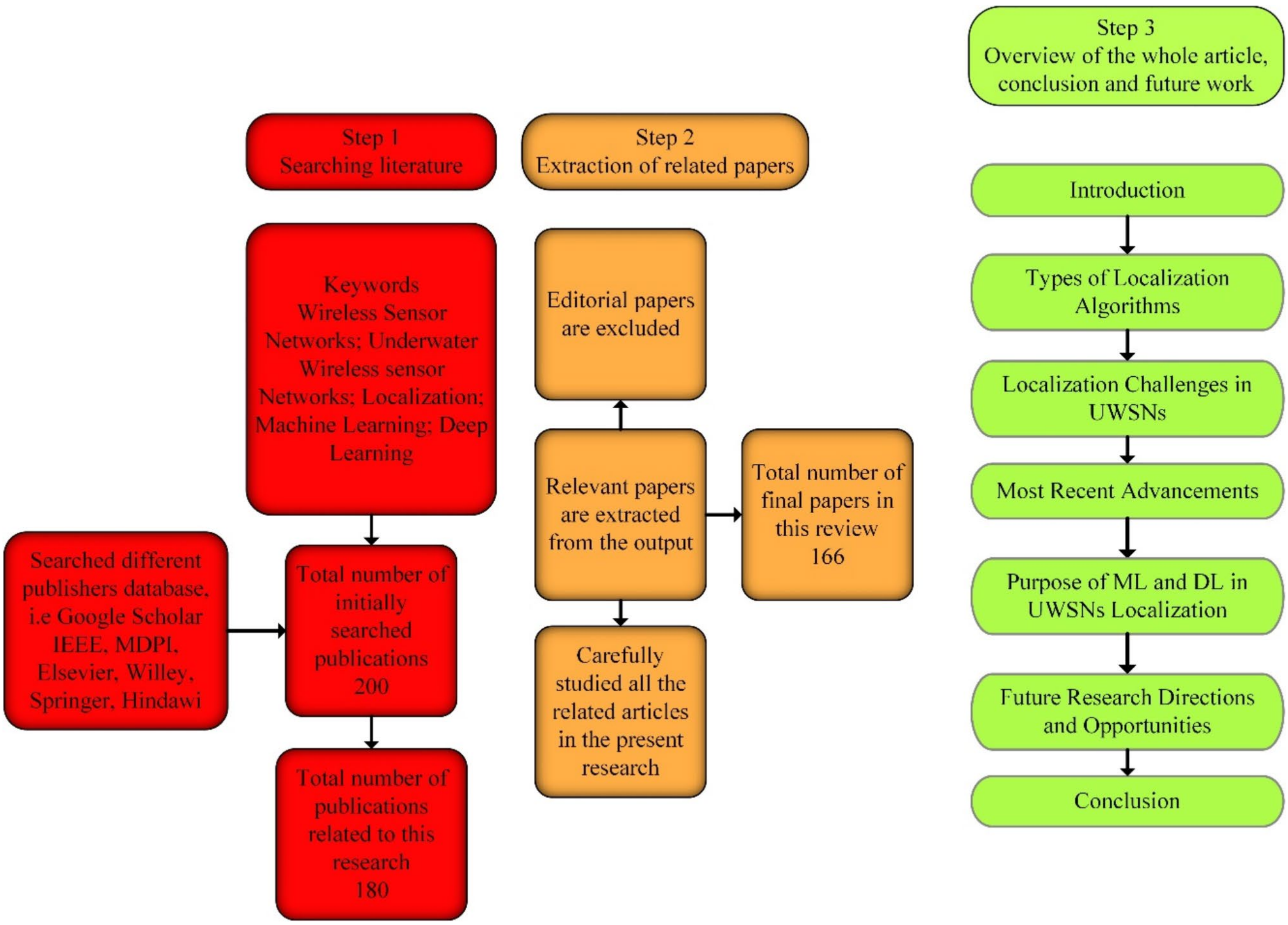

Fig. 2. Methodology of the paper.

by several factors, including the specific application of the network, the importance of energy efficiency, the characteristics of the surrounding environment, and the required accuracy of the positioning system. In the following section, we will provide a brief discussion on each category in the context of UWSNs. In Fig. 3a block diagram is presented that offers a detailed classification of the various types of localization algorithms, carefully organized into distinct subcategories for better clarity and understanding.

Anchor based localization algorithms

Anchor based localization algorithms are often utilized in UWSNs to determine the positions of sensor nodes with the help of predefined reference points, known as anchor nodes. These anchor nodes can be either static anchor nodes, remaining in a fixed position, or mobile, continuously transmitting their location data to nearby sensor nodes[16,17]. By assessing distances or signal strengths between the anchor nodes and the unknown nodes, the algorithm determines the positions. The precision of this localization technique depends on the optimal placement of the anchor nodes and the accuracy of the distance measurements. While this method is suitable for applications that demand reliable and reasonably accurate positioning in a network, but on the contrary it may present challenges related to energy efficiency and the cost effective deployment.

Static anchors

Static anchor node based localization algorithms in UWSNs rely on anchor nodes that are positioned at fixed, predefined locations to determine the positions of other sensor nodes. These static anchor nodes are typically categorized into two main types, i.e. range based and range free, which will be explored further in the following subsections. The accuracy of the localization process, however, depends on the strategic placement of the anchor nodes and the precision of the distance, time and angle measurements.

Range based algorithms Range based localization algorithms for underwater communication determine the locations of sensor nodes by calculating their distances, time of communication or angle of communication from anchor nodes. These algorithms often employ techniques like angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), and received signal strength indicator (RSSI) to estimate distances based on signal propagation characteristics[18]. These methods offer high positioning accuracy when measurements are

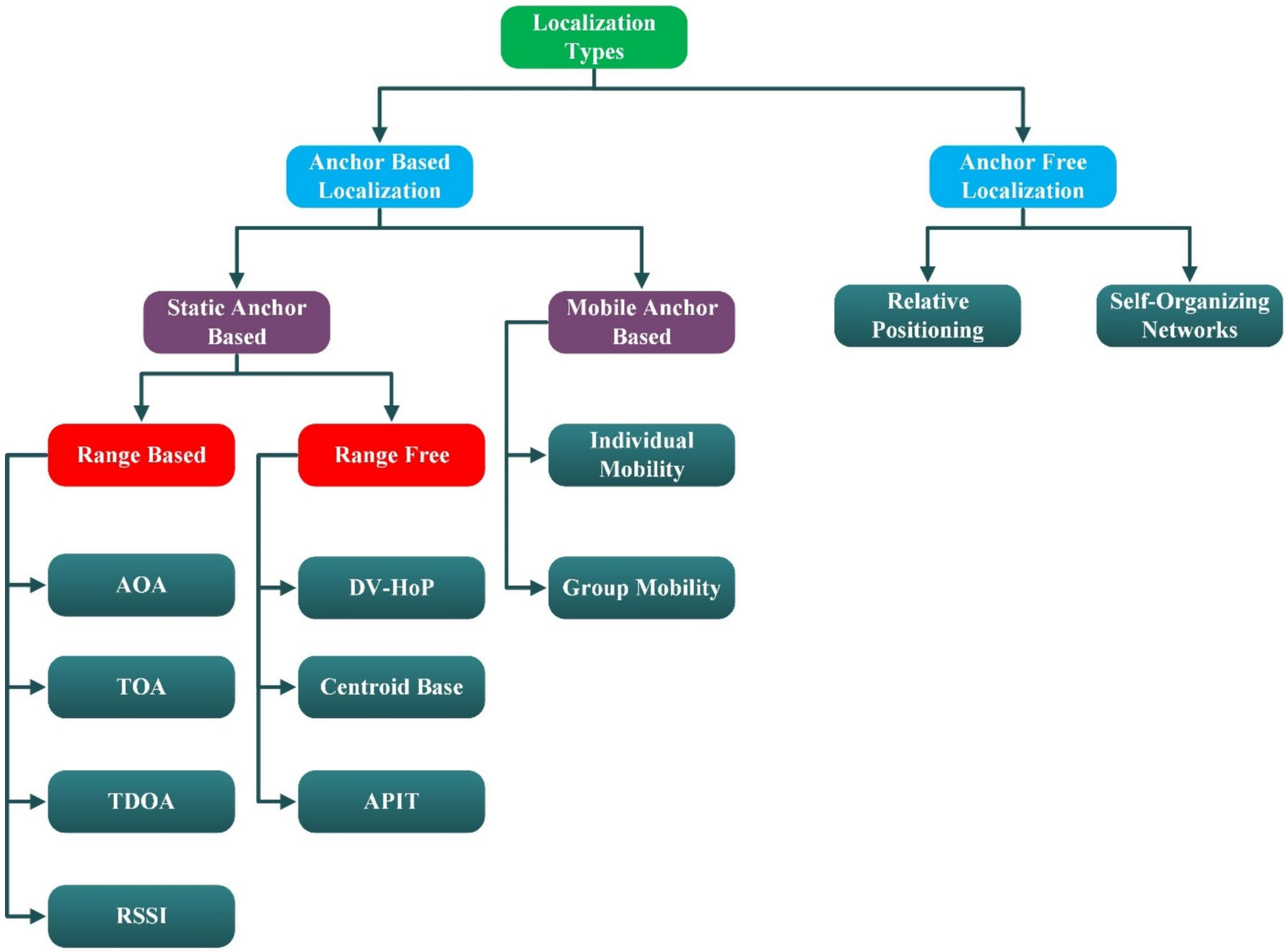

Fig. 3. A block flow diagram on the basic types of localization of nodes in UWSNs.

reliable and environmental factors, such as signal interference and multipath effects, are minimal. However, they may demand significant computational and energy resources, making them more suitable for scenarios where precision is a top priority[10]. A detailed explanation of each type of range based algorithm mentioned earlier is provided in the following subsections within this section, offering a comprehensive understanding of how each approach operates, supplemented by their respective schematic diagrams.

a. Angle of Arrival (AOA)

The AOA technique is a range based localization approach commonly utilized in underwater communication to determine the position of nodes by analyzing the angle at which a signal is received. In UWSNs, this method leverages the benefits from the acoustic signals, which are more effective than radio waves in aquatic environments[19]. The technique involves deploying sensor nodes equipped with hydrophone arrays or directional antennas to measure the angle of signal arrival. Hydrophones, functioning as underwater acoustic sensors, detects sound signals and measure the time differences in their arrival at various points in the array. These time differences are used to calculate the signal's angle of incidence, aiding in localization. By integrating AOA data from multiple receivers or anchor nodes with known positions, the location of an unknown node can be determined through triangulation[20]. However, the performance of AOA in underwater environments is affected by challenges such as signal scattering, multipath effects, and ambient noise. Despite these limitations, AOA offers a high potential for precise localization, especially when combined with other techniques to reduce environmental inaccuracies. In Fig. 4a basic localization scenario is shown where the receiver nodes (submarines) are being localized with the help of a range based AOA algorithm.

b. Time of Arrival (TOA)

The TOA technique is a range based localization method commonly used in underwater communication to identify the position of nodes by measuring the duration a signal takes to travel from a transmitter to a receiver[21]. This method, widely applied in UWSNs, utilizes acoustic signals, which propagates more effectively in water compared to its counter parts used in TWSNs. TOA calculates the distance between nodes by multiplying the signal's travel time with the established speed of sound in water. By obtaining multiple distance measurements from anchor nodes with predefined locations, the position of an unknown node can be accurately determined through trilateration. However, TOA's accuracy can be impacted by variations in the speed of sound caused by changes in water temperature, salinity, and pressure, as well as by environmental noise and signal multipath effects[22]. Despite these limitations, TOA remains a reliable method for underwater localization due to its capability to deliver precise distance estimates under controlled conditions but with proper calibration. Figure 5 illustrates a fundamental scenario that demonstrates the concept of TOA. The anchor node, labeled as A, acts as the sender, while the receiver node, designated as R, receives the transmitted signal. The variable t represents the time it takes for the signal to travel from the anchor node to the receiver node. Using this measured time and the known speed of the signal, the calculated distance between the two nodes is denoted by d. This scenario provides a straightforward explanation of how TOA is used to determine distances in communication or positioning systems by leveraging the relationship between time, speed, and distance.

c. Time Difference of Arrival (TDOA)

TDOA is a range based localization method commonly applied in underwater communication to determine the position of nodes by assessing differences in signal arrival times at multiple receivers. In UWSNs, TDOA makes use of acoustic signals, which are well suited for underwater environments due to their efficient propagation[23]. The technique calculates relative time differences in signal reception across various receivers and

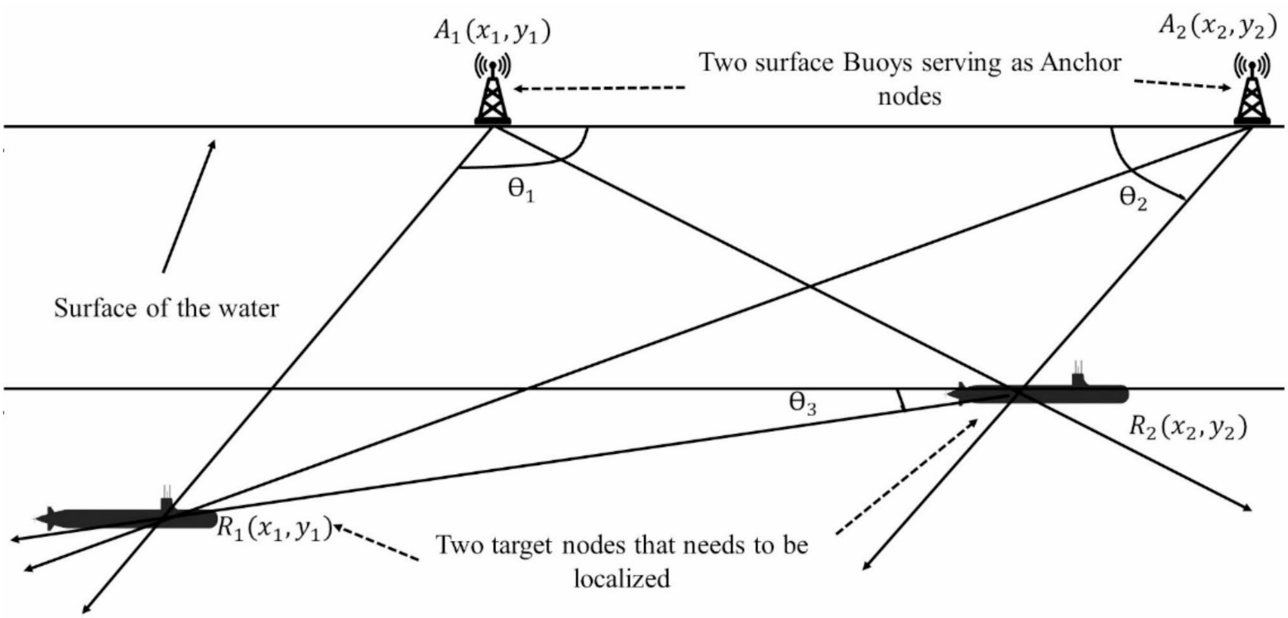

Fig. 4. A basic submarine target tracking scenario with the AOA.

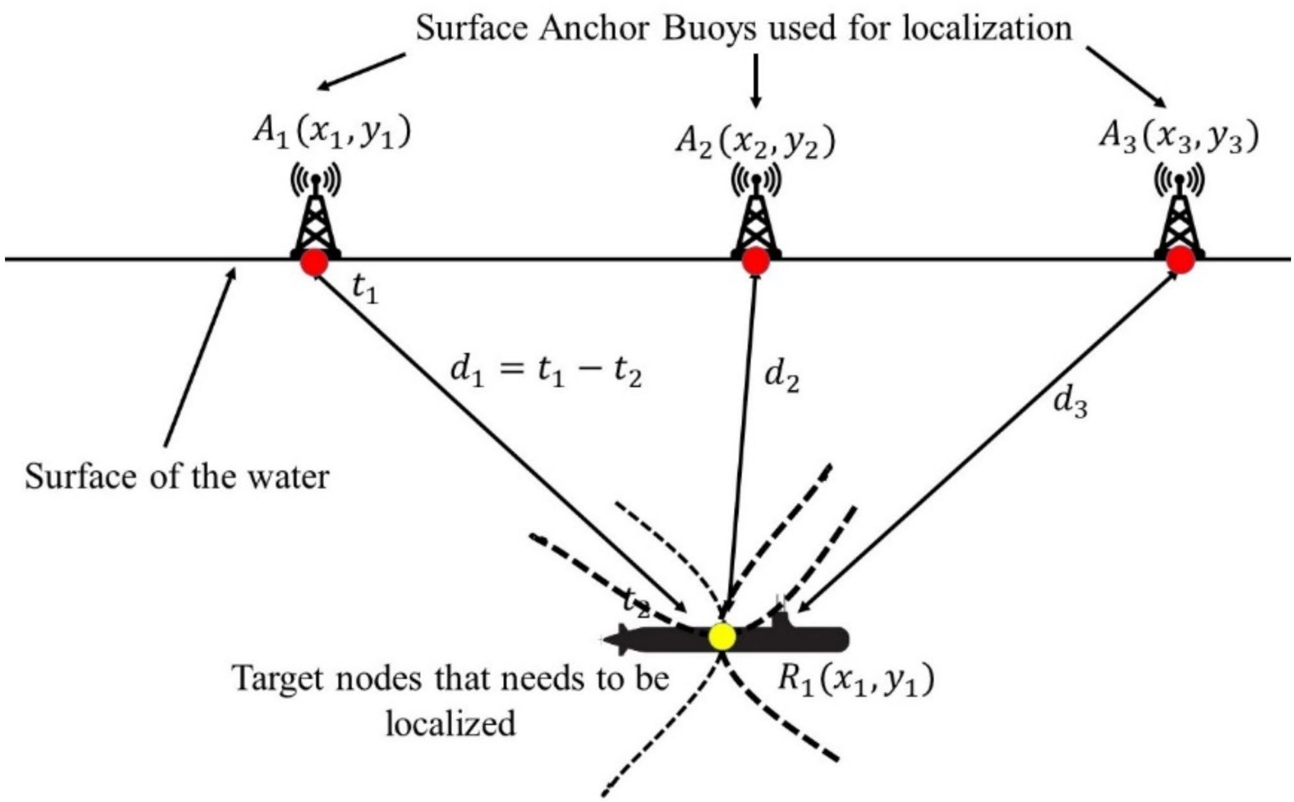

Fig. 5. A basic scenario explaining the TOA.

uses these values to estimate distance differences between the source and the receivers. By utilizing hyperbolic positioning and combining data from multiple receivers with known positions, the location of an unknown node can be accurately determined. Compared to direct time of arrival approaches, TDOA is less impacted by synchronization issues, as it focuses on relative timing rather than absolute travel times. However, its precision can be affected by environmental factors such as noise, multipath effects, and variations in the speed of sound caused by changes in temperature, salinity, and pressure[24]. Despite these challenges, TDOA remains a reliable localization technique, especially when high accuracy synchronization among receivers is feasible. Figure 6 presents a basic scenario designed to enhance the readers' understanding of the TDOA concept. In this illustration, the focus is on comparing the arrival times of two distinct signals as they reach a common sensor or target node, at that time difference between the two signals is the critical parameter being measured. This difference plays a pivotal role in determining the position of the sensor or target node, whether it is stationary or in motion. By analyzing the time disparity, the system can calculate the relative location of the Rx nodes, enabling precise tracking and localization in various applications. This scenario highlights the utility of TDOA in navigation, monitoring, and real time tracking systems.

d. Received Signal Strength Indication (RSSI)

RSSI is a range based localization technique widely applied in underwater communication to determine the positions of nodes by evaluating the strength of the received signals. In UWSNs, this method captures the signal after the attenuation of acoustic signals as they travel through water[25]. Signal strength diminishes with increasing distance due to effects like absorption, spreading, and ambient noise. By recording RSSI values at various nodes and applying established signal attenuation models, the distance between the transmitter and receiver can be estimated. These distance measurements, when paired with the known locations of anchor nodes, enable the localization of unknown nodes through techniques such as trilateration. RSSI offers advantages, including not requiring precise time synchronization or advanced hardware. However, its accuracy can be affected by environmental conditions such as multipath propagation, changes in water salinity, temperature, and pressure, which may cause signal strength fluctuations[26]. Despite these limitations, RSSI remains a viable and cost effective solution for localization in UWSNs, particularly in energy efficient and budget conscious applications. Figure 7 presents a schematic diagram depicting an RSSI based localization scenario utilizing multilateration. In this configuration, two nodes are situated on the surface of the water, and one node is submerged underwater, establishing a practical setup for implementing trilateration. Trilateration typically involves the use of three anchor nodes to determine the location of a target. However, when the number of anchor nodes used in the localization process exceeds three, the approach transitions into what is known as multilateration. This method enhances accuracy and reliability by leveraging additional anchor nodes to refine the position estimation within the scenario.

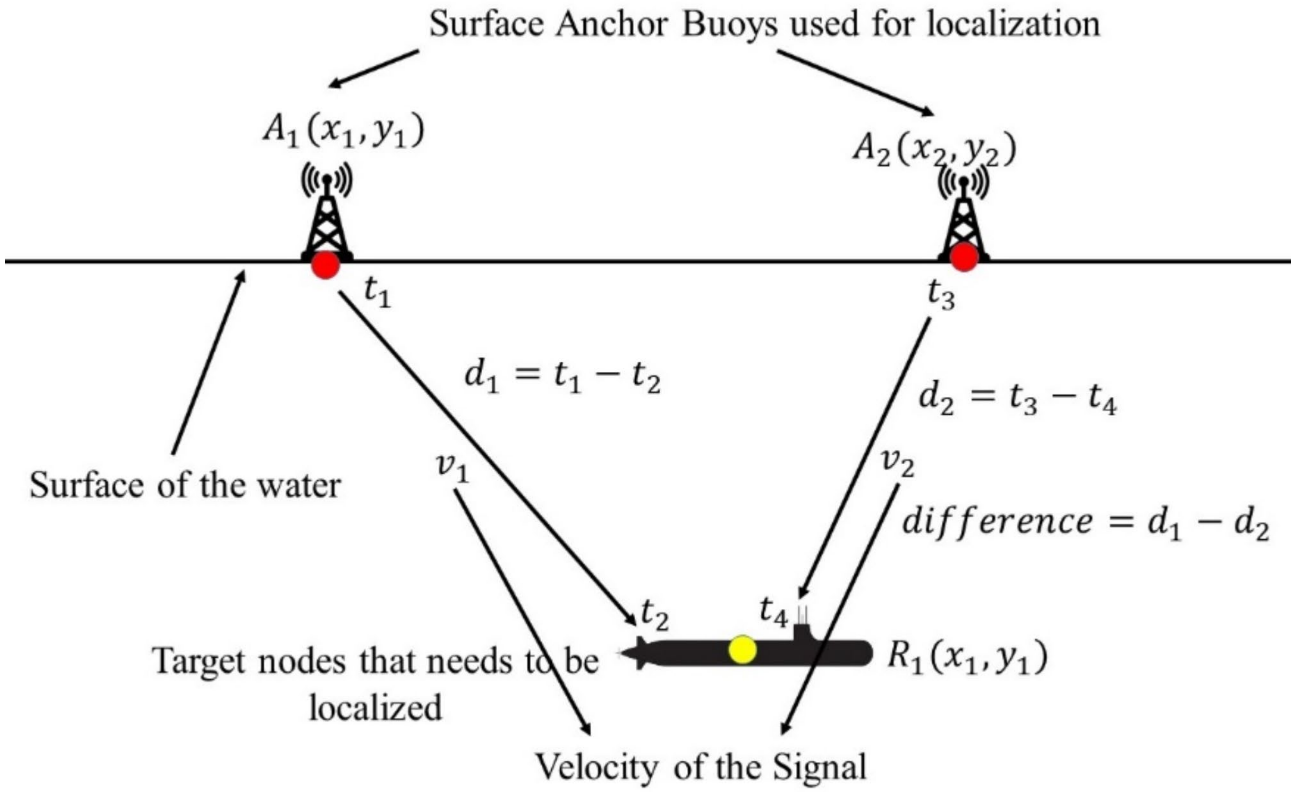

Fig. 6. A basic scenario explain the TDOA phenomenon.

Table 1 provides a comprehensive overview of the various types of range based localization algorithms. It includes the descriptions of their technical mechanisms, the potential communication media they can employ, and an analysis of why MI communication cannot be universally applied across all types of range based localization algorithms.

Range free algorithms Range free localization algorithms for underwater communication identify the positions of sensor nodes without relying on precise distance or angle measurements. Instead, they use connectivity data or relative proximity to estimate node locations, providing improved robustness in underwater environments where signal propagation can be unreliable. Techniques such as centroid based localization, which estimates a node's position as the geometric center of nearby anchor nodes, and distance vector hop (DV-HoP), which uses hop count information to approximate distances, are common examples[38]. These approaches are generally simpler and consume less energy compared to range based methods, making them ideal for large scale networks or scenarios with limited resources. However, their accuracy depends heavily on the density of nodes and the spatial arrangement of anchor nodes[10].

a. DV-HoP

DV-Hop is a range free localization technique commonly utilized in UWSNs to determine the positions of unknown nodes without relying on accurate distance measurements. This method employs a multi hop communication strategy to estimate distance between nodes[39]. Anchor nodes, which have predefined coordinates, broadcast their positions along with a hop count to their neighboring nodes. When a node receives this information, it increases the hop count by one and forwards the data to others, resulting in a network wide hop count map. Using their known locations and the hop count data, anchor nodes compute the average distance per hop. Unknown nodes then use this average hop distance and the hop count data to approximate their distances from multiple anchors. These distances are further used in trilateration to calculate the positions of the unknown nodes. DV-HoP is well suited for underwater settings, as it has the capability to avoid issues like signal attenuation and synchronization problems inherent in range based methods[40].

However, its precision can be affected by factors such as uneven node distribution, network structure, and environmental variables that influence underwater communication. Figure 8 illustrates a fundamental scenario that explains the concept of the DV-HoP algorithm. In this representation, nodes A, B, C, and D serve as beacon nodes, which are utilized to determine the positions of unknown nodes within UWSNs. The distances $d_1,\ d_2,\ and\ d_3$ present the individual distances between beacon nodes that are in direct communication with one another. Meanwhile, d_4 denotes the communication distance between the sender node and the receiver node. This schematic highlights how the DV-HoP algorithm leverages from the hop count between nodes to facilitate localization, emphasizing the role of both direct and indirect communication links in the process.

b. Centroid Base

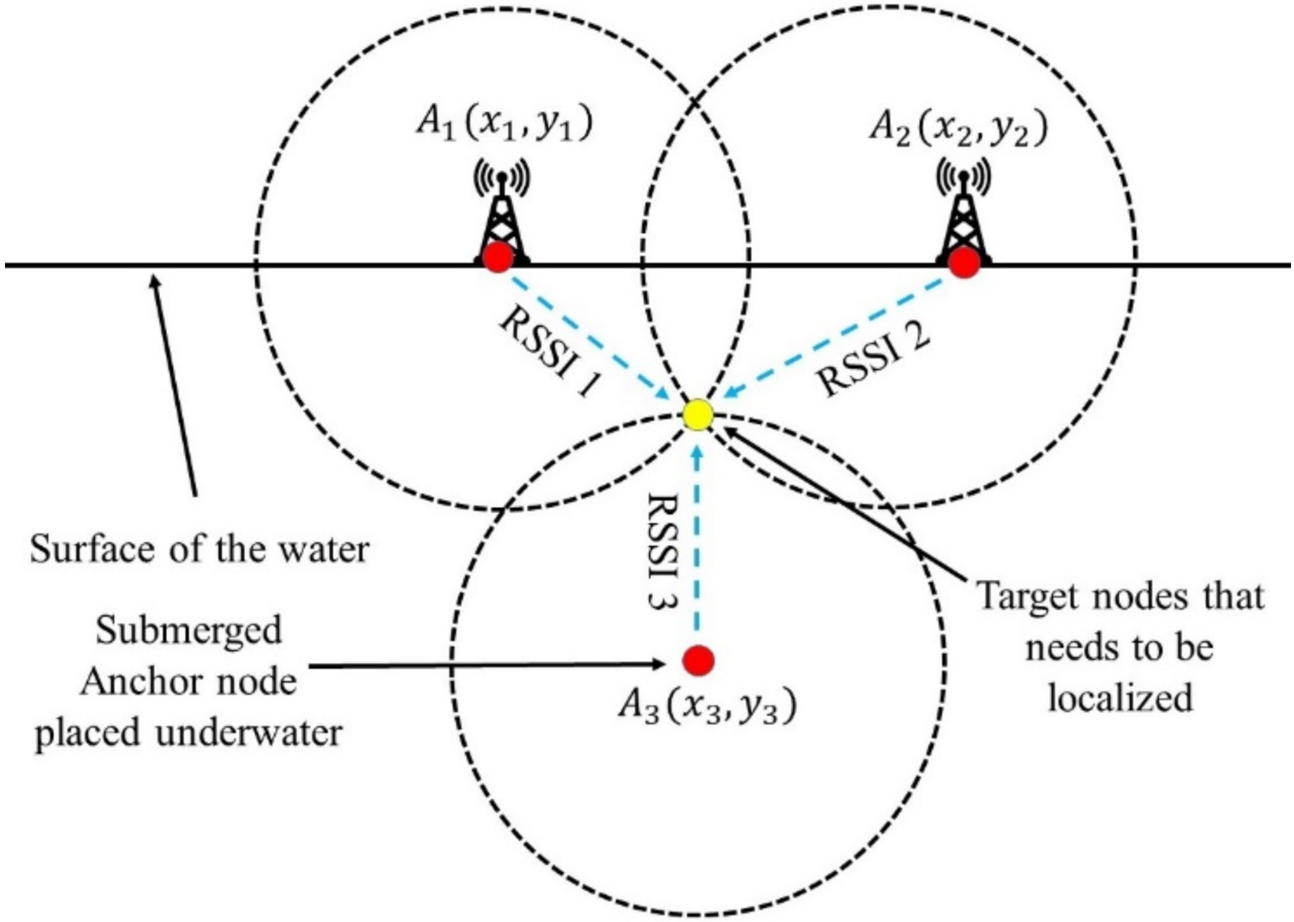

Fig. 7. A basic schematic diagram of RSSI based localization of node in UWSNs.

S.no	Localization Technique	Description	Possible media of communication	Reason for possible media	References
1	AOA	Requires a linear array of receiver nodes	Acoustics ✓ Visible light ✓ Magneto Inductive ☒	Acoustics and Visible light can be used, but no MI because Magnetic signals lacks the time dimension	27–29
2	TOA	Requires a clock to measure the time for successful communication	Acoustics ✓ Visible light ✓ Magneto Inductive ☒	Acoustics and Visible light can be used, but no MI because Magnetic signals lacks the time dimension	29–32
3	TDOA	Calculates the difference between time taken by two distinct successful communication	Acoustics ✓ Visible light ✓ Magneto Inductive ☒	Acoustics and Visible light can be used, but no MI because Magnetic signals lacks the time dimension	29,33,34
4	RSSI	Measure the strength of the signal in decibel for precise acknowledgement	Acoustics ✓ Visible light ✓ Magneto Inductive ✓	Acoustics and Visible light can be used and also MI, Because Magnetic signals can be perceived at a distance that's why supports RSSI	35–37

Table 1. Possible media's of communication for each range based localization scheme in UWSNs.

The centroid based localization technique is a range free strategy often employed in UWSNs to approximate the locations of unknown nodes. This method involves anchor nodes with predetermined coordinates broadcasting their positions after being verified through a specific network validation mechanism. An unknown node calculates its location by determining the geometric center, or centroid, of the anchor nodes within its communication range[41]. This technique is simple and avoids the need for precise distance or angle measurements, making it well suited for underwater environments where range based methods face limitations such as signal attenuation and synchronization issues. The accuracy of the centroid based approach depends on factors like the density and arrangement of anchor nodes, as well as environmental conditions that might affect communication[42]. Although it offers less precision compared to range based techniques, the centroid based method is energy efficient, computationally simple, and ideal for scenarios where approximate localization is

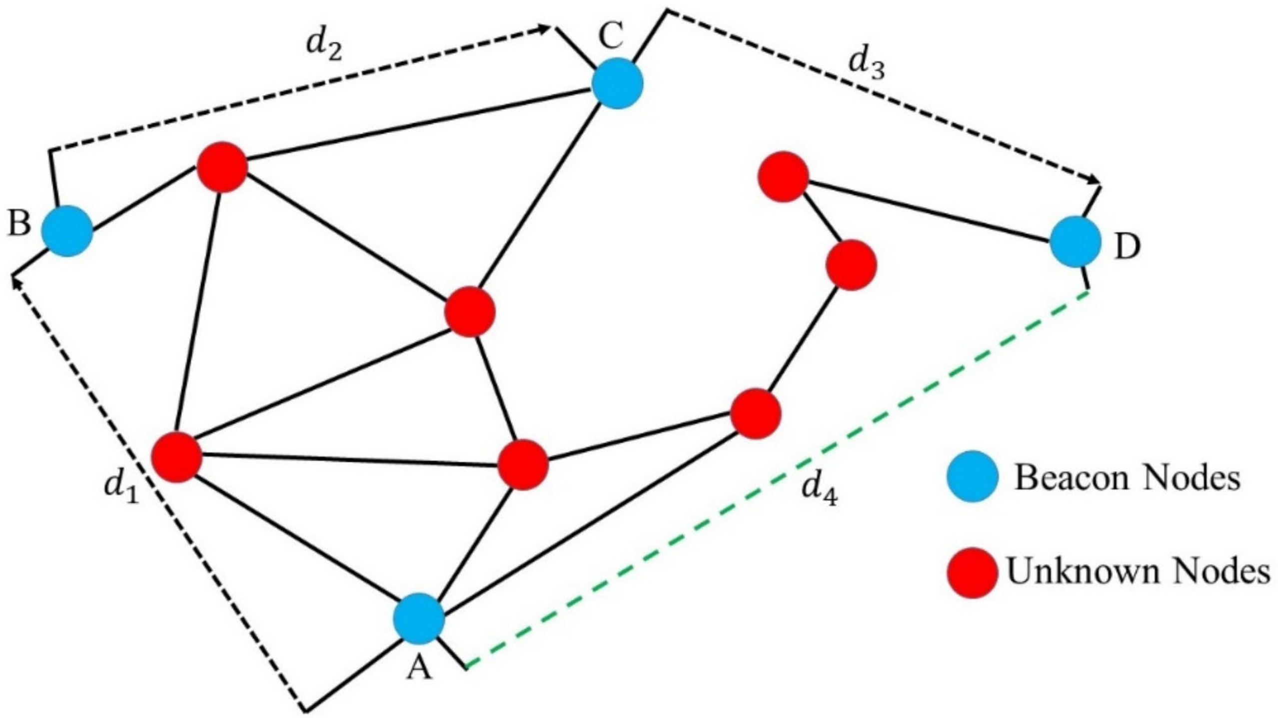

Fig. 8. A basic schematic diagram of DV-HoP localization algorithm for UWSNs.

adequate. Figure 9 provides a detailed representation of the centroid range free localization algorithm, illustrating its underlying concept. In this figure d_a, $d_b$and d_c denotes the communication ranges of anchor nodes A, B, and C, respectively. The overlapping communication areas of these anchor nodes create intersection points labeled as D, E, and F. These intersection points form the basis of the centroid localization algorithm, serving as reference points for estimating the position of an unknown node. The algorithm determines the geometric center, or centroid, of these anchor nodes within the overlapping regions to approximate the unknown node's location. This approach highlights the fundamental principle of using communication coverage and intersection points to achieve localization in UWSNs, offering a straightforward yet effective solution that does not require precise range measurements.

c. Approximate Point in Triangulation (APIT).

The approximate point in triangulation (APIT) technique is a range free localization method widely used in UWSNs to estimate the locations of unknown nodes. This method partitions the underwater network into triangular regions formed by anchor nodes with predefined coordinates. An unknown node identifies its location by determining which triangular region it belongs to, based on signal coverage information[43]. The node evaluates its position by analyzing whether it is within or outside the triangular zones created by various combinations of anchor nodes. This approach utilizes simple signal strength comparisons, eliminating the need for precise distance measurements or complex computational processes. Although the APIT method is straightforward and bypasses issues such as signal attenuation and synchronization problems prevalent in underwater environments, its accuracy largely depends on the distribution and density of anchor nodes[44]. It is especially suitable for scenarios where approximate localization estimation is enough, and energy efficiency is a key consideration. Figure 10 presents a fundamental scenario of the APIT method, showcasing the use of more than three anchor nodes to achieve range free localization of a sensor node. If a sensor node lies within these overlapping communication regions, than the APIT algorithm leverages the signal coverage from multiple anchor nodes to determine the node's approximate location. This scenario highlights the critical role of anchor nodes communication ranges in facilitating localization within UWSNs, emphasizing the method's reliance on signal coverage rather than precise distance measurements or complex calculations.

Mobile anchors

Mobile anchor based localization algorithms for underwater communication utilize anchor nodes that move continuously within the network based on the specific requirements of the application or task, rather than staying stationary. These mobile anchors periodically share their location data with nearby sensor nodes, enabling the sensors to determine their positions[45]. The mobility of these anchors offers key advantages, such as overcoming the constraints of fixed anchor placement and increasing the coverage area for more accurate positioning. By frequently updating their locations, mobile anchors provide sensor nodes with more timely and precise localization information. However, this approach introduces challenges, including the need for precise tracking of anchor movements and the complexity of coordinating the moving nodes[46]. Nevertheless, these algorithms prove highly effective in dynamic underwater environments where stationary anchors may fall short

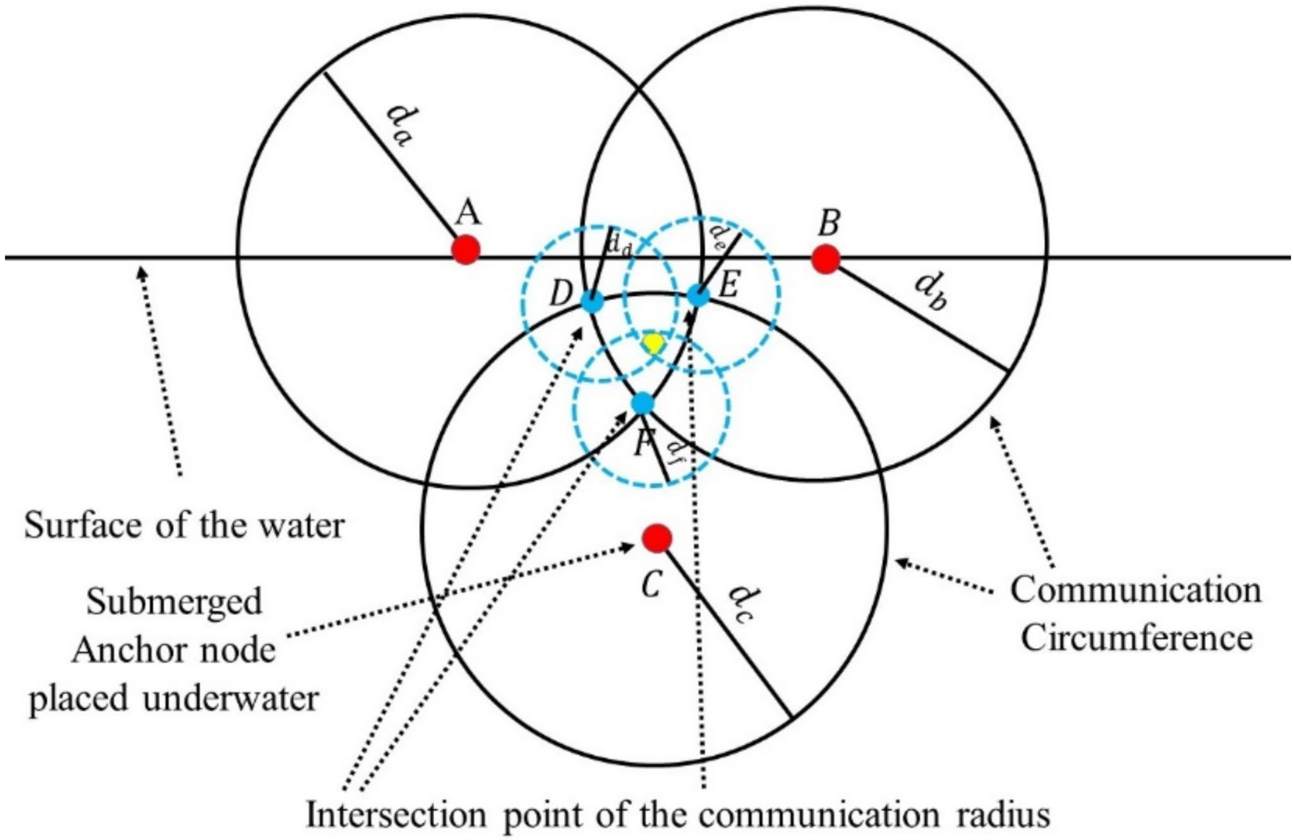

Fig. 9. A schematic diagram elaborating the concept of Centroid Base localization algorithm for UWSNs.

in providing adequate coverage or reliability. The basic types of the localization of nodes with mobile anchor nodes will be discussed briefly in the coming subsections.

Individual mobility In mobile anchor based localization algorithms for underwater communication, individual mobility refers to the autonomous movement of anchor nodes within the network, designed to enhance coverage and improve localization accuracy. Unlike group or coordinated mobility, where anchors follow fixed routes or patterns, individually mobile anchors can dynamically adjust their movements based on environmental factors, network structure, or application requirements[47]. This flexibility enables them to efficiently navigate around obstacles or cover areas with sparse sensor node distribution in dynamic underwater settings. However, implementing this approach requires advanced control strategies to ensure effective movement patterns that maintain localization accuracy, reduce energy usage, and prevent node interference[48]. This method is particularly advantageous in situations where stationary anchors are inadequate or fail to provide sufficient network coverage.

Group mobility In mobile anchor based localization algorithms for underwater communication, group mobility involves the synchronized movement of multiple anchor nodes along the predefined paths and with specific formations. This strategy provides organized coverage of the underwater area, enhancing the efficiency of sensor node localization while minimizing the risk of overlapping paths or unaddressed regions[49]. The synchronized group mobility of anchors ensures consistent communication and improves localization accuracy. This coordination is particularly useful when large scale network coverage is needed or precise positioning is critical. However, managing group mobility requires reliable communication between the anchors and effective algorithms for processing the real time information to preserve formation integrity, reduce energy usage, and adjust to environmental changes or obstacles[50].

Anchor free localization algorithms

Anchor free localization algorithms for underwater communication aim to determine the positions of sensor nodes without the dependence on fixed anchor nodes. Instead, these algorithms typically rely on the relative positioning of data, such as distances or angles between adjacent nodes, to estimate the locations of the sensor nodes within the network. The process is structured around three phases and that are, (i) network bootstrapping, (ii) local position determination, and (iii) global localization[51]. By utilizing communication data between nodes, anchor free approaches overcome the limitations of anchor based methods, such as the need for anchor placement and potential anchor failure. These algorithms are particularly advantageous in dynamic

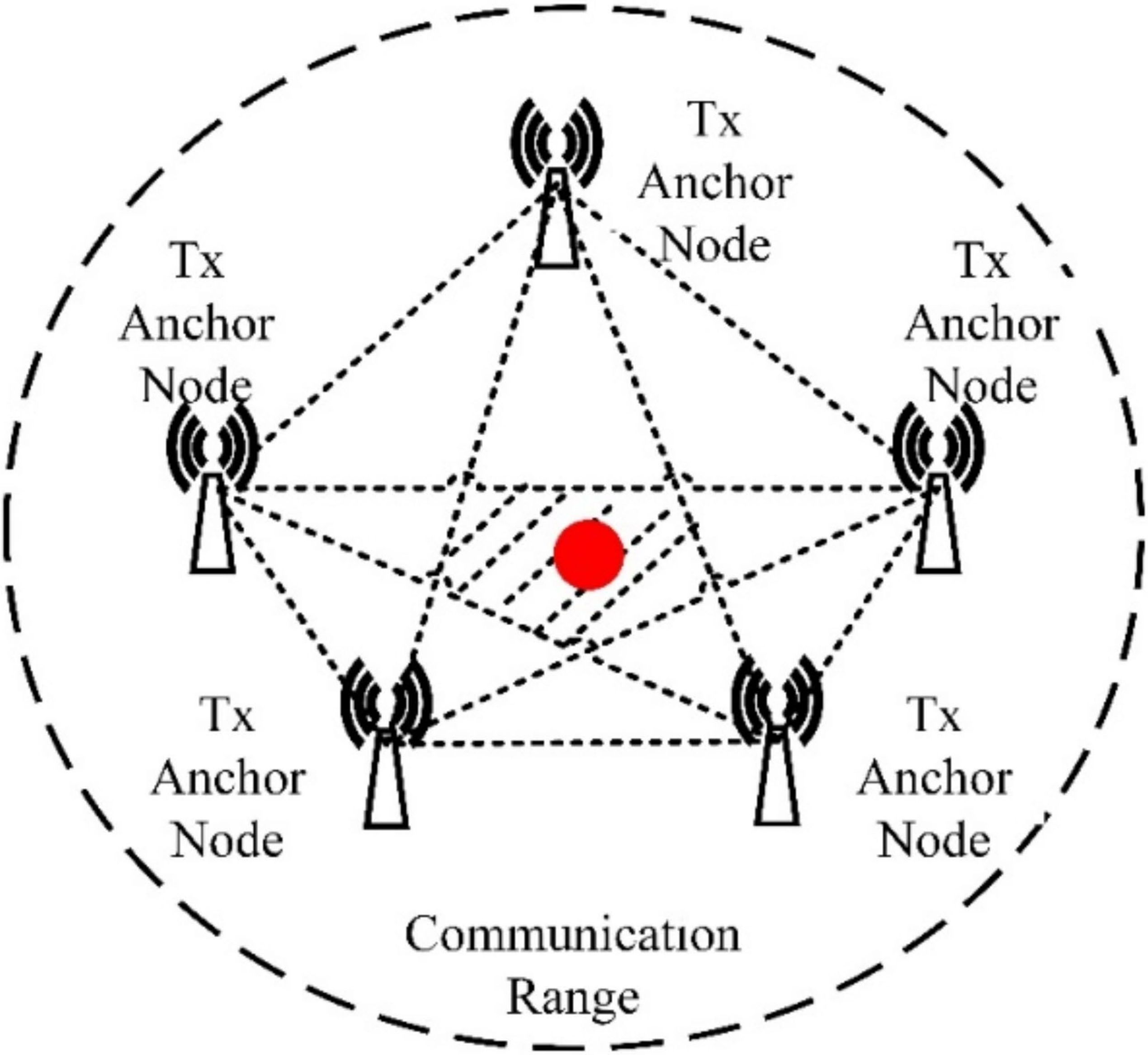

Fig. 10. A schematic diagram for APIT.

environments where deploying or maintaining anchors is challenging. However, anchor free localization may require more complex algorithms and can be impacted by measurement errors or noise between nodes, which could affect position accuracy[52]. Despite these challenges, anchor free techniques offers a promising solution for large scale, adaptable, and scalable UWSNs. The two basic types of the anchor free node localization mechanism are briefly discussed as a subsection in this section.

Relative positioning

Relative positioning in anchor free localization algorithms for underwater communication involves estimating the positions of sensor nodes by measuring their relative distances or angles to neighboring nodes, without the need for fixed anchor nodes. Each sensor node calculates its position by measuring the distance or angle to nearby nodes through communication signals or other sensing techniques[53]. These measurements create a network of relative positions, enabling nodes to determine their locations in relation to one another. This method is particularly advantageous in dynamic underwater environments where anchor deployment may be difficult or unfeasible. However, the accuracy of relative positioning can be affected by factors such as signal loss, environmental variables, and measurement inaccuracies, which may introduce uncertainty into the localization process[54]. Despite these challenges, relative positioning is crucial for achieving scalable and flexible localization in UWSNs.

Self-organizing networks
Self-organizing networks in anchor free localization algorithms for underwater communication are composed of sensor nodes that independently determine their positions and manage communication without the need for central control or fixed anchor nodes. In these networks, each node works with neighboring nodes to calculate its position using relative positioning methods like measuring distances or angles[55]. The nodes share positional information with each other, allowing the network to gradually build a map of relative locations. These self-organizing networks are particularly effective in underwater environments, where deploying traditional anchor based solutions is difficult due to factors like mobility, environmental changes, and deployment challenges. The networks can adapt to shifts in the environment and changes in network structure, offering flexibility and scalability. However, they may encounter challenges concerning position accuracy, network stability, and resource management in dynamic conditions[56]. Despite these challenges, self-organizing networks provide a promising solution for efficient and decentralized localization in UWSNs.

In Table 2, we have carefully outlined the key details and nuanced aspects of the primary localization techniques. By highlighting these subtle yet significant points, we aim to provide a clearer understanding of the core principles and intricacies associated with each localization approach.

Localization challenges in UWSNs
Node localization in UWSNs presents a list of challenges due to the unique and harsh conditions of the underwater environment. The slow speed at which acoustic signals propagate introduces significant delays, making accurate localization a complex task. Additionally, the underwater medium exacerbates these difficulties with multipath effects, where signals reflect off surfaces/obstacles, and signal attenuation, which diminishes the strength of transmitted signals. Also the environmental factors, such as varying water currents, salinity, and temperature, further complicates signal behavior. The three dimensional nature of underwater space adds another layer of complexity to localization algorithms, especially for mobile nodes. Moreover, limited energy availability, restricted bandwidth, sparse deployment of nodes, and synchronization issues contribute to the challenges. Addressing these obstacles requires the design of robust, efficient, and adaptive localization methods specifically suited for underwater environments. Furthering this section, we will encapsulate the challenges in three major categories and that are, (i) Algorithmic challenges, (ii) Technical challenges, (iii) Environmental challenges. Figure 11 presents a block flow diagram designed to comprehensively capture the various challenges associated with the process of localization in UWSNs. The diagram aims to encapsulate and illustrate the broad spectrum of difficulties that arises when implementing localization in such unique and complex environments. By presenting these challenges in a structured visual format, it provides readers with a clear and detailed understanding of the multifaceted issues that must be addressed to achieve efficient and reliable localization in UWSNs.

Algorithmic challenges
The process of localizing nodes in UWSNs presents several algorithmic challenges, each contributing to the complexity of accurately determining node's position in such environments.

Effects of nonlinear propagation
Nonlinear propagation effects significantly impact the localization of nodes in UWSNs. Acoustic signals, which are commonly used for communication and distance measurement in underwater environments, experience changes in speed and behavior due to varying environmental factors such as water temperature, salinity, and pressure[63]. These factors introduce nonlinearities in signal propagation, making it difficult to accurately model and predict the signal's travel time, which is crucial for precise localization. As a result, traditional linear models that are used for node positioning in TWSNs often fails to provide reliable results in UWSNs[64]. Localization algorithms must, therefore, be adapted to account for these nonlinear effects, requiring more sophisticated models and techniques that can dynamically adjust to the fluctuating underwater conditions. Addressing these challenges is vital for improving the accuracy and robustness of localization methods in UWSNs.

Precision and accuracy
Precision and accuracy are essential components in the process of localizing nodes within UWSNs. Precision refers to the extent to which localization results are consistent or repeatable. Specifically, it describes how closely the position measurements of the same node is, when the node is localized multiple times under the same

S.No	Localization Techniques	Key Features	Accuracy	Energy Efficiency	Scalability	Challenges	References
1	Range based	Uses angle and distance estimations	α	β	δ	Sensitive to environmental noise	7,57
2	Range free	Relies on hope count connectivity	β	α	α	Limited accuracy for large scale networks	10,58
3	Hybrid	Integrates range-based and range-free localization techniques	α	β	β	Having high cost of implementation	7,18
4	ML based	Utilizes ML algorithms	α	α	α	Requires large data sets and High computational power	59,60
5	DL based	Uses DL techniques	ϒ	β	α	Prone to overfitting	61,62

Table 2. Encapsulating the aanalysis of major localization techniques for UWSNs where α represents high, β is for moderate, δ is for low, and ϒ is for very high.

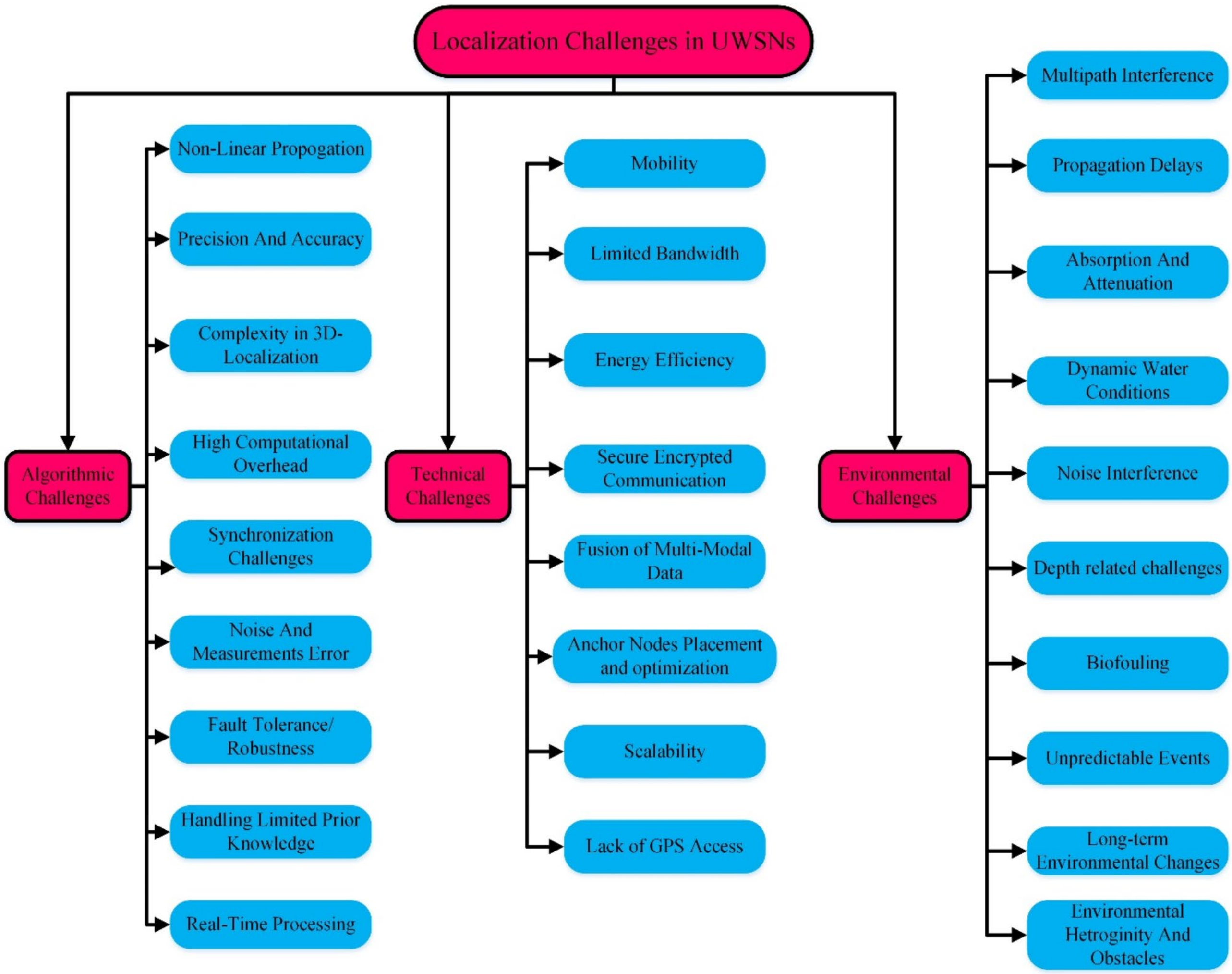

Fig. 11. A flow diagram encapsulating the challenges faced during localization of nodes in UWSNs.

environmental conditions[65]. High precision means that the same localization results will be obtained repeatedly, regardless of the exact true position. In contrast, accuracy is about how close the estimated position of a node is to its true or actual location in the physical space[66]. In other words, accuracy measures the correctness of the localization estimate, ensuring the node's position is as close as possible to its real world location. Both precision and accuracy are critical in ensuring reliable and effective node localization in UWSNs, yet achieving high levels of both is challenging due to the complex environmental factors, such as signal interference, propagation delays, and varying underwater conditions, that impact the performance of localization systems.

Complexity in 3D localization
Three dimensional (3D) localization in UWSNs presents significant difficulties due to its inherent complexities. Unlike TWSNs, that primarily utilize two dimensional (2D) positioning, UWSNs must consider the depth dimension too, which greatly increases computational and algorithmic challenges. The process is further complicated by issues such as irregular node distribution, the constant movement of nodes influenced by water currents, and variations in environmental factors like pressure and temperature etc. Additionally, the unique characteristics of underwater acoustic signals, including their slower propagation speed and sensitivity to multipath effects, makes achieving the accurate 3D localization particularly demanding. Precise depth estimation and synchronization among nodes are further hindered by the lack of line of sight (LoS) in the dynamic nature of the underwater environment. Addressing these challenges requires the development of sophisticated algorithms that can efficiently manage 3D spatial computations, while adapting to the unique constraints of UWSNs[67].

High computational overhead
High computational overhead is a significant obstacle in the localization of nodes within UWSNs. Many algorithms used for localization, especially those involving iterative calculations, advanced optimization strategies, or 3D positioning, demand substantial computational power. This poses a challenge for sensor nodes in UWSNs, which are inherently limited in processing capacity and energy resources. The underwater environment further amplifies this difficulty by requiring sophisticated algorithms to handle challenges such as signal attenuation,

multipath effects, and the dynamic variations in conditions like water currents and temperature. As the size of the network increases, the computational demands grow, resulting in longer processing times and greater energy consumption, which can reduce the network's operational longevity. Overcoming this issue necessitates the design of lightweight and efficient localization algorithms that reduce computational overhead while maintaining accuracy and reliability[68].

Synchronization challenges

Ensuring synchronization is a major challenge in the localization of nodes within UWSNs, primarily due to the distinct characteristics of the underwater environment. Methods like TOA and TDOA rely on precise time synchronization between sensor nodes and reference points[69]. However, the slow propagation speed of acoustic signals, along with delays caused by processing and environmental factors, makes maintaining accurate synchronization particularly challenging. Additional complications arise from signal attenuation, multipath interference, and the dynamic underwater conditions, such as fluctuating currents and temperature changes, which further affect timing accuracy. The limited communication bandwidth and high energy requirements of synchronization protocols exacerbate the difficulty, especially for energy constrained sensor nodes. Overcoming these obstacles requires the development of advanced and energy efficient synchronization algorithms that are designed specifically for the underwater environment to enable reliable and accurate localization[70].

Noise and measurement errors

Noise and measurement errors poses significant challenges to node localization in UWSNs, largely due to the harsh and unpredictable nature of the underwater environment. Acoustic signals, being the primary medium for communication and localization, are highly vulnerable to interference from noise created of natural factors such as marine organisms, water currents, and turbulence, as well as human activities like shipping and underwater industrial operations. These disturbances act as a source of noise and can distort critical signal parameters, such as TOA and RSSI, leading to inaccuracies in position estimation[71]. Additionally, environmental factors, including fluctuations in salinity, temperature, and pressure, further contributes to measurement errors by affecting signal propagation. The combined effects of noise and inaccuracies creates significant hurdles in designing localization algorithms that can ensure both precision and reliability. Implementing robust error handling mechanisms and employing advanced filtering techniques are crucial to mitigating the impact of these challenges in achieving reliable localization estimations in underwater networks[72].

Fault tolerance and robustness

Fault tolerance and robustness are crucial in the localization of nodes within UWSNs, owing to the dynamic and unpredictable nature of the underwater environment. Variables such as shifting currents, pressure changes, and temperature fluctuations can disrupt communication, cause node malfunctions, or uneven result in node losses. Furthermore, the limited energy capacity of underwater sensor nodes increases the risk of failures, adding to the complexity of localization efforts[73]. To address these challenges, effective localization algorithms must ensure accurate positioning by employing redundancy, error correction techniques, and adaptive mechanisms to handle missing data or faulty nodes. Fault tolerance allows the network to operate reliably despite failures, while robustness ensures consistent performance under varying environmental conditions. Together, these attributes are critical for ensuring the resilience and efficiency of underwater localization systems[74].

Handling limited prior knowledge

Addressing limited prior knowledge is a considerable challenge in localizing nodes within UWSNs, as the underwater environment seldom provides adequate details about node's location, environmental factors, or network topology prior to deployment. In contrast to TWSNs, which leverage from the established reference points and detailed mapping, UWSNs operate in vast, dynamic, and largely unexplored underwater domains. This scarcity of initial data complicates the initialization of localization algorithms, requiring them to work with incomplete or uncertain inputs to estimate node positions[75]. Furthermore, issues such as uneven node distribution, varying water conditions, and the lack of reliable infrastructure adds to the complexity. To overcome these limitations, effective localization strategies must employ adaptive approaches, including iterative optimization, self-organizing techniques, and ML models, to enhance the accuracy and reliability in position estimation. Tackling these challenges can contribute to the development of robust underwater localization systems[76].

Real time processing

Processing time is a major concern in UWSNs due to the dynamic nature of underwater environments and the pressing need for real time localization. Efficient network functionality depends on algorithms that can deliver results within tight time constraints. The system must minimize delays and promptly provide localization outputs to accommodate environmental changes or adjustments in network configurations. Real time localization is particularly essential for applications such as underwater vehicle navigation, where delayed position updates can lead to navigational errors and that may compromise mission objectives[77]. However, achieving this is challenging, as localization algorithms demand significant computational power while facing constraints like limited bandwidth and high latency, which is inherent to underwater communication. Delays in processing can undermine the network's reliability and effectiveness. Therefore, robust real time localization systems must employ optimized computational strategies and adaptive techniques to ensure accurate and timely information delivery[78].

Technical challenges

A brief discussion on various technical challenges associated with the localization of nodes in UWSNs will be provided in this section.

Mobility

The mobility of nodes in UWSNs presents a significant obstacles to effective localization. Unlike the nodes in TWSNs, underwater nodes are subject to unpredictable shifts in position due to ocean currents, tides, and waves. This continuous movement undermines the reliability of conventional localization techniques and necessitates for the frequent recalibration, which can be both energy intensive and computationally demanding. Moreover, node mobility introduces challenges such as time varying propagation delays and Doppler effects in acoustic signals, reducing the accuracy of distance and angle estimations[79]. Synchronizing mobile nodes adds another layer of complexity, often leading to greater localization errors that in turn diminishes the network's performance. To address this challenge, energy efficient and robust adaptive localization algorithms tailored to dynamic underwater environments are essential[80].

Limited bandwidth

Limited bandwidth presents a significant challenge in the localization of nodes in UWSNs. Acoustic communication, as being the primary method for transmitting data underwater, provides much lower bandwidth compared to terrestrial radio waves. This limitation constrains the volume of data that can be shared, which ultimately results in complicating the exchange of crucial localization information such as distance measurements, control signals, and node positions. Additionally, the low bandwidth increases transmission delays, making synchronization for accurate localization more challenging[15]. The restricted bandwidth also heightens the risk of interference and packet loss, negatively impacting the effectiveness and precision of localization methods. To overcome this challenge, it is essential to implement efficient strategies such as data compression, aggregation, and optimized communication protocols to maximize bandwidth usage while ensuring localization accuracy[81].

Limited communication range

The limited communication range poses a significant challenge in localizing nodes within UWSNs. Underwater acoustic signals are likely to have a high attenuation factor, resulting in a short effective communication range, particularly in deep or murky environments. This limitation reduces the number of neighboring nodes that can exchange localization information, negatively impacting position accuracy[82]. Expanding coverage often requires multi hop communication, which introduces additional delays, increases energy consumption, and amplifies the risk of cumulative errors in localization data. Frequent short distance transmissions can also cause network congestion and compromise the performance of localization algorithms. Overcoming these challenges necessitates innovative solutions, such as incorporating relay nodes or optimizing communication protocols, to improve the coverage while maintaining energy efficiency and accuracy[83].

Energy efficiency

Energy efficiency is a crucial challenge in the localization of nodes within UWSNs due to the restricted energy reserves available to power underwater sensor nodes. Localization activities often necessitate frequent data exchanges between sensor nodes and anchor nodes, which can quickly deplete the limited battery life of these devices[84]. Furthermore, the high energy consumption associated with underwater acoustic communication compounds the problem, emphasizing the need for energy conservation in UWSNs operations. Additional factors, such as ensuring accurate synchronization, executing iterative computations in localization algorithms, and managing challenges like multipath interference and signal attenuation, further increase energy demands. The harsh underwater environments, combined with the difficulty of recharging or replacing batteries, make energy efficient approaches indispensable. Designing localization methods that minimize communication requirements, lower computational overhead, and enhancing the network's operational lifespan is critical to sustaining the functionality of UWSNs over extended periods of time[85].

Secure encrypted communication

Ensuring encrypted communication for node localization in UWSNs comes with several challenges. The limited energy and computational capabilities of underwater nodes make it difficult to implement strong encryption methods without compromising performance. Furthermore, the high latency and low bandwidth of acoustic communication increase the encryption overhead, reducing overall efficiency[86]. The dynamic underwater environment, with its mobile nodes and frequent topology changes, adds complexity to secure key management and data exchange. Additionally, the susceptibility of underwater networks to interception and spoofing, makes safeguarding localization data crucial, as compromised information can lead to errors in node positioning and network disruptions. Addressing these challenges requires the development of lightweight and energy efficient encryption solutions specifically designed for the unique demands of UWSNs[87].

Fusion of multi-modal data

The integration of multi modal data is crucial for enhancing localization accuracy in UWSNs by leveraging information from various sources, including acoustic signals, VLC, MI signals, and inertial navigation systems. Each modality offers unique strengths while addressing the limitations of others. Acoustic signals provide effective long range communication but are susceptible to noise and multipath effects. VLC delivers high accuracy in clear water, but is constrained by its limited range, whereas MI communication remains unaffected by organic materials present between the LoS, offering reliability in complex underwater environments, though it is limited to short distances[88]. Combining data from these diverse modalities enhances robustness and minimizes individual shortcomings in localization. However, challenges such as achieving precise synchronization, harmonizing data resolutions, and managing the computational complexity of multi modal processing must be addressed. Advanced approaches, including ML based fusion techniques and probabilistic models canplay a critical role in efficiently integrating multi modal data, enabling improved localization performance in the demanding underwater environment[89].

Anchor node placement and optimization
The placement and optimization of anchor nodes are critical challenges in localizing nodes within UWSNs. Anchor nodes act as crucial reference points for pinpointing the positions of other nodes, and their deployment has a substantial impact on localization accuracy and reliability. However, the 3D underwater environment complicates this task, requiring careful consideration of factors such as depth, the mobility of nodes, and uneven network distribution. Additionally, environmental influences like currents, salinity and temperature changes, affect signal propagation, making it difficult to ensure consistent connectivity between anchor and sensor nodes[90]. Sparse deployment of anchor nodes to conserve resources can lead to coverage gaps, diminishing localization accuracy. So striking a balance between the number of anchor nodes, deployment costs, and energy efficiency is vital. Advanced optimization strategies and innovative algorithms are essential for determining the optimal placement of anchor nodes to achieve reliable and precise localization in underwater networks[91].

Scalability issues
Scalability is a key challenge in localizing nodes within UWSNs, particularly as the network expands in size, both in terms of the number of nodes and the area it covers. Adding more nodes to complete specific tasks increases the difficulty of achieving accurate localization, largely due to the rising communication overhead and the need for efficient coordination mechanism among nodes. This highlights the necessity of developing advanced algorithms capable of managing large scale networks while maintaining reliability and precision in localization[92]. In extensive networks, reliance on anchor nodes or reference points can become problematic, as their signals may not consistently reach all nodes due to interference in underwater environments. Additionally, algorithms tailored for smaller networks often encounter performance bottlenecks when applied to larger systems, as they require greater computational resources and energy, complicating the localization process further. These challenges can result in delays, decreased localization accuracy, and heightened resource consumption. Consequently, designing scalable localization solutions that ensure efficiency, accuracy and energy optimization is essential for the successful implementation and operation of UWSNs in practical scenarios[5].

Lack of GPS access
The absence of GPS access presents a significant obstacle to localizing nodes in UWSNs. Since GPS signals cannot penetrate water, underwater nodes cannot depend on satellite based systems for determining their positions. Instead, they rely on alternative methods like acoustic, VLC, or MI signals, which are often less precise and more susceptible to errors. Additionally, the lack of GPS increases the difficulty of achieving accurate localization, particularly in dynamic underwater environments with mobile nodes and fluctuating conditions[16]. Using surface buoys or anchor nodes that are equipped with GPS, as reference points adds to deployment and maintenance costs while introducing potential vulnerabilities. Addressing this challenge requires the development of advanced localization techniques, such as multi hop communication, enhanced signal processing, or hybrid systems that integrate multiple technologies to function effectively without GPS[93].

Table 3 presents a variety of performance metrics of localization techniques, accompanied by detailed and nuanced information designed to enhance the reader's comprehension. By including these critical details, the table aims to simplify the evaluation process and provide a clearer, more intuitive understanding.

Environmental challenges
A brief discussion on various environmental challenges associated with the localization of nodes in UWSNs will be provided in this section.

Multipath interference handling
Multipath interference presents a significant challenge in localizing nodes within UWSNs. Underwater acoustic signals frequently reflect off surfaces such as the seabed, water surface, and submerged structures, creating

S.No	Metric	Description	Typical Values	Impact on Localization	Considerations	References
1	Localization Error	The difference between actual and estimated readings	1 to 10 m (varies by technique)	Directly affects accuracy	Lower is better, varies by environment	7,37
2	Latency	Time delay in communication	10 to 100 m/s (varies by technique)	Affects real-time application	Lower is better, critical for real-time	94,95
3	Energy Consumption	The energy required for the localization process	10 to 1000 J (varies by technique)	Affects network lifespan	Lower is better, varies by node type	96,97
4	Scalability	Ability to maintain performance with an increasing number of nodes	10 to 100 nodes (varies by technique)	Affects network size	Higher is better, depending on the algorithm	98,99
5	Robustness	Resilience to environmental changes and node failures	High/Moderate/Low	Affects reliability	Higher is better, critical for harsh environments	100,101

Table 3. Analysis of different performance matrices used for localization in UWSNs.

multiple signal paths between the transmitter and receiver. These reflected signals overlap with the direct path, introducing errors in localization methods such as TOA and RSS measurements[102]. The inherently unpredictable and complex nature of underwater multipath interference makes it difficult to differentiate the direct signal from its reflections, leading to inaccuracies in position estimations[103]. Furthermore, the dynamic underwater environment, influenced by factors like water currents and temperature changes, adds to the complexity by continuously altering signal propagation patterns. So in order to overcome the multipath interference, it requires advanced algorithms and effective signal processing techniques that are designed to minimize its impact and ensure accurate and reliable localization results[104]. Figure 12 presents a schematic diagram created to illustrate and elaborate on the concept of multipath interference and its significant impact on communication within UWSNs. The diagram visually highlights how multipath interference arises and demonstrates its cascading effects on the communication process. These disruptions, in turn, influence the accuracy and reliability of node localization within UWSNs. By providing this visual representation, we aim to deepen the reader's understanding of the phenomenon and its critical role in shaping the performance and challenges of underwater localization systems.

Propagation delays

Propagation delays presents a major challenge in localizing nodes in UWSNs. Acoustic signals, being the primary means of underwater communication, travel much slower than EM waves in air, causing significant delays. These delays are further influenced by environmental conditions like water temperature, salinity, and depth, which affect the speed of sound. This variability complicates distance measurement between nodes, as conventional time of flight (ToF) techniques rely on stable sound propagation speeds[105]. Additionally, propagation delays lead to synchronization difficulties, hindering the coordination of data exchange and localization calculations among nodes. The problem becomes even more pronounced in dynamic underwater environments with mobile nodes, resulting in increased localization errors. To address these issues, advanced algorithms are needed to account for variable delays and maintain precise synchronization despite these constraints[106].

Absorption and attenuation

Signal absorption and attenuation present significant challenges for node localization in UWSNs. Acoustic signals, as being the primary means of communication in underwater environments, lose considerable energy as they travel through water due to factors such as absorption and scattering. The severity of attenuation is influenced by variables like signal frequency, transmission distance, and environmental conditions, with higher frequencies experiencing greater energy loss over shorter distances[107]. This limits the communication range and compromises the precision of localization data. Additionally, variations in water properties, such as temperature, salinity, and pressure, further exacerbate signal degradation, leading to inconsistent distance measurements. To compensate for signal loss, higher transmission power or additional relay nodes are often required, increasing energy consumption and complicating network architecture. Addressing these challenges necessitates innovative solutions to reduce attenuation effects and ensure accurate, energy efficient localization in UWSNs[108].

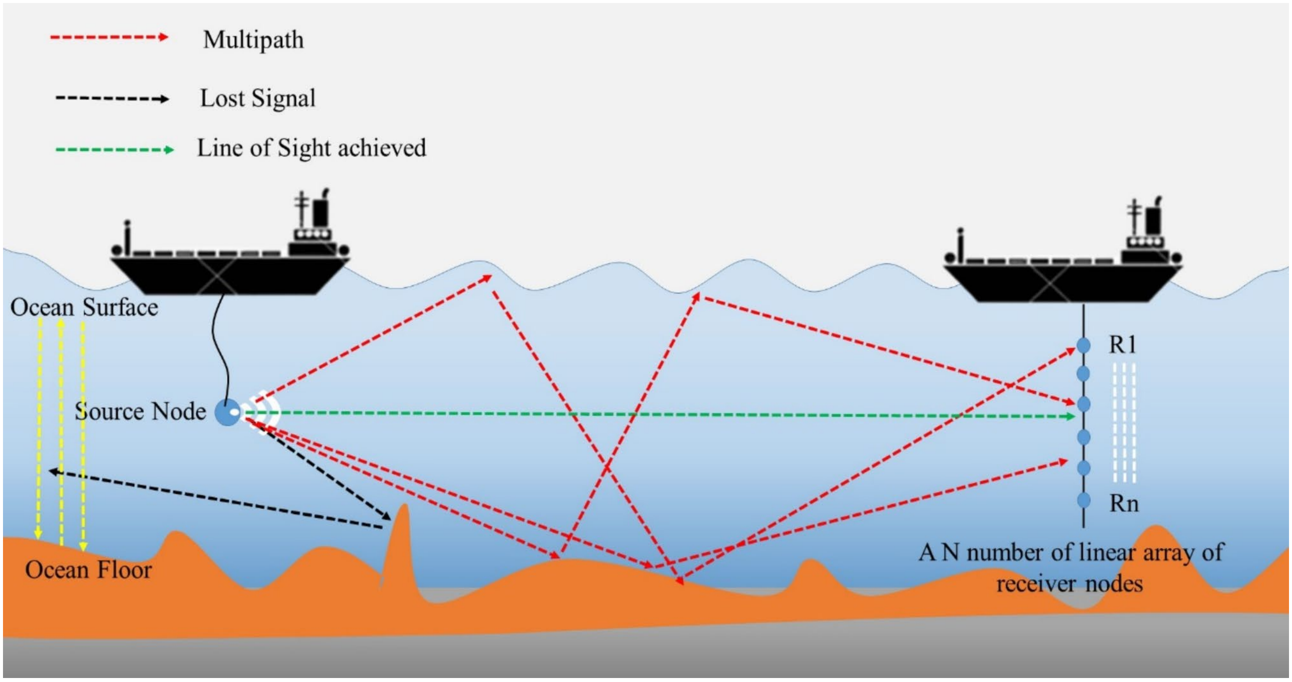

Fig. 12. Schematic diagram to elaborate the multipath scenario in UWSNs.

Dynamic water conditions
The ever changing nature of underwater environments also presents a major challenge to accurate localization in UWSNs. Factors like shifting currents, waves, tides, and temperature variations creates a dynamic environmental condition that impacts signal propagation and node stability. These fluctuations often cause nodes to drift from their initial positions, complicating the static or predictable placement assumptions relied upon by many localization algorithms[109]. Additionally, variations in water temperature, salinity, and pressure alter the speed of sound, leading to inaccuracies in ToF and range based localization methods. The unpredictability of underwater conditions also disrupts acoustic signal reliability, causing intermittent communication and potential data loss. To overcome these obstacles, adaptive localization strategies are essential, enabling systems to account for environmental variability and sustain accuracy in dynamic underwater scenarios[110].

Noise interference
Noise interference in underwater environments poses a substantial obstacle to node localization in UWSNs. Acoustic signal transmission is often disrupted by ambient noise from natural sources like marine life, ocean currents, and seismic events. Human induced noise from activities such as shipping, underwater construction, and sonar operations further compounds this issue, leading to a decline in signal quality[111]. This interference reduces the signal to noise ratio, making it challenging to accurately detect and interpret localization data. Fluctuating noise levels and overlapping frequencies can introduce errors in ToF and AOA measurements, which are critical for accurate node positioning. Overcoming these challenges requires the implementation of effective noise mitigation strategies, including advanced signal processing, adaptive filtering, and error correction techniques, to enhance localization reliability in noisy underwater conditions[112].

Depth related challenges
Depth related factors have a significant impact on the localization of nodes in UWSNs. Changes in depth affect water pressure, temperature, and salinity, which in turn influence the speed of sound and the precision of acoustic signal based localization methods[113]. Nodes at different depths may experience varying propagation delays, leading to discrepancies in range measurements and ToF calculations. Additionally, maintaining accurate depth information is challenging due to the movement of nodes and the dynamic underwater environment, including fluctuating currents and tides. These depth variations also complicate node synchronization and increase the risk of localization errors, especially in multi hop communication scenarios. To address these issues, depth aware localization algorithms that can adjust to environmental variations and integrate real time depth data are necessary to enhance localization estimation accuracy[114].

Environmental heterogeneity and obstacles
Environmental variability and physical barriers, including thermoclines, salinity gradients, and seafloor topography, create substantial challenges for node localization in UWSNs[115]. Irregular sound speed profiles caused by thermoclines and salinity gradients result in signal refraction and unpredictable propagation paths, diminishing the precision of distance and angle measurements. Furthermore, seafloor features and obstacles such as submerged rocks, dense vegetation, shipwrecks, and underwater structures can obstruct signal transmission through attenuation, scattering, or complete loss[116]. These issues not only reduce the reliability of localization algorithms but also increase energy consumption due to frequent retransmissions and the need for alternate routing. Addressing these challenges requires adaptive localization algorithms capable of accommodating environmental variability and implementing robust methods to minimize the effects of physical obstructions on signal propagation[117].

Biofouling
Biofouling is another factor that presents a significant obstacle to effective node localization in UWSNs. The accumulation of biological materials like algae, barnacles, and mussels on sensors and devices can severely compromise their functionality. This buildup often obstructs acoustic transducers, weakening signal clarity and strength, which in turn reduces the accuracy of localization methods[118]. Moreover, biofouling alters the physical and acoustic properties of nodes, such as their buoyancy and weight, potentially causing positional shifts and challenging the assumption of static deployment. In long term deployments, the severity of biofouling increases maintenance demands and decreases system reliability. Implementing anti biofouling measures, such as protective coatings, regular cleaning, or self-cleaning automated technologies, are essential to minimize these impacts and in turn ensures the precise and dependable localization estimation in UWSNs[119].

Unpredictable events
Unpredictable events, including natural disasters, sediment disturbances, and environmental changes, can have a significant impact on node localization in UWSNs. Fluctuations in water temperature, salinity, and currents due to these events can disrupt signal propagation, leading to inaccuracies in distance and angle calculations[58]. Additionally, natural disasters such as earthquakes or underwater volcanic eruptions can produce seismic waves or vibrations that interfere with acoustic signals, further complicating localization efforts. Sediment disturbances, such as shifting seabed's or underwater landslides, may obstruct signal transmission or cause damage to nodes. Human activities like underwater construction or shipping also contribute to unexpected noise or physical barriers, further diminishing signal quality. These unpredictable occurrences introduce variability and uncertainty in localization processes, making it difficult to maintain accurate node positions and posing challenges for developing reliable algorithms. Adaptive techniques are crucial to effectively tackle these dynamic issues and ensure accurate localization in such conditions[120].

S.No	Integration Technology	Description	Opportunities	Challenges	Example Applications
1	Internet of Underwater Things (IoUT)	Extends IoT to underwater environments	Global connectivity, real time data	High energy demand, security risks	Ocean monitoring, submarine cable networks
2	Satellite Communication	Provides connectivity between underwater nodes and surface	Global coverage, remote monitoring	High latency, signal attenuation	Disaster monitoring on surface
3	5G and Beyond	High speed, low latency communication for underwater networks	Enhanced data transfer, real time applications	Signal penetration, high energy consumption	Navigation with Autonomous underwater vehicles
4	Blockchain	Secure, decentralized data management in UWSNs	Enhanced security and transparency	High computational overhead, latency	Secure data transmission, decentralized monitoring
5	Edge Computing	Distributed processing at network edges to reduce latency	Low latency, real time processing	Limited processing power, energy constraints	Real time localization, anomaly detection

Table 4. Opportunities for integrating UWSNs with other technologies.

S.No	Water Condition	Impact on Signal Propagation	Preferred Localization Techniques	Challenges	Solutions	References
1	Shallow Waters	High reflection and refraction of communication signals	Anchor Based	Multipath interference	Advanced filtering, error correction	122,123
2	Deep Waters	Lower signal strength, higher propagation delays	Anchor based, Anchor free	Signal attenuation, increased latency	Power amplification, delay-tolerant protocols	7,124
3	Turbulent Waters	Rapid changes in signal propagation characteristics	Adaptive ML/DL-based techniques	Unstable signal paths, frequent recalibration	Real-time adaptation techniques	125,126
4	Coastal Areas	Variable salinity, and temperature gradients	Hybrid of Range Based and Range Free	Environmental noise, multipath, poor visibility	Environmental modeling, hybrid approaches	127,128
5	Arctic/Sub-Arctic Waters	Cold temperatures, ice interference	Hybrid of Anchor based and Anchor free	Battery power consumption, Harsh working environment	Energy efficient multi-modal sensing approaches	129,130

Table 5. Comparative analysis of UWSNs localization in different water conditions.

Long term environmental changes
Long term environmental changes, including climate change and rising sea levels, create significant obstacles for node localization in UWSNs. Over time, fluctuations in water temperature, salinity, and pressure can transform the underwater environment, impacting the speed of sound and diminishing the precision of acoustic signal based localization methods[121]. These changes can result in cumulative errors in distance and angle measurements, as many localization algorithms depend on fixed environmental parameters. Additionally, continuous shifts in currents, tides, and seafloor movements can cause node displacement, complicating the localization process[57]. To overcome these challenges, adaptive localization algorithms that considers the dynamic nature of environmental factors, including climate change and sea level rise, are crucial for ensuring the continued precision and reliability of node positioning in UWSNs.

After outlining the challenges that the localization process in UWSNs may encounter, we have also included Table 4 to highlight potential opportunities. These opportunities represent strategies or advancements that can be effectively integrated into UWSNs to address or mitigate the identified challenges, thereby improving the overall performance and reliability of the localization process.

Table 5 offers a detailed summary of the key knowledge regarding the localization of nodes in various water conditions across different regions of the world. This comprehensive overview aims to provide readers with a deeper and more specific understanding of the distinct challenges that can arise in different aquatic environments when dealing with node localization. Additionally, the table elaborates on the potential types of localization techniques suitable for each specific water condition, along with the technical rationality behind their selection and the challenges they may encounter in practical application.

Most recent advancements in UWSNs localization

This section explores recent advancements in the application of various localization techniques in UWSNs. To address the challenge of localizing a mobile node in UWSNs, a research group in[131] proposes a methodology that utilizes location with insufficient TOA measurement (LITM) and combined it with the data representing the departure of a beacon signal. Unlike traditional TDOA methods, this approach requires fewer measurements, effectively mitigating issues caused by the scarcity of anchor nodes, which ultimately affect the strength of the received signal. LITM algorithm basically incorporates sub algorithms for monitoring and estimating departure time of a beacon signal (DOBs) and localizing mobile nodes using a closed form solution. Theoretical analysis, simulations, and sea trials confirms that LITM significantly improves the accuracy of location estimates compared to existing localization methods. The study in[132] presents a sophisticated and accurate localization approach designed specifically for mobile anchor nodes in UWSNs. This framework addresses critical challenges, including malicious node intrusions, the dynamic movement of nodes, and variations in sound speed, all of which compromise network efficiency. To overcome these obstacles, the authors introduces an anchor node screening algorithm to ensure the reliability of localization data. By employing an unscented kalman filter (KF)[133], the method detects and compensates for transmission delays caused primarily by node mobility. Furthermore, it leverages a tailored model to convert coastal acoustic tomography inversions into real time sound velocity profiles. Precise range adjustments are then achieved through data derived from acoustic ray tracing. Field trials and simulations conducted in designated experimental reservoirs demonstrates, that the proposed technique significantly reduces localization errors while enhancing the likelihood of accurately locating mobile nodes.

The research presented in[134] delves into the intricacies and applications of UWSNs, with a particular focus on the pivotal role of localization algorithms in accurately identifying regions of interest where marine changes or phenomena manifests. The authors, through detailed simulations, elucidate that localization methodologies developed for TWSNs are largely inapplicable to UWSNs due to inherent environmental constraints. These include the attenuation of radio frequencies and the diminished efficacy of GPS systems, which are restricted to an accuracy of approximately fifteen meters in underwater environments[135]. The study, which serves as a comprehensive survey, meticulously examines numerous underwater localization techniques, systematically categorizing them into range based and range free methods[136]. It underscores the imperative use of acoustic signals for effective underwater communication, given their superior propagation characteristics in aquatic mediums. Leveraging the well-known NS2 simulator, the authors validate the performance enhancing attributes of the opted techniques, while simultaneously identifying areas necessitating further refinement. By providing a nuanced overview, the research equips readers with an in depth understanding of current advancements and challenges in underwater localization systems.

The authors of[137] propose an innovative localization technique that synergizes the red vulture optimization algorithm (RVOA) with TDOA to address the critical challenge of achieving precise node positioning in UWSNs. This advanced approach incorporates a mobility model capable of estimating node velocity and position over time, further optimizing through the use of distance measurements and a windowing mechanism. By significantly reducing errors and latency, the method enhances both the accuracy and dependability of node localization. This groundbreaking methodology marks a significant advancement in UWSNs localization technology, surpassing leading existing techniques such as movement prediction location (MPL), general availability of scalable localization scheme with mobility prediction (GA-SLMP), scalable localization scheme with mobility prediction (SLMP), and localization scheme for large scale UWSNs (LSLS). The aforementioned opted algorithm excels in the betterment of the critical parameters including energy efficiency, end to end delay, error reduction, and localization coverage, establishing itself as a superior alternative in the domain. The research outlined in[138] tackles critical challenges in achieving accurate underwater localization, focusing on factors such as stratification effects, anchor position uncertainties, and clock un-synchronization. The proposed method distinguishes itself by considering the influence of underwater gradients, particularly the sound speed profile (SSP), and addressing anchor location uncertainties through TDOA measurements under realistic environmental conditions. Unlike many traditional approaches that rely on oversimplified or impractical assumptions, this technique offers a pragmatic and dependable framework for underwater localization. The localization process begins with the target node transmitting its coordinates and timestamps to the surrounding anchor nodes. To refine the localization accuracy, Newton's method and iterative linearization techniques are employed, effectively enhancing the precision of the calculated positions. The performance of the proposed method is rigorously evaluated using the cramer rao lower bound (CRLB), a statistical measure for assessing estimation efficiency. Simulation results demonstrates that this approach achieves superior performance while also requiring significantly less computational time compared to existing methods.

The researchers in[139] presented a method for secure data sharing and positioning of underwater sensor nodes that utilizes a single beam sonar with a 30 degree beam width viewing angle, complemented by an innovative pan tilt holder. This method offers a cost effective alternative to multi band sonar systems, greatly reducing both their expense and processing load. It enables thorough coverage of the underwater environment by employing underwater servo motors to accurately scan the entire area. After localizing the nodes using sonar technology, a LoS underwater optical wireless communication (UOWC) connection is established for data transfer applications, achieving a data rate of 200 kbps. Pool based testing reveals that the channel model achieves a link length of 3.13 m with a power consumption of 1 W, reaching a data rate of 1Gbps, a Q factor of 6, and a bit error rate (BER) of 10^{9}. This research provides valuable insights into the efficiency of marine operations, particularly through key performance metrics such as BER and quality factor measurements. The study in[140] explores the weaknesses of current localization techniques in the context of network attacks while tackling the crucial challenge of accurate positioning in UWSNs. To defend against collaborative network attacks, the research introduces an innovative iterative localization algorithm that uses adaDelta gradient descent (AGD) to select the minimum gradient. This method enhances localization accuracy by systematically removing false data from interfering nodes. The effectiveness of the proposed approach is validated through simulations that mimic network threats. The results demonstrate a promising strategy for minimizing localization errors caused by compromised anchor nodes, thereby ensuring the stability and reliability of UWSN operations.

The study in[141] addresses the challenge of node localization using a robust multimodal mobile target approach, where acoustical communication serves as the medium. The proposed method, named robust multi model mobile target localization scheme (RMML), is founded on the base of CRLB knowledge. This algorithm is specifically designed to prioritize the selection of the most reliable localization references, ensuring improved accuracy in the results. After obtaining high quality references, the mobile target localization is refined further using an unscented KF to enhance the initial estimates. The algorithm also integrates a combined multipoint prediction approach and ray tracing technique to boost target state estimation accuracy, even when dealing with asynchronous reception of localization data and the stratification effect. To validate the performance of RMML, extensive simulations and experiments are conducted, confirming its effectiveness. The researchers in[142] proposed a novel algorithm for node localization of both static and dynamic UWSNs, known as the reward based distance vector hop localization (RDVHL) protocol. In this approach, the nodes are first grouped into multiple clusters. A reward measure is periodically assigned to each cluster to aid in the localization of the anchor nodes. Once the anchor nodes' positions are determined, they transmit their locations to the sensor nodes within the cluster. This precise localization enhances the speed of data transmission to the sink nodes. Additionally, the algorithm helps to reduce communication voids and minimize channel collisions. The protocol shows improvements in key performance metrics, including throughput, average latency, average accuracy, and energy consumption, compared to existing protocols used for similar purposes. The challenge of target localization in UWSNs when using inhomogeneous media, open environments, and unreliable communication, are discussed in[143]. The study introduces a consensus fusion based localization approach that mainly comprising of two phases. The first phase leverages from the ToF and the RSSI data, where a ray compensation method is used to mitigate localization biasing. The second phase utilizes a consensus fusion estimator to defend against compromised nodes submitting falsified data. By integrating both RSSI and ToF measurements for consensus interaction, the proposed method demonstrates improved resilience to data manipulation in a non-uniform underwater environment, while also enhancing the overall localization accuracy.

The study in[144] investigates node localization for UWSNs within the framework of the internet of things (IoT), utilizing prior knowledge of the target's location for some specific task and operational depth. The primary objective was to design an early disaster warning system for position, navigation, and timing (PNT), which could be applied to various scenarios, including underwater rescue missions and resource exploration. The research emphasizes that non positional approaches to sound line tracking are insufficient for the task. To address this, they introduced a method called iterative ray tracing 3D underwater localization (IRTUL). They assert that their approach performs most effectively when the working environment's depth is taken into account, achieving an improvement in accuracy by 3 m compared to methods assuming a constant sound velocity. The authors of[145] present a flexible localization method with motion estimation (FLMME) to address the challenges of node coordination in large scale mobile UWSNs. This approach have the ability to distinguish between the localization processes for mobile anchor nodes and regular static anchor nodes. By analyzing each node's historical mobility data, FLMME enables the prediction of future positions. Whereas the fixed location anchor nodes oversee the process, not ensuring improved accuracy and efficient error management. Simulation results demonstrate that FLMME significantly reduces localization errors, thereby improving the overall localization performance of UWSNs. The study outlined in[146] introduces an advanced technique for leveraging navigational data from stationary ships by combining C-band synthetic aperture radar (SAR) with the aid from satellite imagery technology. Central to this approach is the use of a pre trained DL model, originally developed in ArcGIS, which is specifically designed to identify stationary ships in the satellite's field of observation. These detected ships locations are then utilized as crucial reference points for underwater localization tasks. To achieve accurate underwater positioning, the method incorporates a range based multilateration algorithm implemented through UnetStack, a robust platform for underwater communication and localization. This innovative approach not only improves the efficiency and reliability of underwater exploration and localization processes but also ensures a high degree of precision in node localization. Remarkably, the method achieves an error margin of less than 1%, significantly reducing inaccuracies compared to traditional techniques. By integrating advanced satellite and radar technologies with cutting edge algorithms, this study provides a highly effective solution for underwater positioning challenges. The researchers in[147] highlighted the potential of autonomous underwater vehicles (AUVs) for abstract localization in UWSNs. However, they observed a notable limitation, that the restricted coverage area of a single AUV, leads to higher localization errors for the sensor nodes being monitored. To overcome this challenge, they introduced an innovative solution involving two AUV's working collaboratively. These AUV's are designed to communicate and coordinate efficiently, forming the basis of their double AUV cooperative localization based on relative heading angle optimization (DA-RHAO) algorithm. This approach focuses on optimizing the relative heading angles between the AUV's to improve localization precision[148]. The methodology begins by analyzing the communication angles of the AUV's during their movement. Additionally, to simplify computational complexity, the researchers divided the 3D observation area into layers based on depth, which effectively expanded the localization coverage area. This comprehensive strategy resulted in a significant improvement in localization accuracy, achieving an enhancement of 26.89%.

The study in[149] highlights the critical importance of UWSNs in marine based disasters management and advancing marine engineering research. The researchers note that the dynamic nature of the underwater environment makes it unrealistic for sensor nodes deployed for specific tasks to remain stationary, as water turbulence inevitably causes mobility. They emphasize that opportunistic routing protocols have shown superior performance in improving quality of service (QoS) compared to alternative methods[150]. In their research, they propose a framework, with a high speed system built on the principles of opportunistic routing, which is adaptable to various UWSNs platforms. To validate their proposed framework, the researchers conducted simulations using NS-2. The results demonstrated that their methodology outperforms other protocols in terms of energy efficiency and further enhances QoS. By varying the network size between 100 and 500 nodes during the simulation, they also proved that the protocol is effective in handling scalability, making it a robust solution for diverse underwater communication scenarios. The research presented in[151] underscores the crucial role of UWSNs in marine exploration. It discusses the various applications of UWSNs, including surveillance and resource extraction, and emphasizes that precise placement of sensor nodes that is vital for effective underwater communication. To tackle this challenge, the study proposes an efficient localization algorithm to compensate the stratification effect based on an improved underwater SALP swarm optimization technique (LAS-IUSSOT). In this method, nodes are initially deployed in a 3D arrangement, and then localization is performed using centroid positioning and ray theory to enhance stratification. To validate their proposed algorithm, the researchers conducted simulations, which revealed that their approach improved localization results by 40.46% in 3D scenarios and additionally, they achieved a 43.39% improvement in ranging accuracy. Their methodology also outperformed existing techniques in several aspects, including root mean square error (RMSE), computation time, and convergence rate. The study presented in[152] highlights that, in addition to large sized AUV's, small sized AUV's also offer several advantages, such as low noise characteristics, making them particularly effective for use in underwater habitats. The researchers note that many localization processes donot prioritize the cost of equipment for specific tasks, but the use of small AUV's will automatically provide a more affordable and efficient solution. A critical question raised is whether these small AUV's can be equipped with localization technology, to which the researchers affirmatively answer. They demonstrate this by deploying a simulation based on small AUV connected in a weak cooperative underwater communication networks. In this configuration, they address the stratification effect by employing an extended KF method to correct AUV's drifting errors. The localization system they opted is fundamentally based on TDOA. And through simulation results, they claim a significant improvements in both energy efficiency and localization accuracy.

Purpose of ML and DL in UWSNs localization

We know that localization is an essential aspect of UWSNs, enabling the performance of crucial and complex tasks such as real time navigation of submerge vessels, monitoring environmental changes with the help of sensor networks, and studying aquatic ecosystems. However, the unique challenges of the underwater environment, including signal attenuation, multipath propagation, and significant delay spreads, make localization a demanding task. While traditional localization methods have proven to be effective and continue to serve their purpose, there is still considerable room for enhancement in various scenarios. The traditional localization methods often rely on outdated geometric techniques that struggle to adapt to the dynamic and unpredictable nature of underwater environments. Therefore, advancements are required to improve their accuracy, reliability, and scalability to address the increasing demands of underwater exploration, environmental monitoring, and other vital applications.

ML and DL have achieved significant advancements across various domains, such as the possibility of autonomous navigation in vehicles, speech recognition, and image analysis. These cutting edge technologies excels at handling intricate, non-linear relationships within datasets, particularly in scenarios requiring cooperative hybrid communication. Their exceptional ability to process and analyze large datasets generated by sensor networks have made them invaluable in solving challenges across numerous applications. In the context of UWSNs, where sensor nodes generate vast amounts of data, ML and DL can have a great potential for improving overall performance and operational efficiency of the systems. Among the various applications of these technologies, localization emerges as a crucial area that needs to be studied. By harnessing their sophisticated data processing and analytical capabilities, ML and DL can significantly enhance the accuracy, robustness, and scalability of localization techniques, effectively addressing the unique obstacles presented by the underwater environment. In this context a range of ML techniques have been applied to localize UWSNs, each one offering its unique strengths and limitations. For instance, classification methods such as decision trees, support vector machines (SVM), and k-nearest neighbors (K-NNs) rely on training models with labeled datasets. On the other hand, clustering, and unsupervised learning techniques, can group similar data points to estimate spatial relationships, even when training labels are not available. Additionally, reinforcement learning, which focuses on teaching an agent how to make decisions through continuous interaction with its environment, can enhance localization outcomes by allowing the system to learn and adapt over time. However, some of the researcher are also working on the more sophisticated DL techniques that have been emerging as of great use for UWSNs localization, especially neural networks (NNs) and its sub categories such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNN have the capability to process spatial data, and can be applied to signal intensity maps and other geographic representations of the data gathered by sensor nodes. However, RNNs are particularly effective at capturing temporal changes in signals, as they are designed to handle sequential data. The objective of using advanced methodologies is to predict the potential locations of sensor nodes based on the observed data, facilitating the localization process in UWSNs.

Machine learning approaches for UWSN localization

In this section, we have provided a brief overview of the ML techniques and their various types used for node localization in UWSNs. In light of this discussion, a block diagram as Fig. 13 is presented, which illustrates the most commonly employed ML and DL methods used for the localization of nodes within UWSNs.

K-nearest neighbor (K-NNs)

K-NNs is a straightforward and widely used ML algorithm, commonly applied to classification and regression tasks. It operates by identifying the 'k' closest data points to a given query, with 'k' being a user defined number, and making predictions based on that information taken as neighbors. In underwater communication systems, particularly in UWSNs, K-NNs is frequently used for node localization. The algorithm estimates a node's position by evaluating its distance from several known reference points within the network by using both the data from range based and range free localization types[153]. For classification, the predicted class is determined by the majority vote among the nearest communication nodes, while in regression, the prediction is based on the average or weighted average of the values of the closest nodes. As a non-parametric method, K-NNs makes assumptions about the data distribution, offering flexibility for a variety of problems. However, its performance may degrade with high dimensional underwater data, making the prediction process computationally intensive, as it requires calculating distances to all training data points. Despite these drawbacks, K-NNs remains a popular choice due to its simplicity and effectiveness in practical applications, including underwater node localization[154]. K-NNs methods are also applied to predict which cluster of nodes in a specific task is consuming more energy than usual, while also monitoring the end to end delay. By tracking these key parameters in UWSNs, the overall localization accuracy can be improved[155].

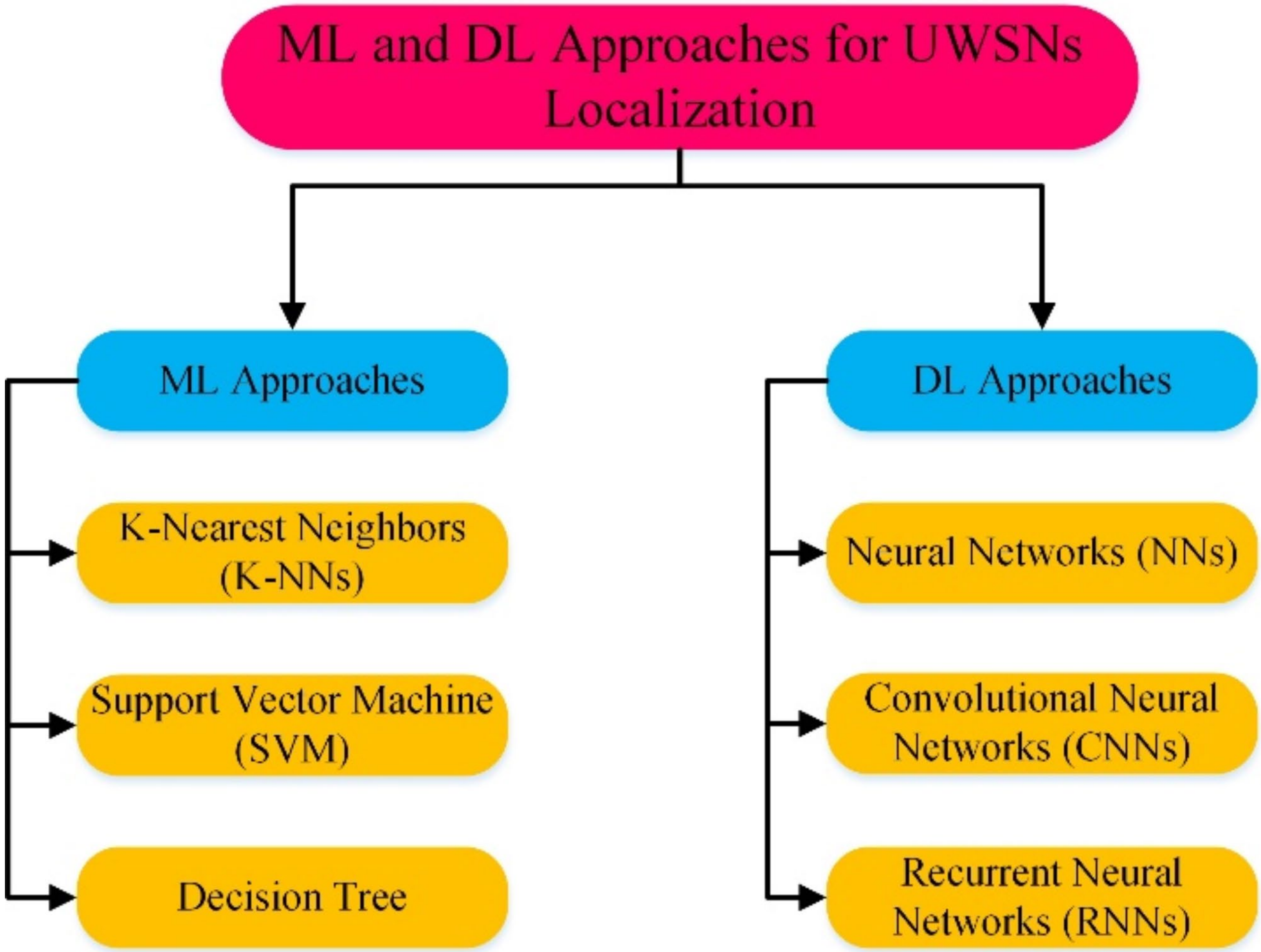

Fig. 13. Types of most used ML and DL methods for localization of nodes in UWSNs.

Support vector machine (SVM)

SVM is a highly effective supervised ML algorithm primarily used for classification tasks, though it is also suitable for regression problems and node localization in UWSNs. SVM functions by identifying the optimal hyperplane that separates data points from different classes in a high dimensional feature space. Its main goal is to maximize the margin, which is the distance between the hyperplane and the closest data points from each class, known as support vectors, thereby improving the model's generalization ability[156]. SVM is capable of handling both linear and non-linear data by applying kernel functions, such as the radial basis function (RBF), to project the input data into a higher dimensional space where linear separation becomes possible. In underwater communication systems, SVM is often employed for node localization, assisting in classifying positions or estimating locations based on available data. While SVM excels in a high dimensional spaces and is resistant to overfitting, it can be computationally intensive, particularly with large datasets. Nonetheless, SVM remains a popular choice for achieving precise and reliable localization. For instance, a synergistic trust model based on SVM (STMS) is proposed in[157], and researchers in[158] have utilized a self-localizing range free binary tree SVM model to localize a smaller number of nodes in AUV based networks, improving battery efficiency for prolonged operation.

Decision Tree

A Decision Tree is a widely used and simple ML algorithm that can be applied to both classification and regression tasks. It operates by recursively dividing the dataset into smaller subsets based on the feature that most enhances the prediction of the target variable. Each internal node in the tree represents a decision rule based on a particular feature, while the leaf nodes indicate the final prediction or result. The splitting continues until a predefined stopping criterion, such as a maximum tree depth or a minimum number of samples per leaf, is met. One of the main advantages of a decision trees is their simplicity and interpretability, as they are easy to visualize and understand[159]. They can handle both categorical and numerical data and are capable of modeling complex, non linear relationships. In underwater communication systems, decision trees can be used for node localization, helping to estimate their positions using environmental and sensor data. However, decision trees are susceptible to overfitting, particularly with complex datasets, though techniques such as pruning, boosting, or bagging can reduce this issue. However to improve security, increase node mobility, and overcoming the bandwidth constraints in UWSNs, the researchers in[160] have developed an advanced version of the decision tree algorithm. This updated approach features energy efficient decision making, enabling the system to make more effective use of available resources. Additionally their approach offers real time adaptability, allowing the algorithm to adjust dynamically to the changes in the underwater environment. The modified algorithm also incorporates key underwater specific factors, such as changes due to water currents and acoustic signal properties, which are critical for accurate decision making. By integrating these factors, the algorithm is better suited to address the complexities of underwater communication networks, resulting in more reliable and efficient solutions for node localization and communication, achieving a 96% accuracy rate and a 2% false positive rate.

However the ML models can encounter several fundamental challenges when applied to specific tasks, such as the localization of nodes in UWSNs. To provide a clearer understanding for the reader, these challenges, along with their corresponding potential solutions, have been concisely summarized in Table 6. This table aims to present the information in an organized manner, facilitating ease of comprehension and highlighting the critical aspects of these challenges.

Deep learning approaches for UWSNs localization

In this section, we have provided a brief overview of the DL techniques and their various types used for node localization in UWSNs that are shown in the form of a block diagram in Fig. 13.

Neural networks (NNs)

NNs are a foundational element of DL, inspired by the structure and operation of the human brain. They are composed of interconnected layers of nodes, that process information and detect patterns through weighted connections. These networks are highly effective in managing complex tasks like image recognition, natural language processing, and time series forecasting, thanks to their ability to model non linear relationships and uncover intricate patterns within data. Their adaptability makes them an excellent choice for various applications, including node localization in UWSNs. Leveraging their capability to handle large datasets and capturing non linear dynamics, NNs can analyze underwater environmental factors, such as signal attenuation and water characteristics, to enhance localization precision. Nonetheless, their dependency on significant computational power and extensive datasets presents challenges, especially in resource limited underwater environments. Despite these hurdles, NNs remain a critical component of modern artificial intelligence (AI) and ML, offering considerable promise for UWSNs related solutions. The researchers in[161] emphasize that localization techniques used in TWSNs are not suitable for UWSNs. So they proposed an environment aware localization system that utilizes the physical properties of water, such as temperature and salinity variations, to enhance the accuracy and reliability of underwater node localization. Their approach employs the RSSI technique to measure the distance of communication between nodes within UWSNs, which is combined with a dynamic response NNs for predicting node localization estimates. Through simulations, they report of achieving an increase in the localization prediction accuracy by 2%. And in[162] the researchers proposed a bio inspired algorithm for node localization in underwater UWSNs. They introduced the improved grey wolf optimization based node localization approach in UWSN (IGWONL-UWSN), which utilizes the RSSI based localization technique. To enhance the localization process, they developed a heuristic neural networks (HNNs) based system that is designed to accurately locate mobile nodes within subterranean environments. Their simulation results reportedly achieved a localization estimation accuracy of 95%.

Convolutional neural networks (CNNs)

CNNs are specialized NNs that are created to process structured grid like data efficiently. They are particularly effective in tasks that involve identifying spatial patterns and hierarchies, such as classification, localization, object detection, and semantic segmentation. CNNs consist of convolutional layers that apply filters to extract essential features from input data sets, pooling layers that reduce spatial dimensions to optimize computational efficiency, and fully connected layers that generate the final outputs. In UWSNs, CNNs have been utilized for node localization by interpreting underwater environmental data and spatial patterns. This method enhances the accuracy of node localization by taking advantage of CNNs capability to learn complex hierarchical features. Moreover, their shared weights and sparse connectivity make CNNs computationally efficient, making them suitable for use in resource limited underwater settings. That's why researchers in[163] introduced a hybrid localization method that integrates CNNs with mobility prediction, termed (HLCM). This innovative approach

S.No	Challenge	Description	Impact	Potential Solutions
1	Limited Training Data	Presently available labeled datasets are insufficient for training the models	Model effectiveness is reduced	Transfer learning and generation of synthetic datasets
2	High Dimensionality	Sparse data points impeding the extraction of substantial patterns	Increased model complexity	Use of dimensionality reduction techniques, i.e. PCA and linear discriminant analysis (LDA) etc.
3	Real Time Processing Needs	Requires managing the enormous volume of data produced instantaneously.	Latency issues	Real time discarding of faulty samples from the datasets
4	Energy Constraints	High computational demand on resource limited devices	Cost of power source replacement, reduced network lifespan	Use of cooperative networks and energy efficient hardware
5	Model Generalization	Difficulty in deployment across multimodal scenarios	Poor performance in new conditions	Use of domain adaptation techniques

Table 6. Implementation challenges of ML in UWSNs.

sets itself apart from other recently developed localization techniques by significantly enhancing the accuracy of source localization. The HLCM method employs a CNNs based model to effectively reduce range errors and address uncertainties arising from variations in sound speed, ensuring more precise localization. Additionally, it incorporates a weighted superposition of the speeds of anchor nodes to refine its predictions and successfully mitigates the effects of node drifting caused by ocean currents. Through extensive simulations, the researchers demonstrate that HLCM outperforms existing algorithms in multiple aspects, providing superior localization accuracy, broader target coverage, and enhanced fault tolerance. These capabilities make it a robust and reliable solution for addressing the complexities of underwater localization challenges. And the researchers in[164] proposed a system designed to provide stable and accurate target localization in UWSNs. They emphasized that traditional KF is not suitable for environments with significant fluctuations, as KF can only address linear problems. To overcome this challenge, they introduced the LSTM KF method, which combines the strengths of Long Short Term Memory (LSTM) networks with KF to handle non linear and dynamic environments, additionally CNNs were used to track the movement of targets. By merging these techniques, they created a hybrid system that can predict both the azimuth and actual distance of the target, which they named the long term and short term memory neural network (LSTM-NN). The results from sea trials showed a 60% reduction in error, and simulations demonstrated a 72.25% decrease in error, validating the proposed method's potential for effectively localizing moving targets in UWSNs.

Recurrent neural network (RNNs)
RNNs are a specialized form of NNs designed to process sequential data by capturing temporal dependencies. Unlike traditional neural networks, RNNs have feedback connections that allow them to retain information over time, making them highly effective for tasks involving time series data. At each time step, RNNs combine the current input with previous outputs, enabling them to preserve context and identify patterns in sequences. However, standard RNNs encounter difficulties with long-term dependencies, often facing challenges like vanishing or exploding gradients during training. To address these issues, more advanced variants like LSTM and gated recurrent units (GRU) have been developed, which include gating mechanisms to regulate the flow of information and improve learning. These enhanced networks have been successfully applied to UWSNs for node localization, where they leverage their ability to model temporal dynamics and environmental changes to boost localization accuracy. In a study presented in[165], the researchers utilized RNNs to focus on minimizing estimation errors in performance metrics. They employed a network of microphones to track changes in audio emissions from equipment performing specific tasks in UWSNs. Through real time experimentation and lab simulations, they reported a significant reduction in mean estimation error (MEE), a key performance measure in the context of localization. And the researchers in[166] have made a significant contribution to improving the security of data in UWSNs, highlighting Sybil attacks as a major threat to communication within these networks. They proposed a hybrid system that integrates ML and DL approaches. This system utilizes principal component analysis (PCA) to identify critical attributes, aiding in the detection/localization and mitigation of security vulnerabilities in UWSNs. The simulations conducted to validate their RNNs based study demonstrated an impressive accuracy of 97% after optimization. The findings suggest that their approach could be instrumental in developing secure routing protocols capable of localizing nodes and defending against cyberattacks in UWSNs.

DL models are also often confronted with numerous intrinsic challenges when deployed for specific tasks, such as node localization in UWSNs. For the reader's enhanced comprehension, these challenges, with some subtle explanations and expected outcomes, have been succinctly delineated in Table 7. This tabular representation endeavors to systematically convey the information, thereby simplifying its assimilation and accentuating the pivotal facets of these challenges.

Comparative analysis of ML and DL for localization in UWSNs

This section offers a comparative analysis of ML and DL techniques that have been adopted by research groups across the globe. These methods have been specifically employed to improve the precision of localization estimation for nodes in UWSNs. The findings presented in this comparative evaluation are derived from comprehensive simulations conducted in the simulation softwares. By highlighting these methods and their outcomes, this section aims to provide valuable insights into the effectiveness of various approaches in refining localization accuracy.

Figure 14 depicts the localization error (measured in meters) as a function of the signal-to-noise ratio (SNR) in decibels (dB). The results presented in the figure are based on the application of four distinct methods that are K-NNs, SVM, Decision Trees, and NNs for UWSNs. The localization error was assessed across varying the number of iterations (10, 20, and 30) and exploring a range of SNR levels from – 10 dB to 0 dB. The red markers in the figure specifically denotes the outcomes obtained using K-NNs. From the graph, it is evident that the localization error is significantly high, especially when the SNR is below – 10 dB. Although the error shows a slight reduction with subsequent trials, the improvement remains marginal. Consequently, the overall performance of K-NNs lags behind the other methods presented in the analysis, indicating that its effectiveness in minimizing localization error under low SNR conditions is comparatively limited. This emphasizes the need for alternative approaches for achieving better accuracy in such scenarios. This indicates that despite having all the advantages of being simple, K-NNs might be at a disadvantage in noisy and complex underwater environments. The lines shown with blue color are the results obtained with SVM, which reveals very low localization errors at all the SNR levels. And we can observe that SVM improves with every iteration, especially at higher SNR values, indicating that iterative enhancement of the model could greatly improve its accuracy. Green markers indicating the results obtained by using the decision trees, where we can see that the obtained results are an intermediate between the K-NNs method and the SVM, and with a closer look we can observe that with the increase in SNR the results gets better and better with every iteration. Among all the approaches, the localization results represented by black

S.No	Opportunity	Description	Deep Learning Technique	Expected Outcome	Challenges
1	Feature Extraction	Automatically discovering features relevant to localization	CNNs	Improved accuracy, reduced manual effort	High computational demand
2	Temporal Pattern Recognition	Identifying patterns in time series data for better prediction	LSTM, RNNs	Better prediction of node movements	Training complexity, long term dependency issues
3	Multi View Learning	Combining multiple sensor data for more robust localization	Multi view neural networks	Enhanced reliability	Data fusion challenges, model complexity
4	Anomaly Detection	Detecting abnormal communication of sensor data to improve security	Auto encoders, GANs	Enhanced network security	Data scarcity, model interpretability
5	Transfer Learning	Intra environment communication	Pre trained neural networks	Reduced training time, improved generalization	Domain adaptation, overfitting risk

Table 7. Challenges and opportunities in DL for UWSNs.

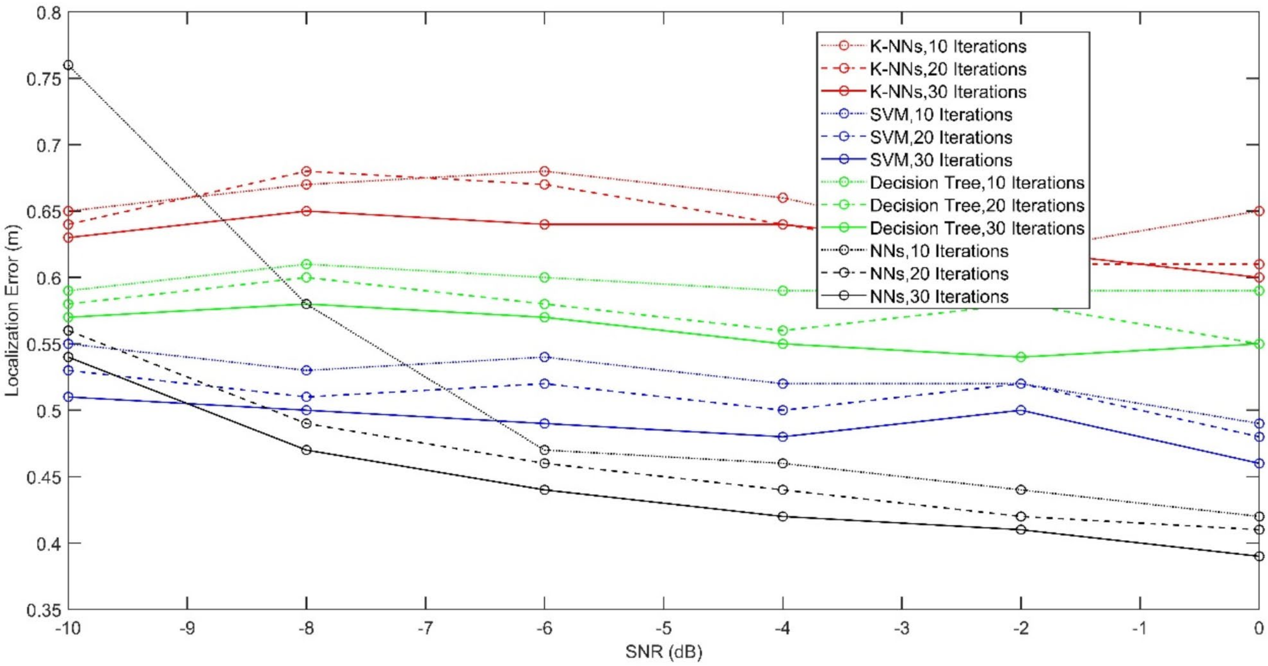

Fig. 14. Localization error vs. SNR.

lined markers, corresponding to NNs exhibit the lowest localization error, particularly at higher SNR levels. And regarding the number of iterations, NNs consistently deliver superior performance, as evident from the results displayed. This indicates that NNs are highly effective in noisy underwater environments, making them suitable for various applications.

The importance of velocity estimation error in relation to SNR is a crucial factor in various applications, including underwater acoustic sonar signal processing in UWSNs, radar signal processing in TWSNs, and autonomous systems operating across both UWSNs and TWSNs. Accurate velocity estimation is essential for real time decision making and ensuring safety in critical operations. However, low SNR conditions present significant challenges, as noise can obscure vital features that are necessary for reliable predictions. ML and DL techniques to enhance the robustness of velocity estimation by extracting complex patterns and identifying temporal dependencies from noisy data are used. These models can also be trained to optimize metrics directly tied to velocity error, enabling them to adapt dynamically to varying SNR levels. The integration of advanced algorithms with domain specific knowledge has significantly improved accuracy and reliability in practical applications. Figure 15 illustrates, showing that K-NNs results, represented by the red line, achieves the lowest accuracy and the highest deviation in velocity error estimates. This outcome indicates that K-NNs is less effective for dynamic UWSNs. On the other hand, SVM and decision trees, depicted by the blue and green lines, respectively, strike a better balance between computational efficiency and accuracy, making them suitable for real time applications requiring moderate precision. Moreover our simulation results reveals that NNs outperform other methods in terms of velocity estimation accuracy, delivering the lowest error rates. However, this superior performance comes with the drawback of increased energy consumption. This comparative analysis highlights the advantages of DL approaches, particularly NNs, for velocity estimation in UWSNs. NNs offer superior accuracy and robustness compared to traditional ML methods and perform effectively across diverse environmental conditions, making them ideal for complex and challenging scenarios. Conversely, SVM and decision trees, as traditional ML models, provide an optimal balance of accuracy and energy efficiency, making them suitable for scenarios where precision is required within a reasonable time frame. In contrast, K-NNs demonstrates poorer performance, making it less suited for complex and noisy environments such as underwater systems.

In Fig. 16 we can observe that, the K-NNs algorithm consistently records the highest RMSE values, as shown by the red line in the results portrayed. At the minimum observation range during the first iteration, the RMSE value is 2, and it steadily increases with each iteration as the communication range grows. This performance establishes, that K-NNs is the least effective algorithm for predicting RMSE. Conversely, the SVM technique, represented by the blue line, demonstrates improved RMSE prediction, with an initial value of 1.8. This enhanced performance is due to SVM's ability to handle complex datasets, its resilience to outliers, and its effectiveness in managing high dimensional data. The decision tree method results that are depicted by the green line, outperforms both SVM and K-NNs, achieving an initial RMSE value of 1.6 during the first iteration. However, NNs, represented by the black line, deliver the best performance overall, with the lowest RMSE value of 1.4 in the first iteration. This demonstrates the superior capability of NNs in minimizing RMSE compared to the other approaches. These results indicate that NNs excel because of their ability to learn complex nonlinear patterns and effectively handle nuanced data, which is a common characteristic of underwater environmental datasets.

While ML and DL methods offer significant advantages, their energy consumption during task execution is an important factor to consider. As shown in Fig. 17, ML algorithms like K-NNs, decision trees, and SVM generally consumes less energy due to their simpler models and lower computational requirements. In contrast, DL methods, particularly the NNs used in our study, the results of which are represented by the black line exhibit higher energy demands/consumptions because of their deep architectures, large parameter sets, and intensive matrix computations. Our findings reveal that while NNs are highly effective for complex and nonlinear tasks, their elevated energy consumption can be a constraint in resource limited environments, such as systems designed for cooperative communication in UWSNs.

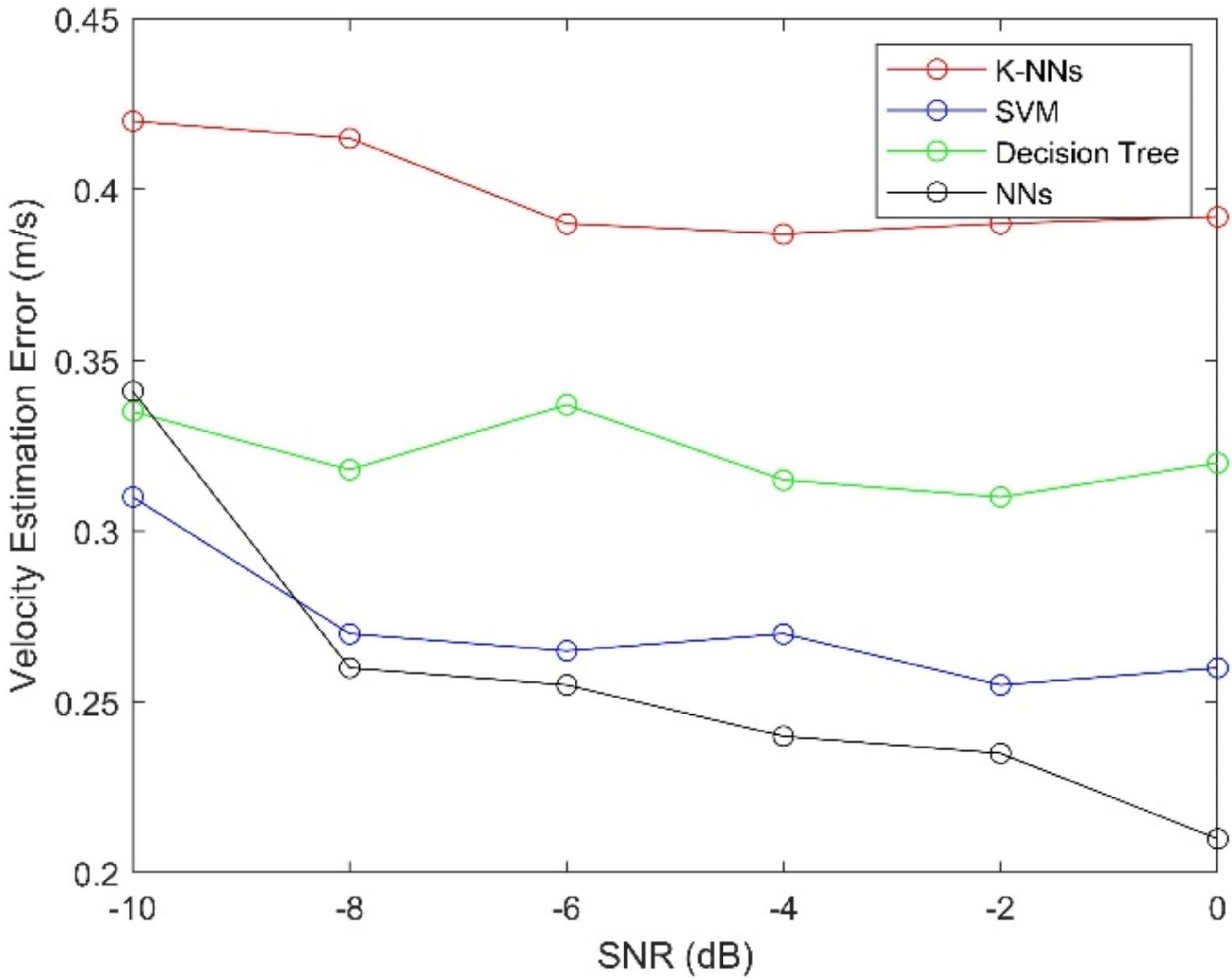

Fig. 15. Velocity Estimation Error in (m/s) vs. SNR.

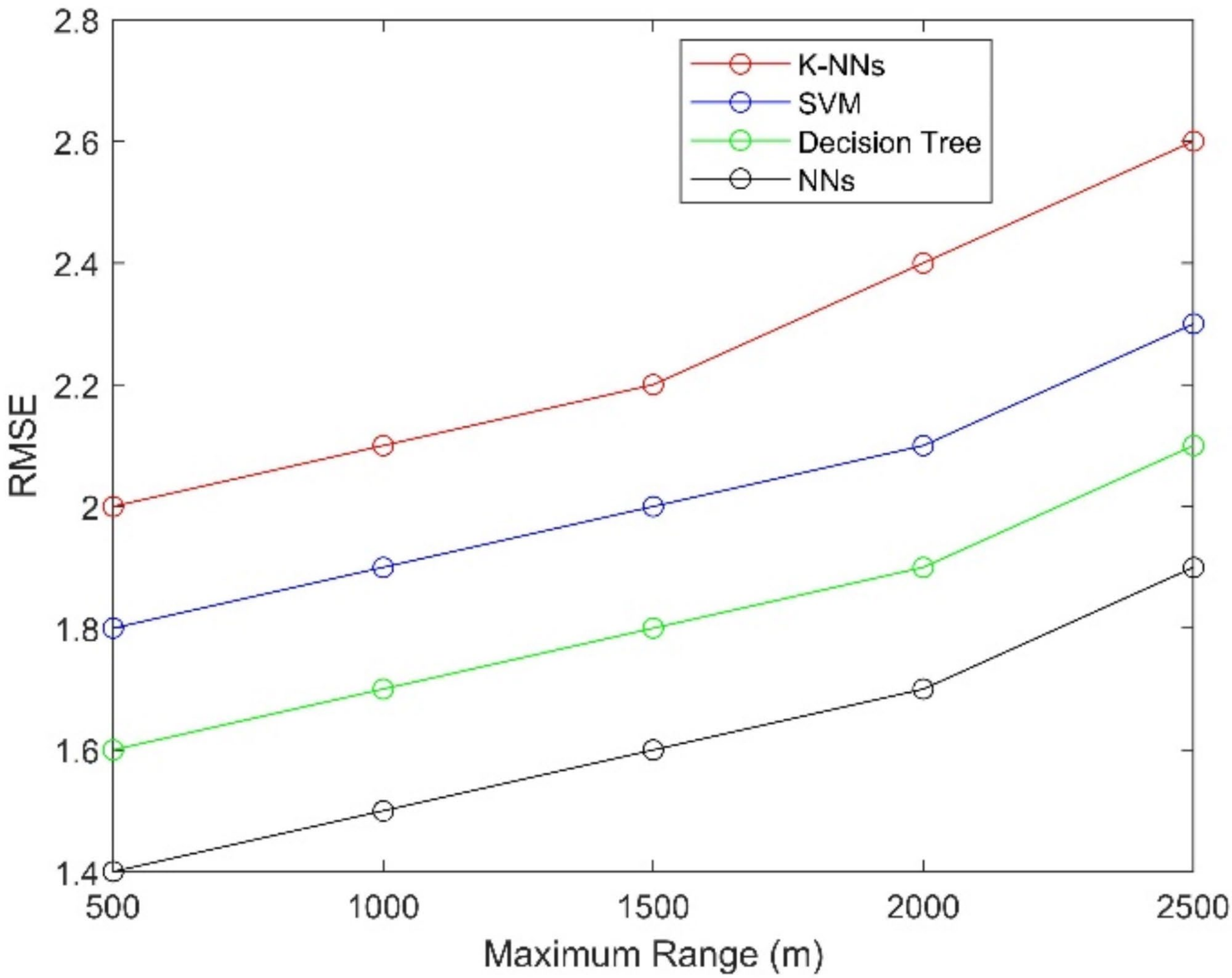

Fig. 16. RMSE vs. Maximum Range.

Apart from MATLAB, there exists an extensive array of simulation environment, creators and analyzers specifically designed for tasks related to UWSNs. Table 8 provides a comprehensive list of such simulators, accompanied by concise descriptions of their primary features and their optimal applications. The table also includes insights into factors such as the user friendliness of each simulator, the reliability and accuracy of the results they produce, and their potential for guiding hardware development for real time experimentation. Additionally, the scalability of each simulation tool has been emphasized to help assess its suitability for varying research needs.

Future research directions and opportunities

However, extensive research is being conducted by many research groups on the topic of node localization in UWSNs, and significant advancements have been made over time, showcasing the progress achieved by researchers and engineers in this field. However, despite these advancements, there remain several challenges and unresolved issues that present opportunities for further explorations and innovations. These gaps in knowledge and technology serve as potential research directions for future endeavors, offering a chance for researchers to develop novel solutions and make meaningful contributions to the domain of underwater communication. Below are provided some future research direction in the form of pointers.

• There is a critical need for energy efficient models, that can achieve robust real time localization of nodes in UWSNs, with comparable computational accuracy while significantly reducing energy consumption at the same time. As the underwater environment is inherently constrained in resources.

• Given that it is not feasible to constantly monitor a network setup, particularly in underwater environments. So there is a crucial need for hybrid techniques that combine unsupervised and semi supervised learning approaches to address this challenge effectively.

• We must have to develop such ML and DL model that may have the capability to cope with transfer learning, federated learning and also multimodal integration of data in the ever changing unknown underwater environment.

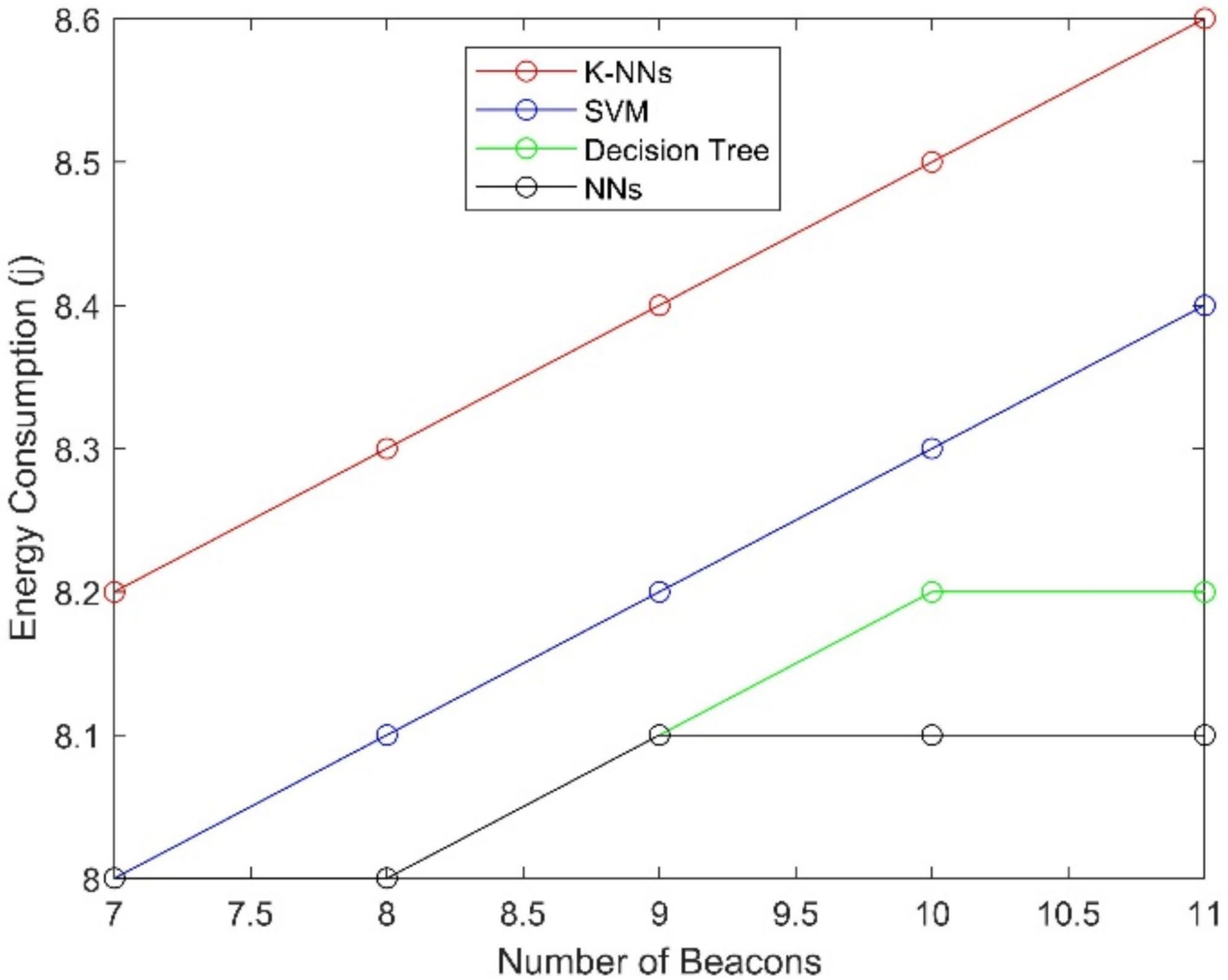

Fig. 17. Energy Consumption vs. Number of beacons.

S.No	Simulation Tool	Features	Ease of Use	Accuracy of Results	Scalability	Best for
1	Aqua-Sim	NS2-based simulator used specifically for underwater networks	β	α	α	Protocol testing, network performance evaluation
2	DESERT Underwater	Provides modular design for simulating underwater networks	β	α	β	Protocol development, application testing
3	UW-Sim	3D underwater simulator for testing algorithms and protocols	α	β	δ	Algorithm validation, small-scale experiments
4	UnetStack	Versatile simulator with a focus on acoustic communications	α	α	β	Acoustic communication, localization studies
5	Aqua-Net	Supports both acoustic and optical communication simulations	δ	β	α	Mixed communication environment research
6	NS-3	Advanced version of NS-2 with improved scalability options	α	β	δ	Facilitates model creation, provides problems resolutions, the analysis and dissemination of results
7	TOSSIM	Made up of TinyOS, customizable for UWSNs	α	α	β	Excellent for troubleshooting, evaluating, and examining algorithms
8	J-SIM	A component based simulation platform created in JAVA	δ	β	α	Provides assistance for physical and sensory phenomenon's.
9	OPNET	Works best for sensor specific devices	β	α	α	Each simulation operates at the packet level within the UWSNs.
10	OMNET++	In simulations, OMNET + + exhibits better scalability compared to NS2.	δ	β	α	Best to operate in energy modules analysis

Table 8. Comparative analysis of different simulation tools used for localization in UWSNs, where α represents high, β is for moderate, and δ is for low.

• There is an urgent need for hybrid ML and DL models capable of adapting to changes in transmission media. These models should effectively leverage benefits from the datasets of various media's currently used in underwater environments, such as acoustical, VLC, and MI.

• Scalable and robust ML and DL models are also essential to handle variations in dataset size as the network scales to ensure they can perform tasks effectively in real time applications.

Conclusion

Localization in UWSNs plays a vital role in determining the effectiveness and reliability of various underwater applications. Throughout the course of this review, it became evident that numerous challenges related to the underwater environment, technology, and algorithms remain underexplored or insufficiently addressed. Despite significant advancements, there are still many aspects of these challenges that have not been fully examined or tackled to the degree necessary for improving the overall performance and accuracy of localization in UWSNs. This underscores the importance of continued research and development to address these lingering issues. Some of these challenges have been identified and presented as potential avenues for future research and exploration. In the comparative analysis presented in this article, we assessed the performance of ML and DL models in predicting crucial parameters such as localization error, velocity estimation error, RMSE, and energy efficiency. The results revealed that the DL NNs model significantly outperforms the ML models, including K-NNs, SVM, and decision tree, in accurately estimating parameters like RMSE, localization error, and velocity estimation error. However, when it comes to energy efficiency, the DL NNs model shows a considerable drawback. Despite its superior performance in terms of accuracy, it fails to optimize energy usage effectively for tasks at hand, consuming substantially more energy compared to the ML models mentioned. In essence, through the comprehensive analysis conducted in this study, we have deduced that the process of localization in UWSNs represents a fundamental tradeoff between precision and the careful utilization of resources, which may encompass both financial expenditure and energy consumption. This intricate balance underscores the necessity of energy optimization as an imperative focal point for enhancement, particularly within DL models. The refinement of energy efficiency, without compromising the accuracy of localization, emerges as a pivotal challenge, demanding substantial attention and advancement in future research endeavors.

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions
"For research articles with several authors, this short paragraph specifies their contributions. A.M (Methodology), F.L (Software, Writing an original draft), Z.U.K (Software, Validation), F.K, J.K, and S.U.K (Data curation, visualization), F.L (Resources, Project Administration, Funding Acquisition), A.M, and Z.U.K (Investigation, Writing, review, and Editing)."

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Declarations

Competing interests
The authors declare no competing interests.

Additional information

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