ADVANCING EARTH AND SPACE SCIENCES

Radio Science

RESEARCH ARTICLE

10.1029/2023RS007782

Enhancement of Precise Underwater Object Localization

Sathish Kaveripakam[1], Ravikumar Chinthaginjala[1], Rajesh Anbazhagan[2], Mohammad Alibakhshikenari[3], Bal Virdee[4], Salahuddin Khan[5], Giovanni Pau[6], Chan Hwang See[7], Iyad Dayoub[8,9], Patrizia Livreri[10], and Raed Abd-Alhameed[11]

[1]School of Electronics Engineering, Vellore Institute of Technology, Vellore, India, [2]School of Electrical and Electronics Engineering, SASTRA University, Thanjavur, India, [3]Department of Signal Theory and Communications, Universidad Carlos III de Madrid, Leganés, Spain, [4]Center for Communications Technology, London Metropolitan University, London, UK, [5]College of Engineering, King Saud University, Riyadh, Saudi Arabia, [6]Faculty of Engineering and Architecture, Kore University of Enna, Enna, Italy, [7]School of Computing, Engineering and the Built Environment, Edinburgh Napier University, Edinburgh, UK, [8]Université Polytechnique Hauts-de-France, Institut d'Électronique de Microélectronique et de Nanotechnologie (IEMN) CNRS UMR 8520, ISEN, Centrale Lille, University of Lille, Valenciennes, France, [9]INSA Hauts-de-France, Valenciennes, France, [10]Department of Engineering, University of Palermo, Palermo, Sicily, Italy, [11]Faculty of Engineering and Informatics, University of Bradford, Bradford, UK

Key Points:

- The approaches of localization that are distance-based and angle-based are both covered in this article
- To perform distance-based measurements, a total network field of 100 m × 100 m in which mobile sensor nodes are permitted to roam is established
- The network size for angle-based measurement is also 100 m × 100 m, which provides the mobile sensor nodes significant space to move

Correspondence to:

R. Chinthaginjala and M. Alibakhshikenari,
cvrkvit@gmail.com;
mohammad.alibakhshikenari@uc3m.es

Citation:

Kaveripakam, S., Chinthaginjala, R., Anbazhagan, R., Alibakhshikenari, M., Virdee, B., Khan, S., et al. (2023). Enhancement of precise underwater object localization. *Radio Science*, *58*, e2023RS007782. https://doi.org/10.1029/2023RS007782

Received 22 JUN 2023
Accepted 21 JUL 2023

Author Contributions:

Data curation: Sathish Kaveripakam, Ravikumar Chinthaginjala, Rajesh Anbazhagan
Formal analysis: Iyad Dayoub
Funding acquisition: Mohammad Alibakhshikenari
Investigation: Ravikumar Chinthaginjala, Bal Virdee, Giovanni Pau, Raed Abd-Alhameed
Methodology: Sathish Kaveripakam, Rajesh Anbazhagan, Chan Hwang See
Project Administration: Mohammad Alibakhshikenari
Resources: Sathish Kaveripakam, Ravikumar Chinthaginjala, Rajesh Anbazhagan
Software: Sathish Kaveripakam, Ravikumar Chinthaginjala

Abstract Underwater communication applications extensively use localization services for object identification. Because of their significant impact on ocean exploration and monitoring, underwater wireless sensor networks (UWSN) are becoming increasingly popular, and acoustic communications have largely overtaken radio frequency broadcasts as the dominant means of communication. The two localization methods that are most frequently employed are those that estimate the angle of arrival and the time difference of arrival. The military and civilian sectors rely heavily on UWSN for object identification in the underwater environment. As a result, there is a need in UWSN for an accurate localization technique that accounts for dynamic nature of the underwater environment. Time and position data are the two key parameters to accurately define the position of an object. Moreover, due to climate change there is now a need to constrain energy consumption by UWSN to limit carbon emission to meet net-zero target by 2050. To meet these challenges, we have developed an efficient localization algorithm for determining an object position based on the angle and distance of arrival of beacon signals. We have considered the factors like sensor nodes not being in time sync with each other and the fact that the speed of sound varies in water. Our simulation results show that the proposed approach can achieve great localization accuracy while accounting for temporal synchronization inaccuracies. When compared to existing localization approaches, the mean estimation error (MEE) (MEE) and energy consumption figures, the proposed approach outperforms them. The MEEs is shown to vary between 84.2154 and 93.8275 m for four trials, 61.2256 and 92.7956 m for eight trials, and 42.6584 and 119.5228 m for 12 trials. Comparatively, the distance-based measurements show higher accuracy than the angle-based measurements.

1. Introduction

Even though it only accounts for roughly 0.05% of the total mass of the Earth's landmass, water has covered approximately 70% of the planet's surface. Nevertheless, water has always been an essential component in the expansion of life on Earth, particularly in the form of creatures. If there were no water on Earth, it would be nothing more than a lifeless rock in the universe. More research or exploration needs to be done on the planet beneath the waves to benefit humanity. Underwater communication systems have swiftly acquired widespread adoption due to the many potential uses that can be implemented in the aquatic environment (Almutairi & Mahfoudh, 2017).

Due to the high level of attenuation that increases with the conditions of sea, that is, temperature, and salt (Siddiqi et al., 2017), electromagnetic (EM) waves propagating underwater travel over relatively small distances. Also, underwater radio frequency (RF) communications exhibit high levels of inter-symbol interference. Because of these issues, terrestrial wireless networking standards cannot be used in underwater environments; over the past year, various routing algorithms have been proposed to address the unique characteristics of this type of environment, and the unique challenges it presents in terms of application scenarios (Thulasiraman & White, 2016).

Acoustic communications are the most popular choice for underwater wireless sensor networks (UWSN) since they facilitate efficient network planning and operation. The low data rate and significant propagation latency of acoustic communications necessitate an accurate understanding of underwater sensor position information

Supervision: Ravikumar Chinthaginjala, Rajesh Anbazhagan, Mohammad Alibakhshikenari
Validation: Sathish Kaveripakam, Ravikumar Chinthaginjala, Rajesh Anbazhagan, Mohammad Alibakhshikenari, Bal Virdee, Salahuddin Khan, Giovanni Pau, Chan Hwang See, Iyad Dayoub, Patrizia Livreri, Raed Abd-Alhameed
Visualization: Sathish Kaveripakam, Bal Virdee, Salahuddin Khan, Patrizia Livreri
Writing – original draft: Sathish Kaveripakam, Ravikumar Chinthaginjala
Writing – review & editing: Rajesh Anbazhagan, Mohammad Alibakhshikenari, Bal Virdee, Salahuddin Khan, Giovanni Pau, Chan Hwang See, Iyad Dayoub, Patrizia Livreri, Raed Abd-Alhameed

for developing network design and routing algorithms. Because nodes move around while submerged, these protocols must regularly save location updates. This circumstance results in a very high data load and significant energy consumption. Similarly, to Terrestrial Wireless Sensor Networks (TWSN), the sensor nodes require batteries for operation; however, replacing or recharging such batteries in a marine setting presents several challenges. Therefore, the upkeep of sensor node availability and the extension of the network's lifetime presents a formidable challenge to any UWSN approach. Underwater localization is a problematic issue because of the harsh conditions of the ocean, such as its restricted bandwidth, long propagation delay, spreading, and so on. Figure 1 depicts the UWSN according to their system architecture.

Underwater WSNs are the foundation for various applications that manage observed data. This sensor node can be in various forms, including static, mobile, and hybrid nodes, all of which send data via a wireless network. While Global Positioning System (GPS) and RF IDentification (RFID) are today the most often used technologies for terrestrial localization, WSNs and several other technologies are paving the way for the future. However, RF transmissions are severely attenuated underwater, and underwater sensor networks can only use RF signals ranging from 30 to 300 Hz. As a result, either a powerful signal or a large antenna is necessary.

Some characteristics of underwater sensor networks set them apart from their terrestrial counterparts. The physical parameters under which underwater acoustic channels operate are often considered to impose severe bandwidth constraints. Similarly, optical signals are attenuated and dispersed significantly in aquatic environments (J. Luo et al., 2018; Sathish, Hamdi, Chinthaginjala, Pau, et al., 2023; Sathish, Hamdi, Chinthaginjala Venkata, Alibakhshikenari, et al., 2023; Sathish, Ravikumar, et al., 2023; J. Yang et al., 2015). As a result, neither of these techniques is appropriate for application in submerged environments. Sound waves are, in any event, the utmost auspicious means of communication for UWSN. Lower acoustic frequencies (10 Hz–1 MHz) have a large wavelength but a narrow bandwidth.

Management and network protocols are intrinsically linked to the network's overall architecture. Underwater localization is essential since it serves as the foundation for all other possible capabilities, such as monitoring data and mobility of nodes (Erol-Kantarci et al., 2011). When developing localization algorithms, it is essential to consider the desired quality features. These are rapid coverage, extensive coverage, high accuracy, minimal communication costs, and scalability. These elements add complications to the algorithm, which must be circumvented if we are to achieve success. In addition to localization and temporal synchronization, the problems mentioned above need unique network and transit design methodologies for UWSN. Earlier studies, such as (Ullah et al., 2017; Zarar et al., 2016), and so on, have covered some of these topics in greater detail. In the context of WSNs, pin-pointing the specific locality of each sensor node in a UWSN is referred to as "localization." Several localization techniques for TWSNs have been proposed. In contrast, UWSNs have access to a limited number of localization approaches. The distinctive qualities of UWSN distinguish it from TWSN in fundamental ways.

Additionally, UWSNs have come a long way during the previous decade. Early warning systems for earthquakes and tsunamis, underwater martial surveillance, ocean research, celestial navigation, biological applications, and pollution control are just a few fields that can benefit UWSNs (Ullah et al., 2017). However, localization in an underwater environment poses a unique set of challenges due to factors such as the depth-dependent speediness of sound and the motion of sensor nodes due to activities like shipping and water current. Additional challenges are given by an underwater setting, such as the deployment of nodes, fluctuations in signal intensity, time synchronization, variations in sound speed, and acoustic wave characteristics, to name a few. Problems with energy efficiency, localization, and routing protocols are just a few examples of the many that still need to be addressed in the UWSN. Once a sensor node is localized, the observed data can be understood. Many localization mechanisms have been designed for WSNs, but they cannot be used in UWSNs without significant modification.

In the field of UWSNs, there has recently been a surge in the amount of interest in using distributed antenna systems to connect to wireless communication networks. In a WSN, individual antennas are dispersed and connected by UWANs, an external connection that connects sensor nodes via radio (Carroll et al., 2014; Sathish, Hamdi, Chinthaginjala, Pau, et al., 2023; Sathish, Hamdi, Chinthaginjala Venkata, Alibakhshikenari, et al., 2023; Sathish, Ravikumar, et al., 2023). Two or more of the internal sensor components of a sub-merged or acoustically isolated by cluster and cluster head sensors followed by sink and base station, as shown in Figure 2.

A variety of commercially available underwater navigation systems perform their own self-localization based on readings of direction and speed. When put through their paces in a laboratory context, some of these algorithms,

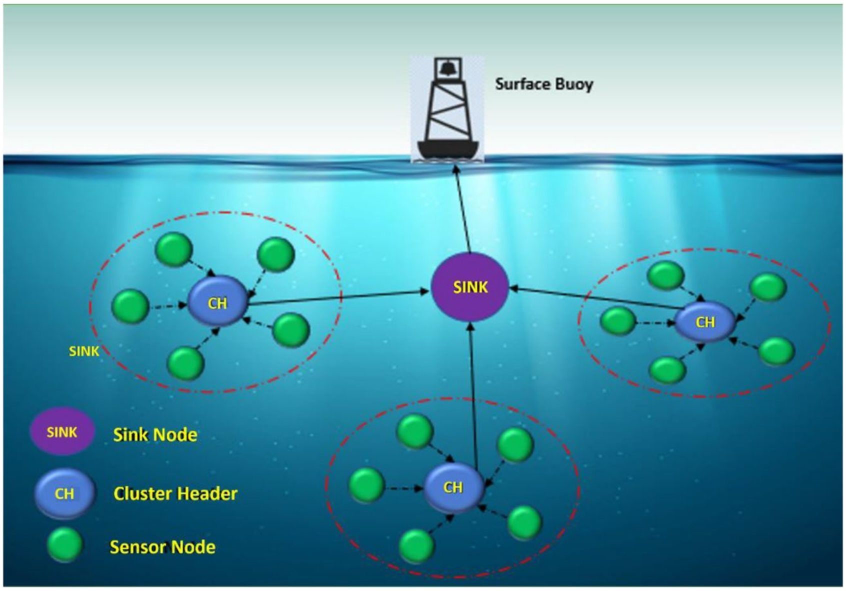


Figure 1. Underwater wireless sensor network system architecture.

on the other hand, demonstrate a navigational function that is dependable across relatively short distances. In contrast, the cumulative errors in these systems often cause a decline in their performance over time, resulting in a loss of precision. As a result, network localization algorithms must use both range approaches and submerged acoustic emissions as essential components. It is within the realm of possibility for sensor nodes to independently estimate their depth, possibly through the utilization of pressure probes. In order for these methods of localization to be effective, it is necessary to acquire distance readings from a minimum of three anchor nodes or other reference nodes that are already known (Diamant & Lampe, 2013). Because of the high attenuation of acoustic signals when traveling through water, the topology of the positioning network will probably be impeded.

Information gathered by sensor nodes in a two-dimensional underwater sensor network is gathered at anchor nodes placed at various depths around the ocean. The anchored nodes and the submerged sinks can communicate via acoustic linkages. The sinks collect data from the sensor nodes and send it to the offshore base station through the surface station. As a result, we can now purchase sinks outfitted with horizontal and vertical transceivers. While the vertical transceiver communicates with the base station, the horizontal transceiver communicates with

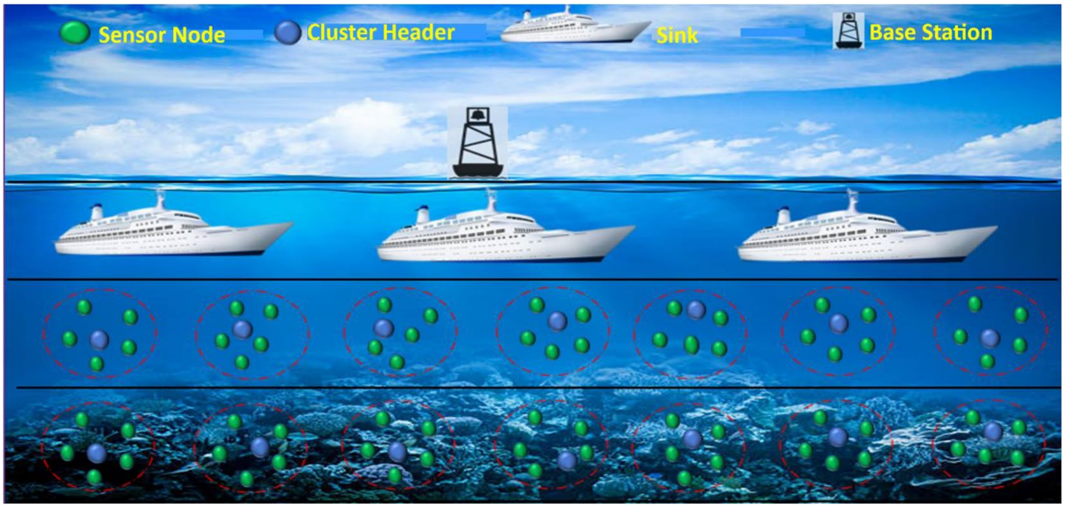


Figure 2. Internal structure of underwater wireless sensor networks system architecture.

the sensor nodes to collect data and send commands. Because of the greater depth at which a vertical transceiver may operate can cover a large area (Awan et al., 2019). The acoustic transceiver-equipped surface links can control parallel communication between many sinks at different depths. After that, long-range RF transmitters will establish a link between the surface and offshore sinks.

Localization algorithms are often classified into two types: Range-based algorithms and Range-free algorithms (Zandi et al., 2013). Sensor nodes in a range-based algorithm use angle or distance information to localize themselves and anchor sensor nodes. This information can be determined using time of arrival (ToA), time difference of arrival (TDoA), angle of arrival (AOA), and received signal strength indicator (RSSI). Furthermore, range-free localization makes use of connectivity information to find sensor nodes.

The primary goal of data mining in WSNs is to precisely and swiftly extract application-oriented patterns from a continuous stream of quickly changing data that originates from a sensor network. This goal can be accomplished through the use of specialized software. Because it is impossible to save all of the data under these circumstances, the data must be processed as quickly as possible (Mahmood et al., 2013; Sathish, Hamdi, Chinthaginjala Venkata, Alibakhshikenari, et al., 2023; Sathish, Ravikumar, et al., 2023). Processing high-velocity data at a higher rate is therefore required for data mining. The management of static data makes use of data mining techniques that were developed in the past. Both the multi-step and the multi-scan methods should be utilized in order to analyze static data sets. The data that WSNs produce cannot be mined efficiently using traditional data mining techniques because of its high dimensionality, massive volume, and distributed nature.

Underwater communication and positioning are indeed areas of ongoing research and development due to the challenges posed by the dynamic underwater environment and increasing interference. While it's important to recognize the significance of accurate and precise underwater positioning, it is also crucial to ensure that research in this field incorporates innovative approaches.

We can enhance its innovativeness and contribute to the advancement of underwater communication and positioning research by considering the following aspects:

1. Novel Techniques: Investigate and propose new techniques or methodologies that can overcome the existing limitations in underwater positioning. This could involve incorporating advancements in signal processing, machine learning, or sensor technologies specifically tailored for underwater environments.
2. Multi-Sensor Integration: Explore the fusion of multiple sensors or data sources, such as acoustic, optical, or inertial sensors, to improve the accuracy and reliability of underwater positioning systems. Developing innovative algorithms that combine information from different sensors can lead to more robust positioning solutions.
3. Cooperative Localization: Investigate cooperative localization techniques that leverage collaboration among underwater nodes or vehicles to enhance positioning accuracy. This could involve designing distributed algorithms or communication protocols that enable cooperative positioning using information exchanged among networked underwater devices.
4. Autonomous Underwater Vehicles (AUVs): Focus on the integration of positioning capabilities into AUVs, allowing them to navigate autonomously and accurately in complex underwater environments. Consider exploring advanced algorithms for AUV localization and path planning, taking into account factors such as underwater terrain mapping and obstacle avoidance.
5. Energy-Efficient Solutions: Address the energy constraints typically encountered in underwater communication and positioning systems. Innovative techniques for optimizing power consumption, such as low-power communication protocols, energy harvesting, or energy-efficient signal processing algorithms, can contribute to longer operational lifetimes and improved system performance.
6. Underwater Network Architectures: Investigate novel network architectures or communication protocols that can enhance the reliability and efficiency of underwater positioning systems. For instance, exploring the use of underwater sensor networks, underwater acoustic networks, or hybrid communication approaches can offer new perspectives on underwater positioning.

The severe physical characteristics of the undersea environment characterize UWSN and contribute to the network's limited bandwidth. Underwater environments bring a distinct set of challenges for the localization process. These difficulties result from the significant delay in transmission induced by the variable speed of sound. In this article we have proposed two effective localization methods for UWSNs: measurements based on distance and angles. The sensor nodes are first determined underwater using the proposed approaches. When it comes to the localization and detection of targets in the underwater environment, the measurement of mean estimation errors (MEEs) is second to the localization of nodes as the most crucial step. The two fundamental aspects that make up localization are the localization of sensor nodes and the measurement of MEEs while localization is in progress. The simulation findings make it abundantly evident that proposed localization algorithms can significantly cut down on the MEEs, resulting in decreased communication costs and a high level of accuracy.

The contributions of this manuscript are:

1. The design and implement the optimization of precise and efficient object localization for underwater wireless sensors network.
2. Analyzes of the object localization as a function of the number of underwater wireless sensor nodes.
3. Trade-off analyzes between distance-based localization and angle-based localization algorithms in the UWSN environment.
4. Recommendation of an appropriate localization algorithm based on the targeted performance metric for UWSN.

The remainder of the manuscript is organized as follows. The related studies that are discussed in Section 2 include the associated work, the context, the data, the information, the UWSN communication technologies, and the underwater localization methods. In Section 3, an explanation is given for each of the localization strategies that have been suggested. In addition, the proposed design and simulation parameters are discussed in Section IV. Simulation results are assessed in Section 5. In Section 6, a conclusion is drawn on the proposed results.

2. Related Studies

This section explains the idea of underwater localization. Then, we will look at some more popular methods for locating underwater things.

Park et al. (2019) modified the well-known ALOHA (Medium Access Convention) model in 2019 to enhance channel utilization. The new model features enhanced ALOHA-Q (UW-ALOHA-Q). Unusual activity, a reduction in the number of openings per outline, and a unified arbitrary conspiracy are suggested as ways to improve UW-ALOHA-Q (Ravikumar & Bagadi, 2019). The suggested methodology comprehensively improves utilization regarding the number of openings per outline while providing yet another arbitrary back-off mechanism to achieve impact-free planning. For subsea systems with a range of 1,000 m, UW-ALOHA-Q boosted channel usability by up to 24.6 times (Sathish, Ravikumar, Rajesh, & Pau, 2022; Sathish, Ravikumar, Srinivasulu, & Gupta, 2022).

Erol et al. (2008) described that most oceanographic applications rely on localizing sensor nodes along long or short baselines (LBL or SBL). In both instances, sensor positions are deduced from auditory interactions between sensors and a network of receivers placed in predetermined places (Rx). The region of operations includes subsurface moorings and the seafloor, which are home to acoustic antennas for the LBL system. In contrast, SBL involves a spacecraft passing behind sensor nodes and using a short-range emitter source. Additionally, a vessel is used as part of a commercially available SBL localization system to locate underwater machinery. Prior to deployment, both algorithms needed substantial preparation and financial expenditures.

Cheng et al. (2007) gave two types of underwater acoustic localization: range-based and range-free. The range-based approach first uses TDOA, TOA, AOA, and RSSI to calculate distances or angles to selected anchor sensor nodes, as shown in Figure 3. They then translated the ranges into several coordinate systems using multilateration and triangulation techniques. As an alternative, the range-free method forecasts the positions of sensor nodes in the network based on the locations of neighboring anchor sensor nodes. Radar, sonar, and wireless communication devices depend on accurate distance assessment of targets. The minimum variance method, conventional beam forming, the weighted subspace fitting algorithm, and the Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT) algorithm are just a few of the distance of arrival (DOA) estimation algorithms that have been developed in the past.

Biao et al. (2015) provided a DOA estimate method for underwater acoustic targets and the micro underwater localization platform. In order to do this, the authors looked into several formulations for the acoustic target localization with sensor array problem within the context of sparse signal representation. Both narrow-band and

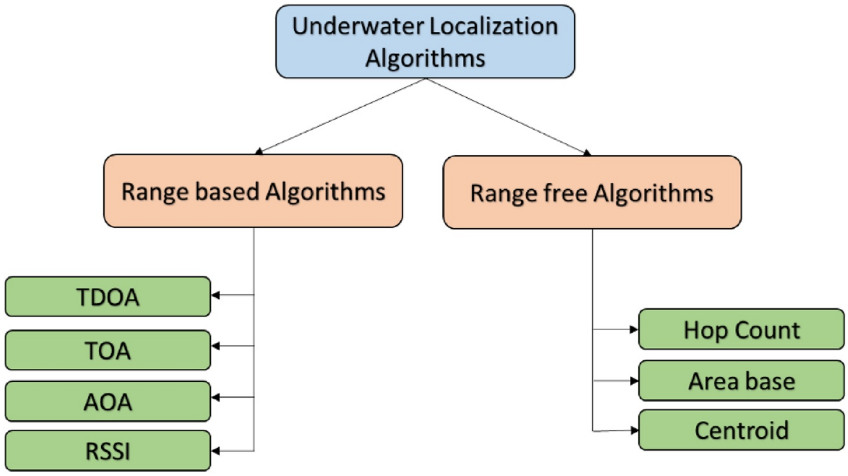


Figure 3. Underwater localization algorithms.

wide-band environments are compatible with the strategy. The position of a signal at a dumb node is determined by its DOA. One can determine the signal's direction by calculating the receiver's propagation delay with the reference angle, which can be worked out with the help of a direct reference (Ravikumar & Bagadi, 2017). Using this method, the AOA for a dumb node's location is found using at least three beacon nodes. To find the dumb node, it is necessary to know where at least three beacon nodes and the three AOA are. When directional antennas are used, it is possible to figure out the AOA. Directional antennas can be put on beacon sensor nodes if they are used. A directional antenna at the top of a rotating sensor node sends beacon signals in all directions (Sathish, Ravikumar, Rajesh, & Pau, 2022, Sathish, Ravikumar, Srinivasulu, & Gupta, 2022).

Rahman et al. (2018) proposed that the fundamental goal of a localization strategy is to find the location of sensor nodes in a network of sensors (nodes that already know where they are) relative to or precisely concerning a small number of anchor nodes. There are two ways to accomplish this. Furthermore, the article presents a system that uses less energy and can identify and collect data on moving objects. The localization algorithm can be classified into two groups based on the approaches used to establish the location of anything: range-based and range-free.

Han et al. (2015) given range-based localization methods, the position of a sensor node can be computed by measuring the angle or distance between the node and its neighbors. Range-free algorithms, on the other hand, assume that the distance or angle information gathered by neighboring sensor nodes cannot be used for positioning due to hardware limits and costs, which spreads anchor sensor nodes over all networks and uses long-range acoustic channels to communicate with buoys on the water's surface, is widely regarded as one of the best attempts at a localization method in UWSN.

Isik and Akan (2009) shared that Ordinary localization and anchor node localization constitute the majority of the Localization method, which can be further subdivided into its component pieces. The messages transmitted to the ordinary sensor node originate at the anchor sensor node. The anchor communicates with the surface buoys using the anchor sensor node. Following that, an ordinary node will identify its location by calculating its distance from surface buoys in the same manner as an anchor node. As a result, it is not required because a normal sensor node can establish its location. Furthermore, the researchers assume that many stationary sensor nodes underwater have the same bearing (Bagadi et al., 2022). Some sensor nodes can run the range algorithm by transmitting messages only in one way and synchronizing their clocks, both challenging operations in UWSNs.

H. Zhang et al. (2016) reported that due to the underwater environment's features for signal propagation, UWSNs face a particular set of obstacles in developing wireless communication and network protocols. In a mobile sink design, a mobile sink moves across the network to disseminate non-information without first waiting for it to be sent by the sensors, hence avoiding multi-hop transmissions. Some networks use a method known as area partitioning to decrease the travel time between the sink sensor node and the sink and to create clusters that boost output. We suggest a transmission strategy based on superposition coding to increase the throughput of down-link command messages to sensor nodes.

Emokpae et al. (2014) discovered that because signals transmitted by the GPS cannot penetrate water, it will be necessary to find an alternative way to locate sensor nodes. Most of these techniques needed either the alignment of two approaches or range measurements between the talking sensor nodes, such as TDoA, ToA, AoA, and RSSI. Recent years have seen a rise in the focus placed on locating sensor nodes deep within the water. The vast majority of the localization systems that have been discussed aim to establish a reference sensor node before proceeding (Emokpae et al., 2014). However, this method has a significant limitation because it requires many reference sensor nodes in a distributed network. Without these reference sensor nodes, localization is difficult, if not impossible. The high cost of electricity, transport, and other infrastructure requirements makes it unfeasible to install many reference sensor nodes in the vast majority of underwater fields. This situation is because these demands must be met. The UWSN, taken into consideration by Hu et al. (2019) comprises several sensor nodes dispersed throughout the network's physical space. In order to keep the cost of the network to a minimum, sensor nodes are developed with constrained processing capabilities and simplified computational complexities. Because marine environments are in a permanent state of flux, the sensor nodes are in a constant state of motion, following the flow of water and reacting to activity in the marine environment.

G. Yang et al. (2018) proposed that as a consequence of these difficulties, localization needs to be done as quickly if possible; otherwise, the estimated positions will remain the same even as the sensor nodes move from one location to another. Therefore, it is essential to organize a localization process that is both quick and economical with energy in a sensor network that has limited resources. The continual motion causes specific sensor nodes to have a greater chance of moving outside of the functioning field of the network, which exacerbates recycling and sustainability issues. The brininess, temperature, and depth of the water all have an effect, in addition to the elements estimated on the rate at which the waves below move.

He et al. (2018) presented two techniques for underwater target localization in the study mentioned above: nonlinear weighted least squares-based underwater target localization and space-altering generalized expectation maximization-based underwater target localization (SAGE-UTL). Submarine target localization using nonlinear weighted least squares (UTL) is also known as UTL using a state-action-event model. Based on the information collected by a swarm of dispersed star receivers, these algorithms can pinpoint the location of a target with great accuracy. The network is hypothesized to perform the functions of both a primary receiver and several additional conventional receivers. A sound speed profile (SSP) with an iso-gradient and a network anchored to the water's depth is assumed. As temperature and salinity tend to fluctuate throughout the ocean, the iso gradient SSP theory makes sense for the environment under investigation.

Additionally, Yin et al. (2016), Hao et al. (2017), and B. Zhang et al. (2018) have researched the TDoA localization algorithms and the ToA localization algorithms. The unknown source location and hybrid estimations are initially connected to evaluate a solution with a closed form. The best sensor node association is then determined. The solution is then assessed. According to all of the Cramer-Rao Lower Bound (CRLB) is the lowest bound of any unbiased estimator and can be used to transmit details about the accuracy of localization. Even when there is just a small amount of inaccuracy, the MEE matrix can be derived. However, its actual value can only be realized in the context of practical application. First, a localization technique for closed structures must be studied before using the error covariance matrix that this strategy generates to estimate the CRLB. By recasting the issue as an optimization problem to identify the ideal node association, they could convert an unsolvable issue into a convex one. They were able to solve the issue as a result successfully.

Mridula and Ameer (2018) provided a localization approach for UWSNs that considers the problems in sensor node localization caused by ambiguity in the anchor location. When the anchor is submerged, it moves a lot. This circumstance is because water currents harm the network's environment. It is easier to carry out rigorous localization when clarity is inside an anchor node. The undersea environment's ray-bending quality must be considered for accurate location readings. This situation is because the speed of sound is considerably lowered under the surface. Using ray theory, one may determine the path that sound rays take when immersed in water. Because the positions of the anchors are inherently imprecise, it is necessary to use Maximum likelihood to determine the precise location of the required sensor node. It is compared to several methods, each of which provides precise data on the exact location of the anchor node. If the anchor nodes are unclear, CRLB is calculated to help estimate the target's location. The UWSN is a collection of sensors that work together to monitor activity in marine habitats. To achieve these objectives, sensor nodes organize themselves into self-contained networks capable of characterizing a marine ecosystem. Because they do not require cable to be put beneath the water's surface and do not interfere with marine operations, USNs are designed to be easy and affordable to outfit. This circumstance is one of their primary goals. Because of their one-of-a-kind qualities, UWSNs necessitate a fresh approach to a wide range of localization-related difficulties.

3. Localization

Because of the lack of essential infrastructure, underwater networks have more difficulty performing localization tasks than their terrestrial equivalents. Propagation delays, in particular, can be highly significant when bandwidth is limited. The limited capability of building modems capable of simultaneous signal transmission and reception is another constraint that must be considered while designing and implementing UWSNs. A well-prepared transmission can prevent data loss due to the near-far effect. To keep network management overhead minimal, the amount of information sent between nodes must be limited by the node discovery mechanism. Another area of speculation in UWSNs is the connectivity of the sensor nodes. Several factors exacerbate the connection process, including noise, relative node orientation, fading, and propagation losses. This connectivity is influenced by several elements, including sensor node relative motion, sensor node and link failure, sensor node installation, and a range of other issues. Even if there is no direct link between standard sensor nodes and anchor sensor nodes, networks can be built to facilitate range measurement. Depending on the network architecture, a few additional localization methods can be utilized, such as the Euclidean, DV-hop, and DV-distance.

The Euclidean distance yields some promising results when dealing with anisotropic topologies. When doing a more complex calculation, higher overhead and communication costs are incurred. A sensor node can only localize itself if its position can be determined uniquely. The sensor node cannot pinpoint its precise location if it lacks it. Even if a node cannot localize itself, many alternative locations may still be measured (H. Luo et al., 2008). This circumstance is because potential locations are more precise than actual locations. Only a small number of sensor nodes have the potential to be precisely located. The great majority of approaches to localization include the sensor node being localized by doing a partial localization with the assistance of a collection of reference sensors. Specific sensor nodes, known as reference or sink nodes, must get their location information before the sensor node must be localized. This activity will commence at the beacon sensor node as its point of departure. It is preferable to use as little energy as possible whenever possible. It is also critical to consider the localization algorithm's level of precision. A method called UDB (underwater directional beacon) is provided in reference (Bian et al., 2009) for underwater localization.

3.1. Measurement Based on Distance

When operating in an underwater environment, sensor data is frequently interpreted based on the location of a sensor node. Following a target, keeping an eye on the environment, or reporting an event are all examples of this. As previously stated, finding something on land is more accessible than finding something underwater. This is because RF waves do not decrease as underwater as on land. GPS cannot be used underwater as a result of this. There were numerous approaches to localization in the various localization schemes (Ullah, Chen, et al., 2019, Ullah, Liu, et al., 2019). These methods consider various factors, including the device's capabilities, the rate at which the signal spreads, and the quantity of energy available, to name a few. Most systems for determining where something is considered a sensor node's location in the network field. The nodes whose placements are known are the anchor sensor nodes. Most localization techniques employ these nodes. In Poursheikhali and Zamiri-Jafarian (2015), there is a plan for locating a target based on predicting the TDoA in a non-uniform underwater field. TDoA, which stands for "target depth of approach," is the strategy's concept. Because the underwater environment is not uniform, waves follow a curved path. As a result, locating the TDoA is far more complex than locating the terrestrial position. This method, which employs the methodology, considers TDoA-based localization in an algorithmic manner that varies over time. The approach is getting closer to the CRLB and has the potential to move beyond the line-of-sight (LoS) TDoA. This situation is accomplished by considering where an asynchronous target is located and how precise that location is.

Kouzoundjian et al. (2017) offer a method for calculating the TDoA between different underwater beacon signals. The algorithms for this system rely on distance measurements. The suggested approach does not require beacons and receivers to be set simultaneously for propagation to end in underwater conditions. As a result, the TDoA estimate depends on the location of the beacon sensor node. The solution is demonstrated to be a series of hyperbolic equations, with the theoretical location of the node being where these hyperbolas intersect. On the other hand, one popular method for determining the TDoA is to examine how strongly the signals cross-correlate. The underwater field generates a lot of phase and amplitude distortion in the waves that are picked up because the waves bounce back and forth in the water and cause reverberation. Another method for determining the TDoA is to examine the central section of the received signals for a succession of equal zero-crossing intervals that may be used to determine when they began and how much time has passed since they began. This method entails examining the primary portion of the received signals. Valente and Alves (2016) approach is implemented as a programmable system-on-chip coupled to an embedded ARM CPU and equipped with a custom-designed digital signal processor. The strategy was tested in both a closed environment (a tank) and an open environment (a field).

Using the relative antenna, the beacon may compute the distance between itself and a stationary or mobile node. For this reason, a Doppler speed measurement is used; however, the precision of the result depends on the position of both the mobile device and the beacon. The following are assumed to exist if N is the number of participating antenna nodes like r_i, s_i, t_i, where $n = 1, 2, ,\ldots.N$ (Ullah, Chen, et al., 2019; Ullah, Liu, et al., 2019):

$$\theta(i) = \left[r(i), r'(i), s(i), s'(i), t(i), t'(i)\right] \tag{1}$$

The Zero Mean Additive White Gaussian noise for the active nodes is

$$\begin{aligned}\theta(i) = Arg_{\theta(i)} \min \frac{1}{2(k\sigma_t)^2} \sum_{n=2}^{N} \left[k\delta\hat{t}_{n,1}(i) - (d_{sn}(i) - d_{s1}(i))\right]^2 \\ + \frac{1}{\sigma_v^2} \sum_{n=1}^{N} \left(\hat{v}_n(i) - \sqrt{r'(i)^2 + s'(i)^2 + t'(i)^2 V_n(i)}\right)^2\end{aligned} \tag{2}$$

where $V_n(i)$ is

$$V_n(i) = \left(\frac{r(i) - r_n}{l_n(i)} + \frac{s(i) - s_n}{l_n(i)} + \frac{t(i) - t_n}{l_n(i)}\right) \tag{3}$$

and $l_n(i)$ is

$$l_n(i) = \sqrt{(r(i) - r_n)^2 + (s(i) - s_n)^2 + (t(i) - t_n)^2} \tag{4}$$

In case of two sensor nodes Equation 4 will be

$$l_n(i) = \sqrt{(r(i) - r_n)^2 + (s(i) - s_n)^2} \tag{5}$$

3.2. Measurement Based on Angle

Recent research has shown that angle-based metrics are an effective method for underwater localization, and that this method is feasible.

The method described in Choi et al. (2018) provides an accurate approximation of the AoA of an audio source. Two hydrophones are mounted on a marine vehicle traveling across the water, and the directional angles of the source are measured. Utilizing the properties of acoustic waves that occur in the ocean, specific equipment can send out signals sporadically or continually. The foundation of this strategy is based on the presumption that a particular acoustic source consistently produces the same signal. An initial probability is calculated by utilizing the state transition model in the first step (Jia-Tong et al., 2018). In the second step, an algorithm known as a generalized cross-correlation is used for the already collected acoustic data to derive directional information. A comparison of the likelihood with the entropy of the current correlation is performed in the very last stage. However, the system that is being proposed needs to go into research the physical properties of a wide variety of acoustic sources depending on their frequency ranges. This situation is because such research is yet to be feasible. These measurable qualities centered on precisely measuring the directional angle of the acoustic sources to make use of the information already available regarding the frequency band (Wilding et al., 2018).

In addition, a wide variety of AoA localization schemes are utilized in Choi and Choi (2015) and Huang and Zheng (2016). We provide a technique for real-time AUV localization based on bearing estimation alone and use the depth of a beacon already known in advance. The system is based on the Extended Kalman Filter (EKF) and uses a State-Space model. This goal is done to account for the mobility of the AUV in two degrees of freedom. In a similar vein, a technique for identifying and removing acoustic target signals from a variety of underwater sources by making use of frequency bands is required. A Bayesian technique is used to derive the data on the directions, while an EKF model calculates the angles associated with those directions. In addition, a localization technique that can be used in underwater Ad-hoc networks is given. This strategy uses AoA to calculate the distance between anchors and sensor nodes in two-dimensional and three-dimensional space. Once a sensor node has received distance estimates from at least three or four anchor nodes, it will be possible to calculate the sensor node's location.

To approximate the distances and angles between nodes P and Q, which are initially located at coordinates l_1, m_1 and l_2, m_2, respectively (Ullah, Chen, et al., 2019; Ullah, Liu, et al., 2019).

Checking out the two nodes, P and Q:

$$P_0 = \sqrt{l_1 + m_1} \tag{6}$$

and

$$Q_0 = \sqrt{l_2 + m_2} \tag{7}$$

The distance between the sensor nodes P and Q is

$$PQ = \sqrt{(l_1 - l_2)^2 + (m_1 - m_2)^2} \tag{8}$$

The angle between nodes P and Q is

$$\cos\theta = \frac{P_0 + Q_0 - (PQ)^2}{2P_0Q_0} \tag{9}$$

also

$$\cos\theta = \frac{l_1 l_2 + m_1 m_2}{\sqrt{l_1^2 + m_1^2} + \sqrt{l_2^2 + m_2^2}} \tag{10}$$

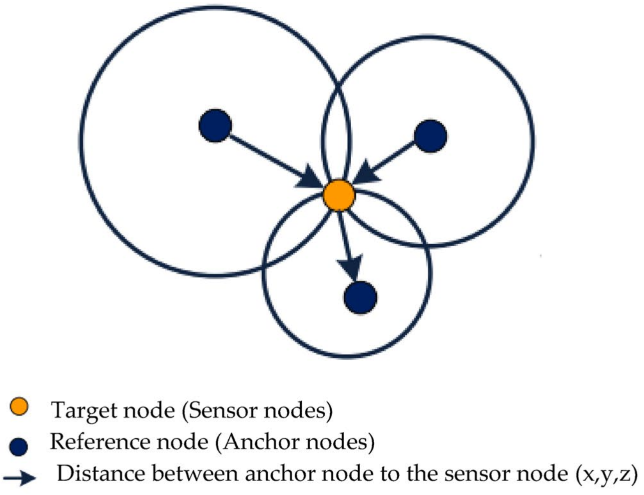
and the angle θ is

$$\theta = \cos^{-1}\left[\frac{l_1 l_2 + m_1 m_2}{\sqrt{l_1^2 + m_1^2} + \sqrt{l_2^2 + m_2^2}}\right] \tag{11}$$

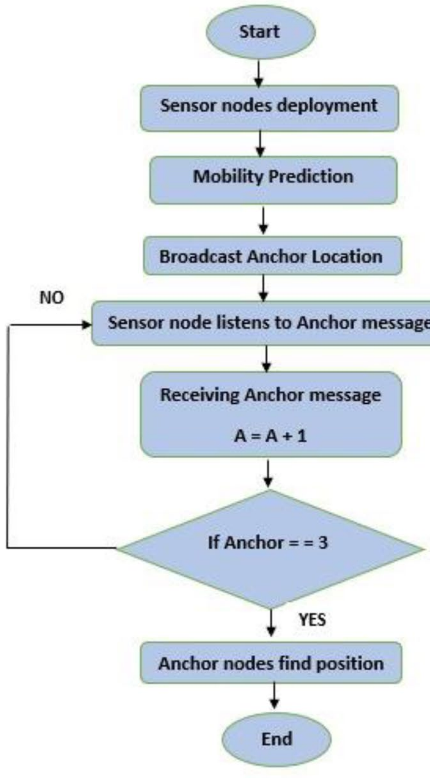
3.3. Proposed Localization Algorithm

To enhance the precise underwater object localization using TDoA and AoA, we need to consider introducing the following innovations:

1. Hybrid Localization Algorithm: Develop a hybrid localization algorithm that combines the AoA and TDoA measurements to improve the accuracy and precision of underwater object localization. The algorithm should leverage the strengths of both measurements to mitigate the limitations of each technique. This can involve using a weighted fusion approach or a Bayesian framework to integrate the angle and distance information effectively.



(a)



(b)

Figure 4. (a) Localization algorithm illustration with trilateration method and (b) Localization process flowchart.

2. Advanced Signal Processing Techniques: Incorporate advanced signal processing techniques to enhance localization accuracy. This can include adaptive beamforming, array processing, or super-resolution algorithms to improve the quality of the received signals and reduce the effects of multipath propagation and interference. By processing the received signals more effectively, the localization accuracy can be significantly enhanced.

Table 1
Simulation Attributes

Parameters	Values
Field dimension in meters	100,100
Sensor nodes	100
No. of Mobile nodes	10
BS location	(0,0,0)
No. of Anchor nodes	4
No. of Beacon nodes	6
No. of Trails	4–12
Initial UWSN energy	5 J

3. Intelligent Sensor Selection: Develop an intelligent sensor selection mechanism that dynamically selects the most suitable sensors for angle and distance measurements based on the environmental conditions. This can involve considering factors such as sensor characteristics, signal quality, and noise levels to ensure optimal localization performance. By adaptively selecting the sensors, the algorithm can optimize the use of available resources and improve the overall localization accuracy.
4. Machine Learning-Based Localization: Integrate machine learning techniques into the localization algorithm to learn and adapt to the underwater environment. This can include training a model to predict the localization errors based on various environmental factors and using this information to refine the localization estimates. By leveraging machine

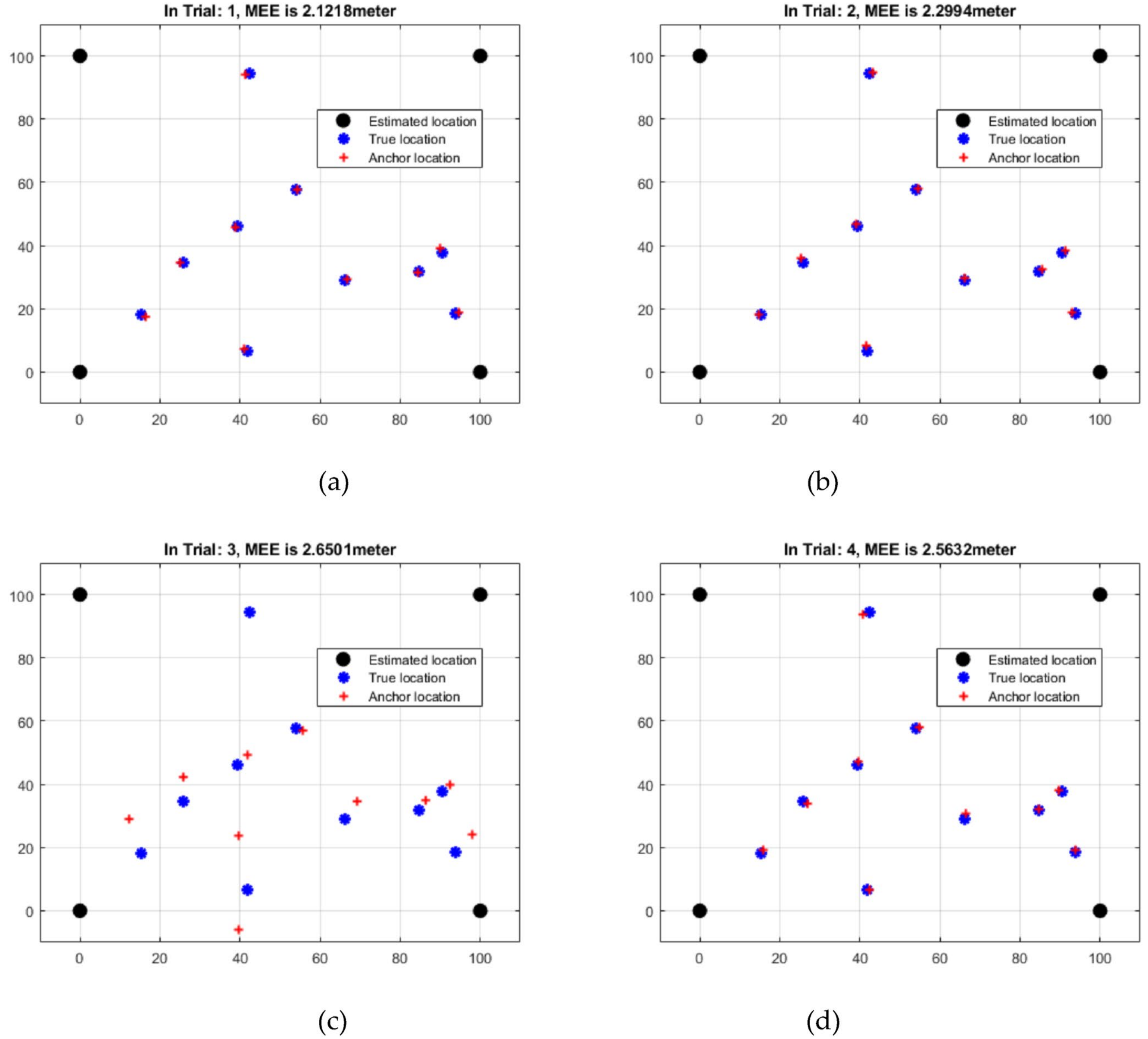


Figure 5. Measurement based on distance mean estimation errors for four trials.

Table 2
Measurement Based on Distance Mean Estimation Errors for Four Trials

Trail number	Distance measurement (mts)
Trail no. 1	2.1218
Trail no. 2	2.2994
Trail no. 3	2.6501
Trail no. 4	2.5632

learning, the algorithm can continuously improve its accuracy and adaptability over time.

5. Experimental Validation: Conduct comprehensive experimental validations to assess the performance of the enhanced localization algorithm. Utilize realistic underwater testbeds or simulation environments to evaluate the algorithm's effectiveness in different underwater conditions, such as varying distances, angles, noise levels, and multipath scenarios. Compare the results with existing methods to demonstrate the superiority and precision enhancement achieved by the proposed approach.

It is important to ensure that the proposed enhancements are aligned with the objective of improving precision, and thoroughly validate the algorithm's performance to establish its superiority over existing methods. A basic localization algorithm for an underwater WSN can be based on trilateration, which involves estimating the position of a sensor node by measuring the distances to multiple anchor nodes with known positions. Here's a simplified version of the algorithm with its mathematical equations:

1. Initialization:
   1-1. Assign initial positions to anchor nodes.
   1-2. Initialize the sensor node positions as unknown.
2. Distance Measurement:
   2-1. Sensor nodes measure the distances (d) to multiple anchor nodes using techniques such as ToA, TDoA, or RSSI.
3. Trilateration:
   3-1. Select a set of anchor nodes (at least three) with known positions and corresponding distance measurements.
   3-2. Use trilateration to estimate the position of the sensor node based on the distances and anchor node positions.
   3-3. The position (x, y, z) of the sensor node can be calculated using the following equations:

$$\text{For 2D Localization}: (x - x_a)^2 + (y - y_a)^2 = d_{a^2}\ (x - x_b)^2 + (y - y_b)^2 = d_{b^2}\ (x - x_c)^2 + (y - y_c)^2 = d_{c^2}$$

$$\text{For 3D Localization}: (x - x_a)^2 + (y - y_a)^2 + (z - z_a)^2 = d_a(x - x_b)^2 + (y - y_b)^2 + (z - z_b)^2$$
$$= d_{b^2}\ (x - x_c)^2 + (y - y_c)^2 + (z - z_c)^2 = d_{c^2}$$

   3-4. Solve the system of equations to find the coordinates (x, y, z) of the sensor node.
4. Iterative Refinement:
   4-1. Repeat steps 2 and 3 with different sets of anchor nodes to improve the localization accuracy.
   4-2. Use more sophisticated algorithms like least squares estimation or maximum likelihood estimation to refine the position estimates.
5. Localization Update:
   5-1. Periodically update the positions of the anchor nodes based on their actual movements or changes in the underwater environment.
   5-2. Re-estimate the sensor node positions using the updated anchor node positions and distance measurements.

It's important to note that the actual implementation of the algorithm may involve additional steps and considerations, such as error handling, filtering techniques, and robustness to deal with issues like measurement noise, multipath propagation, and localization outliers. The equations provided above represent a basic framework for trilateration-based localization in an underwater WSN and an illustration diagram as shown in Figures 4a and 4b shows the localization process flow chart.

The localization process in an UWSN involves determining the positions of sensor nodes in an underwater environment. Here's an explanation of the steps in a typical localization process flowchart for UWSN:

1. Start: The localization process begins.
2. Node Deployment: Deploy the sensor nodes in the underwater area of interest. These nodes may have limited or no knowledge of their own positions.

10.1029/2023RS007782

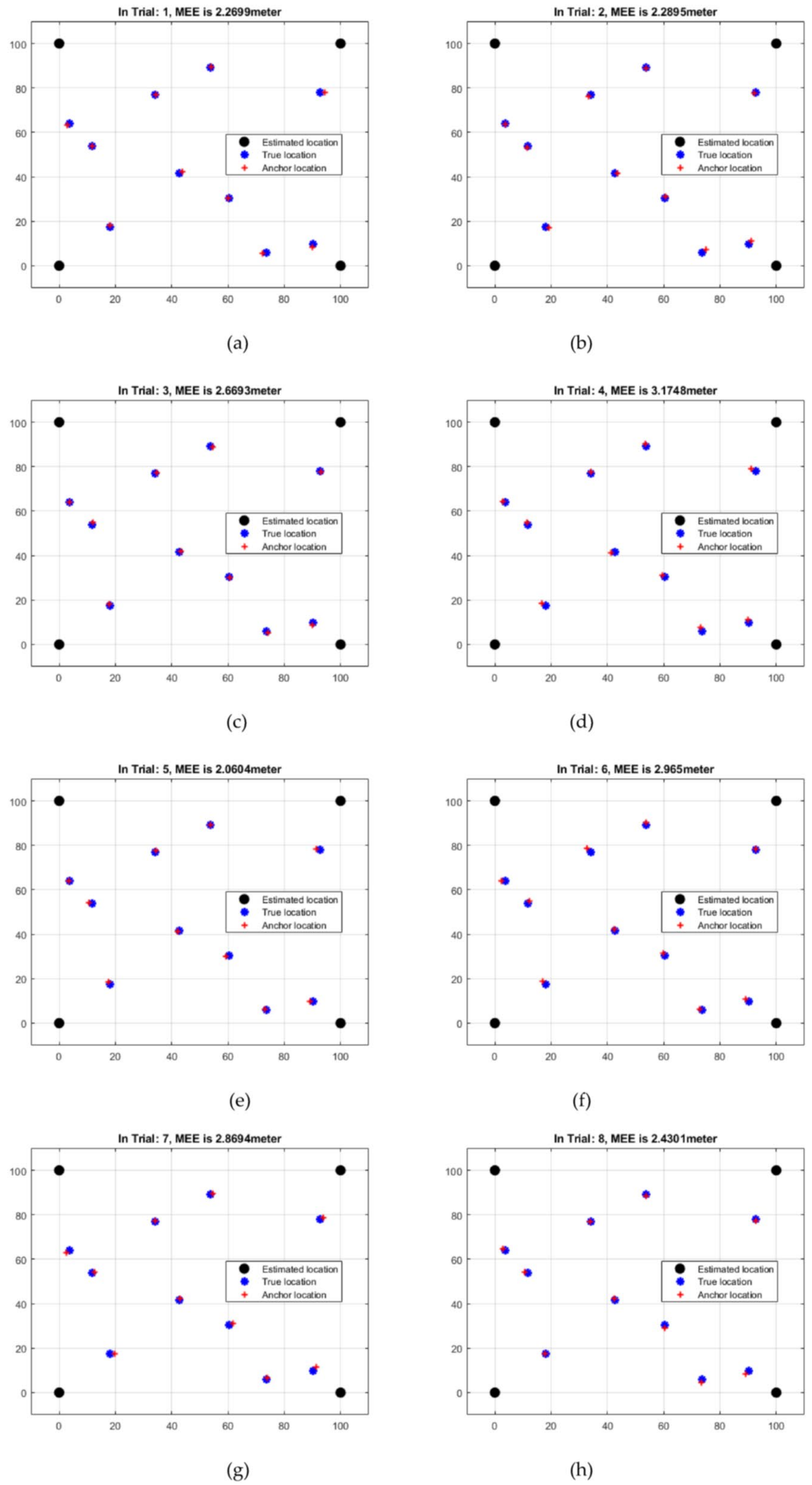


Figure 6. Measurement based on distance mean estimation errors for eight trials.

Table 3
Measurement Based on Distance Mean Estimation Errors for Eight Trials

Trail number	Distance measurement (mts)
Trail no. 1	2.2699
Trail no. 2	2.2895
Trail no. 3	2.26693
Trail no. 4	3.1748
Trail no. 5	2.0604
Trail no. 6	2.965
Trail no. 7	2.8694
Trail no. 8	2.4301

3. Distance Measurement: The sensor nodes measure the distances to their neighboring nodes using techniques such as acoustic signals, time of flight, or signal strength-based methods. This information helps establish connectivity and gather data for localization.
4. Distance Calculation: Based on the measured distances, each node calculates its relative position with respect to its neighboring nodes. Techniques like trilateration or multilateration can be used to estimate positions based on the distances.
5. Anchor Selection: Select a subset of nodes as anchor nodes. Anchor nodes are stationary and have known positions. They act as reference points for localization.
6. Localization Algorithm: Apply a localization algorithm that utilizes the distance measurements and anchor node positions to estimate the positions of the remaining nodes. There are various localization algorithms available, such as iterative closest point, weighted multidimensional scaling (WMDS), or particle filtering.
7. Iteration: Repeat steps 3 to 6 until convergence or a desired level of accuracy is achieved. Iterative refinement helps improve the accuracy of the estimated positions.
8. Position Refinement: Refine the estimated positions by considering additional factors such as node mobility, environmental constraints, and sensor calibration errors. This step helps account for uncertainties and improves localization accuracy.
9. Localization Error Assessment: Evaluate the accuracy of the localization by comparing the estimated positions with ground truth positions if available or using statistical measures such as root mean squared error or MEE. This step provides a quantitative assessment of the localization performance.
10. Localization Output: Provide the final localized positions for each sensor node in the UWSN. These positions can be represented in a coordinate system, such as Cartesian or geographic coordinates, for further analysis or application-specific purposes.
11. End: The localization process concludes.

It's worth noting that the specific techniques, algorithms, and parameters used in each step may vary depending on the localization method chosen, the characteristics of the UWSN, and the environmental conditions. The flowchart above provides a general framework for the localization process in UWSNs, highlighting the key steps involved in estimating node positions in an underwater environment as shown in Figure 4b.

3.4. Proposed Hybrid Localization Algorithms of TDOA and AOA

Hybrid algorithms that combine TDoA and AoA measurements can provide more accurate and robust localization in UWSN. Here are the mathematical equations for a common hybrid algorithm known as TDoA/AoA fusion:

1. TDoA Equations: The TDoA equations relate the time differences of arrival between anchor nodes and the distances between them. Let's consider three anchor nodes A, B, and C, and a sensor node S. The TDoA equations can be written as:

$$\begin{aligned}\text{TDoA\_AB} &= (\text{Distance\_AB} / \text{Speed\_of\_Sound}) + \text{Measurement\_Error\_AB TDoA\_AC}\\ &= (\text{Distance\_AC} / \text{Speed\_of\_Sound}) + \text{Measurement\_Error\_AC TDoA\_BC}\\ &= (\text{Distance\_BC} / \text{Speed\_of\_Sound}) + \text{Measurement\_Error\_BC}\end{aligned}$$

   Here, TDoA_AB, TDoA_AC, and TDoA_BC are the measured time differences of arrival between the anchor nodes, Distance_AB, Distance_AC, and Distance_BC represent the distances between the anchor nodes, Speed_of_Sound is the speed of sound in water, and Measurement_Error_AB, Measurement_Error_AC, and Measurement_Error_BC account for any measurement inaccuracies or noise.
2. AoA Equations: The AoA equations relate the angles of arrival from anchor nodes to the sensor node's position. Let's consider the angles of arrival from anchor nodes A, B, and C to the sensor node S. The AoA equations can be formulated as:

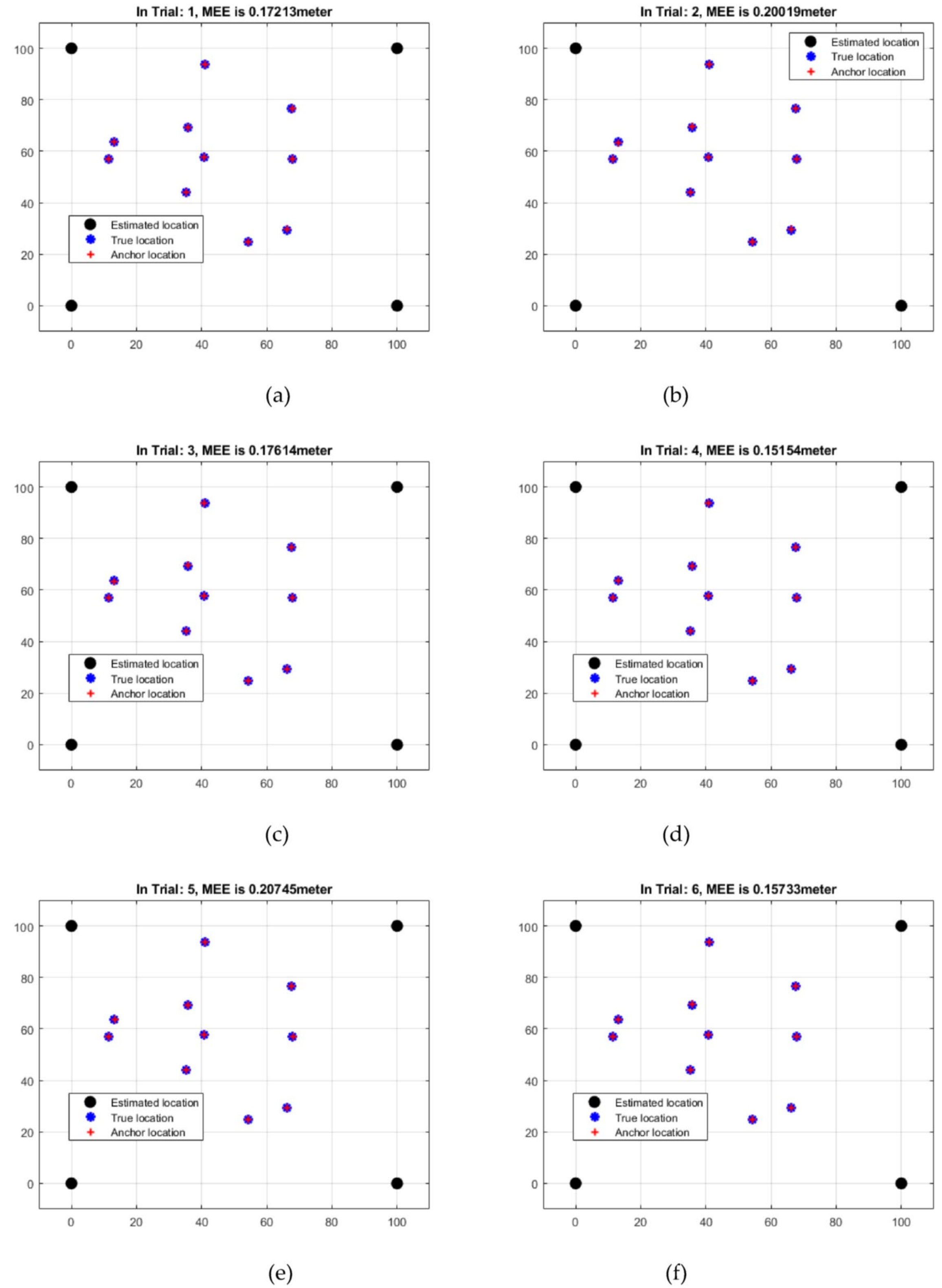


Figure 7. Measurement based on distance mean estimation errors for 12 trials.

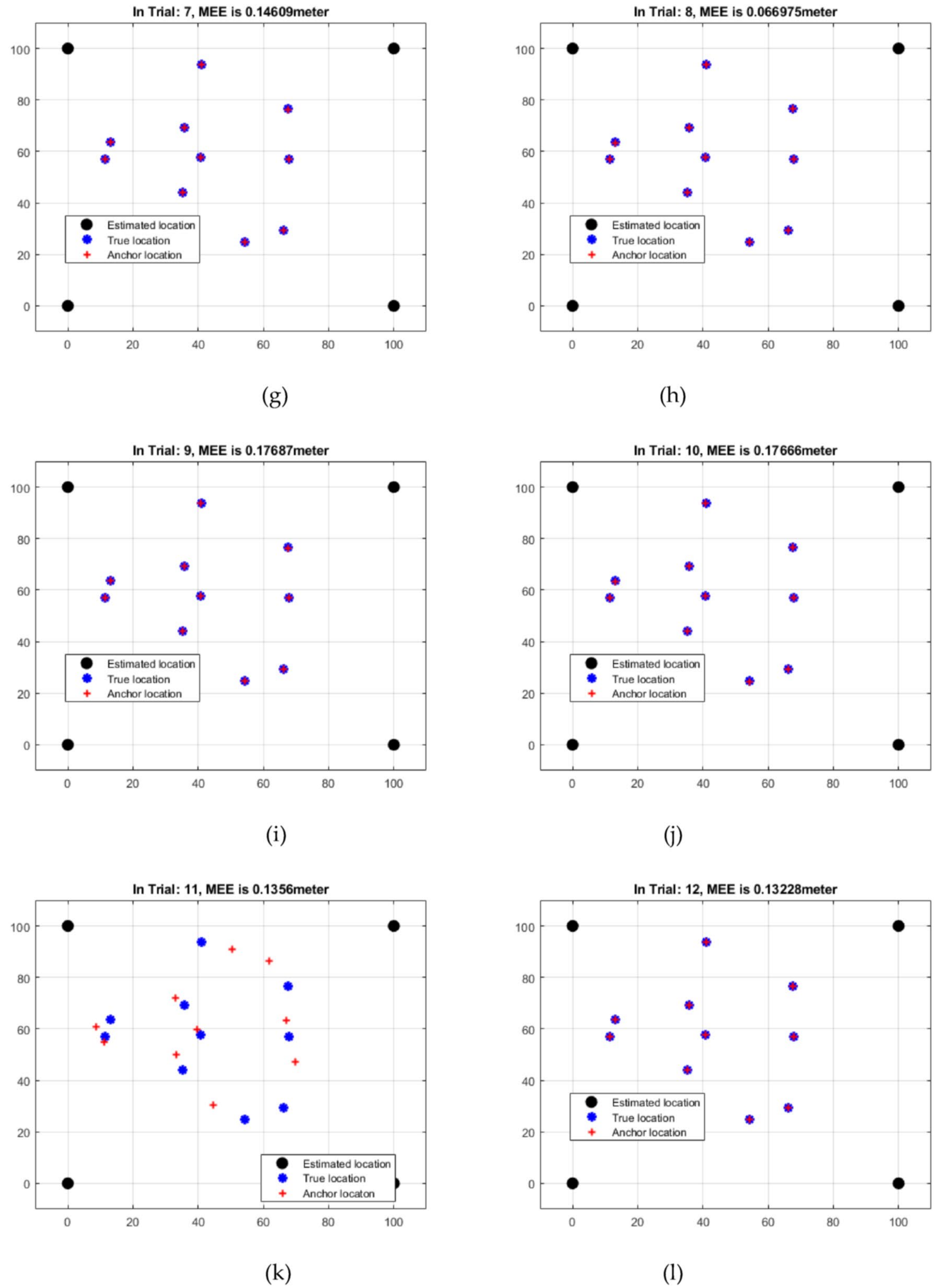


Figure 7. (Continued)

$$\tan(AoA\_A) = (y\_A - y\_S) / (x\_A - x\_S)\ \tan(AoA\_B) = (y\_B - y\_S) / (x\_B - x\_S)\ \tan(AoA\_C) = (y\_C - y\_S) / (x\_C - x\_S)$$

Here, AoA_A, AoA_B, and AoA_C are the measured angles of arrival, (x_A, y_A), (x_B, y_B), and (x_C, y_C) are the known positions of the anchor nodes, and (x_S, y_S) represents the estimated position of the sensor node.

3. TDoA/AoA Fusion Equation: To combine TDoA and AoA measurements, a fusion equation is used to estimate the position of the sensor node. One common fusion approach is to minimize the error between the TDoA and AoA measurements and the predicted values. This can be done through an optimization process, such as nonlinear least squares. The fusion equation can be written as:

$$\begin{aligned} \text{Minimize}: MEE = {} & w1 * (TDoA\_AB - (Distance\_AB / Speed\_of\_Sound))^2 \\ & + w2 * (TDoA\_AC - (Distance\_AC / Speed\_of\_Sound))^2 \\ & + w3 * (TDoA\_BC - (Distance\_BC / Speed\_of\_Sound))^2 \\ & + w4 * (\tan(AoA\_A) - (y\_A - y\_S) / (x\_A - x\_S))^2 \\ & + w5 * (\tan(AoA\_B) - (y\_B - y\_S) / (x\_B - x\_S))^2 \\ & + w6 * (\tan(Ao\_AC) - (y\_C - y\_S) / (x\_C - x\_S))^2 \end{aligned}$$

Here, E represents the overall error, and w1 to w6 are the weight factors assigned to balance the influence of TDoA and AoA measurements. The weights can be adjusted based on the expected accuracy and reliability of the measurements.

The goal is to minimize the error MEE by finding the optimal values for (x_S, y_S), representing the estimated position of the sensor node. It's worth noting that the specific implementation of the fusion equation may vary depending on the localization algorithm and optimization technique used. Additionally, considerations such as environmental factors, measurement errors, noise mitigation, and calibration techniques should be taken into account to achieve accurate localization in UWSN.

3.5. Pseudo Code for Proposed Hybrid Localization Algorithms of TDOA and AOA

1. Initialize the underwater sensor array with the required parameters:
   - Number of sensor nodes: N
   - Sensor nodes positions: array of N coordinates (x, y, z) relative to a reference point
   - Sampling frequency: fs
   - Speed of sound in water: c
2. Initialize the necessary variables:
   - Detected object position: (x_obj, y_obj, z_obj)
   - Detected object angle: θ_obj
3. Acquire the underwater acoustic signal from the sensor array:

   $$underwater\_signal = AcquireUnderwaterSignal(N, fs)$$

4. Perform signal preprocessing:

   $$preprocessed\_signal = PreprocessSignal(underwater\_signal)$$

5. Apply signal processing techniques to estimate the AOA (θ_obj):

   $$estimated\_angle = EstimateAngle(preprocessed\_signal)$$

6. Apply signal processing techniques to estimate the DOA:

   $$estimated\_distance = EstimateDOA(preprocessed\_signal)$$

7. Calculate the object position using the estimated angle and distance:

   $$\text{x\_obj} = \text{estimated\_distance} * \cos(\theta\text{\_obj})$$

   $$\text{y\_obj} = \text{estimated\_distance} * \sin(\theta\text{\_obj})$$

   $$\text{z\_obj} = 0\ //\ \text{Assuming the object is at the same depth as the sensor nodes}$$

8. Output the precise underwater object localization:

   $$\text{Print}(''\text{Object Position}: ('', \text{x\_obj}, '','', \text{y\_obj}, '','', \text{z\_obj}, '')''))$$

9. End

4. Proposed Design and Simulation Parameters

We shall now look at the techniques offered for underwater localization, which are first and foremost expected to achieve underwater target localization. After finding the target location, the MEE must be estimated. It takes advantage of previously defined distance and angle data. It is critical to first estimate the location of a sensor node before attempting to estimate the MEE in target localization. The simulation attributes of the proposed design are considered in Table 1.

4.1. Measurement Based on Distance

Assessing the network field over a region of 100 m by 100 m is the first step in putting into practice the distance-based localization strategy presented here. An area measuring 100 m by 100 m is open for exploration by underwater sensor nodes. In the first scenario, we test the method in a relatively tiny region that is only 100 m squared. This situation allows us to establish how big of an impact the distance has on the accuracy of the localization. We contact the four anchor nodes at the four cardinal points of the localization network to establish where anything is situated concerning other things. In this particular instance, there are just 10 mobile nodes that roam the network field that is 100 m × 100 m. For MEE monitoring, a sensor node in an irregular position is chosen. After the position of a sensor node has been produced randomly, numerous trails are used. However, just a subset of those trails is first studied in this situation. In this particular instance, the results of four trials are analyzed, MEEs are computed, and the same is extended for eight and 12 trials. Because the beacon sensor nodes are connected to a reference antenna, it is possible to calculate the distance between a mobile sensor node and a beacon node.

4.2. Measurement Based on Angle

In this part, we discuss the methods utilized to implement the proposed angle-based measuring methodology. With distance-based measurement in mind, we start by deciding on a 100 m × 100 m rectangle as the network field within which the mobile nodes can operate. Each of the four corners of the network field contains an anchor node, while the field as a whole contains 10 mobile nodes. There may likely be some variation in the positioning of the mobile nodes. Once the nodes' random positions have been estimated, the Euclidean distance may be calculated. Once the derivatives have been calculated, then the MEEs can be calculated. In this section, we can only use 10 sensors over 100 m × 100 m. We will also cover the effects of coverage and sensor density on the precision of localization in the following sections. Since the MEEs tend to fluctuate between the selected iterations, we use an angle-based measurement method in the first scenario. Skip occasionally across, but more often between, these four, eight, and 12 versions. This situation allows us to determine the angle between sensor nodes and calculate MEEs. The variability of MEEs is mainly attributable to the ever-changing nature of marine habitats, including ocean currents and shipping activity. Even though the proposed method increases the difficulty of underwater localization, it outperforms previous localization strategies in terms of accuracy.

Table 4
Measurement Based on Distance Mean Estimation Errors for 12 Trials

Trail number	Distance measurement (mts)
Trail no. 1	0.1721
Trail no. 2	0.2001
Trail no. 3	0.1761
Trail no. 4	0.1514
Trail no. 5	0.2074
Trail no. 6	0.1573
Trail no. 7	0.1460
Trail no. 8	0.0669
Trail no. 9	0.1768
Trail no. 10	0.1766
Trail no. 11	0.1356
Trail no. 12	0.1322

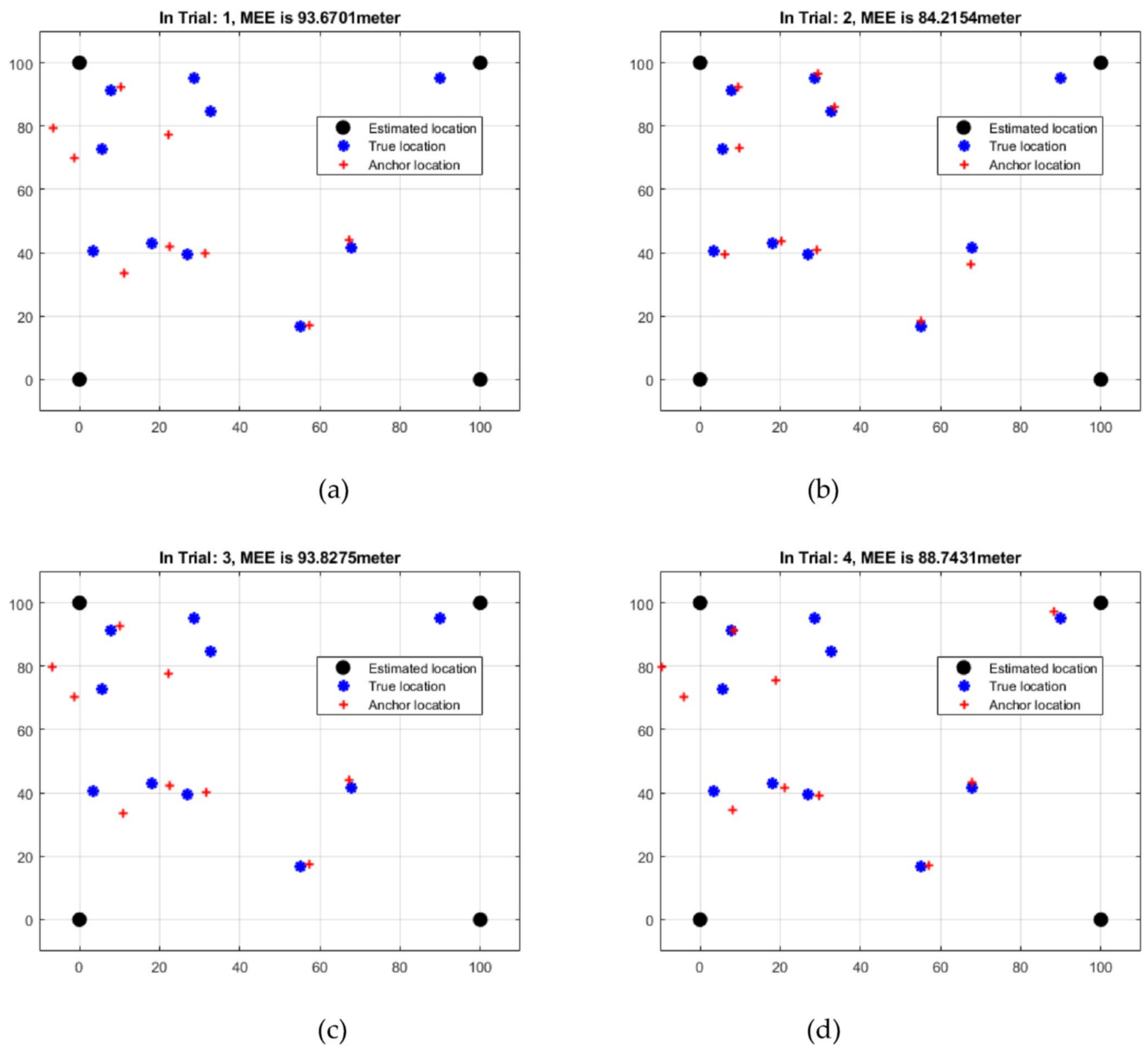


Figure 8. Measurement based on angle mean estimation errors for four trials.

Table 5
Measurement Based on Angle Mean Estimation Errors for Four Trials

Trail number	Angle measurement (mts)
Trail no. 1	93.6701
Trail no. 2	84.2154
Trail no. 3	93.8275
Trail no. 4	88.7431

4.3. Measurement Based on Hybrid TDoA and AoA Algorithm

The new innovation in this scenario is the measurement-based angle localization strategy for underwater sensor nodes. Here's an explanation of the key elements and steps involved:

1. Network Field and Anchor Nodes: The experiment is conducted within a 100 m × 100 m rectangular network field. Each of the four corners of the field is equipped with an anchor node. These anchor nodes serve as reference points for localization.
2. Mobile Nodes: The network field contains 10 mobile nodes that move within the area. These nodes contribute to the localization process by measuring angles between themselves and other nodes.

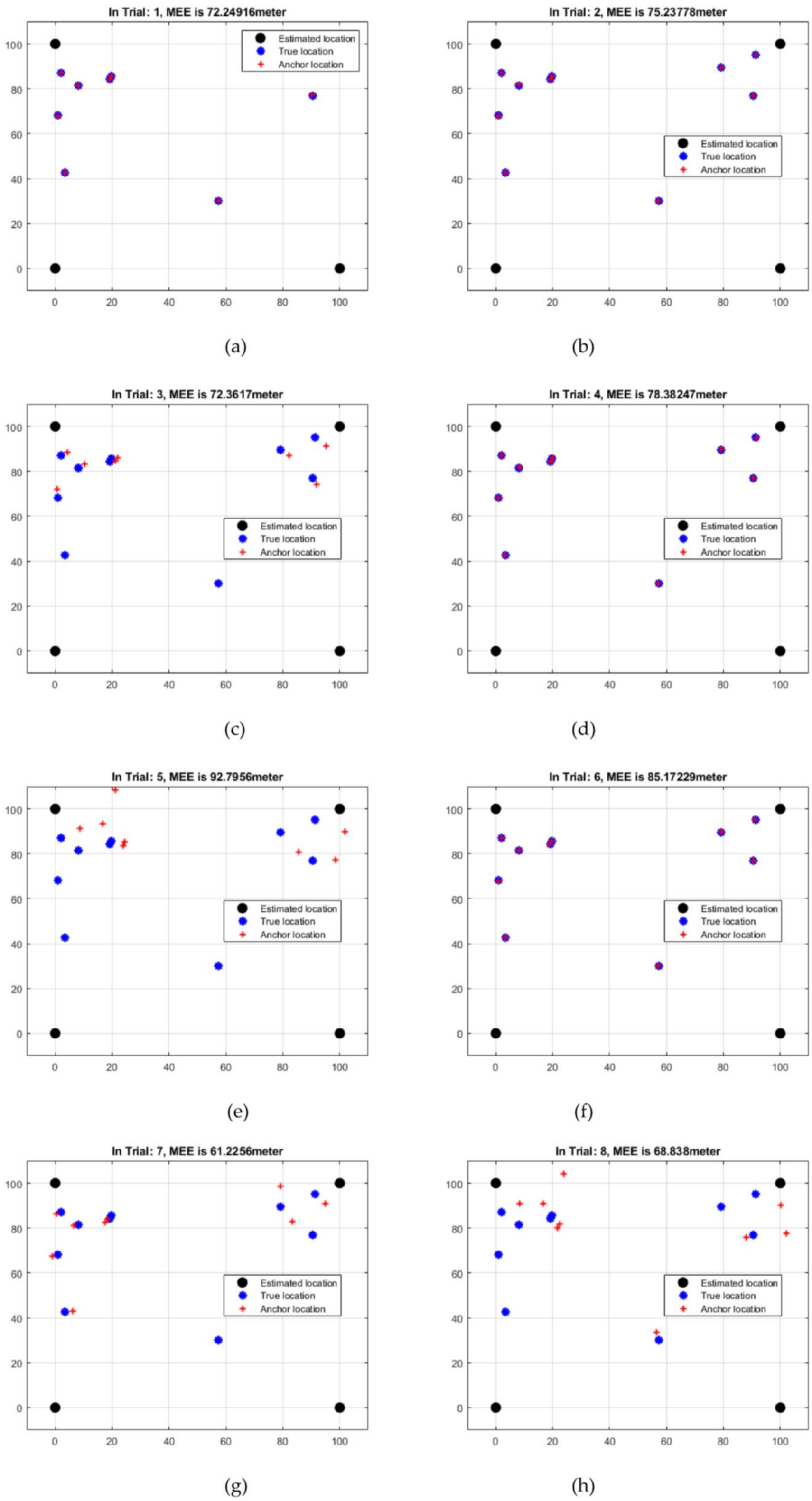


Figure 9. Measurement based on angle mean estimation errors for eight trials.

Table 6
Measurement Based on Angle Mean Estimation Errors for Eight Trials

Trail number	Angle measurement (mts)
Trail no. 1	72.2491
Trail no. 2	75.2378
Trail no. 3	72.3617
Trail no. 4	78.3824
Trail no. 5	92.7956
Trail no. 6	85.1724
Trail no. 7	61.2256
Trail no. 8	68.838

3. Random Node Positions: The positions of the mobile nodes are randomly determined within the network field. This introduces variation in the node positions, reflecting real-world scenarios.
4. Euclidean Distance Calculation: Once the node positions are established, the Euclidean distance between nodes can be calculated. This distance measurement is likely used as a reference for subsequent angle-based calculations.
5. Derivatives and MEEs: Derivatives are computed based on the calculated distances between nodes. Using these derivatives, MEEs are determined. MEEs are a measure of localization accuracy and represent the minimum error between estimated and actual positions.
6. Angle-based Measurement: In this scenario, an angle-based measurement method is used. The angle between sensor nodes is determined, and this information is utilized in the localization process. The angle measurements help refine the localization accuracy and overcome variations caused by marine habitats, such as ocean currents and shipping activity.
7. Multiple Iterations: To assess the performance and stability of the localization strategy, multiple iterations are conducted. This helps account for the variability in MEEs and allows for a more robust evaluation of the angle-based measurement method.
8. Localization Accuracy: Despite the challenges posed by the underwater environment, the proposed angle-based measurement method outperforms previous localization strategies in terms of accuracy. The fluctuation of MEEs is mitigated, leading to improved localization precision.

The innovation lies in the utilization of angle-based measurements in underwater localization. By incorporating angle information alongside distance measurements, the proposed strategy enhances the accuracy of object localization, even in the presence of environmental factors that may affect the measurements.

Hybrid TDoA and AOA algorithm for Enhancement of Precise Underwater Object Localization Using Angle and DOA.

1. Initialize the underwater sensor array with the required parameters:
   - Number of Sensor nodes: N
   - Sensor nodes positions: array of N coordinates (x, y, z) relative to a reference point
   - Sampling frequency: fs
   - Speed of sound in water: c
2. Initialize the necessary variables:
   - Detected object position: (x_obj, y_obj, z_obj)
   - Detected object angle: θ_obj
3. Acquire the underwater acoustic signal from the sensor array:

   $$underwater\_signal = AcquireUnderwaterSignal(N, fs)$$

4. Perform signal preprocessing:

   $$\text{preprocessed\_signal} = \text{PreprocessSignal}(underwater\_signal)$$

5. Apply TDoA-based signal processing techniques to estimate the DOA:

   $$\text{estimated\_distance} = \text{EstimateTDoA}(\text{preprocessed\_signal})$$

6. Apply AoA-based signal processing techniques to estimate the AOA (θ_obj):

   $$\text{estimated\_angle} = \text{EstimateAoA}(\text{preprocessed\_signal})$$

7. Calculate the object position using estimated angle and distance:

   $$\text{x\_obj} = \text{estimated\_distance} * \cos(\theta\text{\_obj})$$

   $$\text{y\_obj} = \text{estimated\_distance} * \sin(\theta\text{\_obj})$$

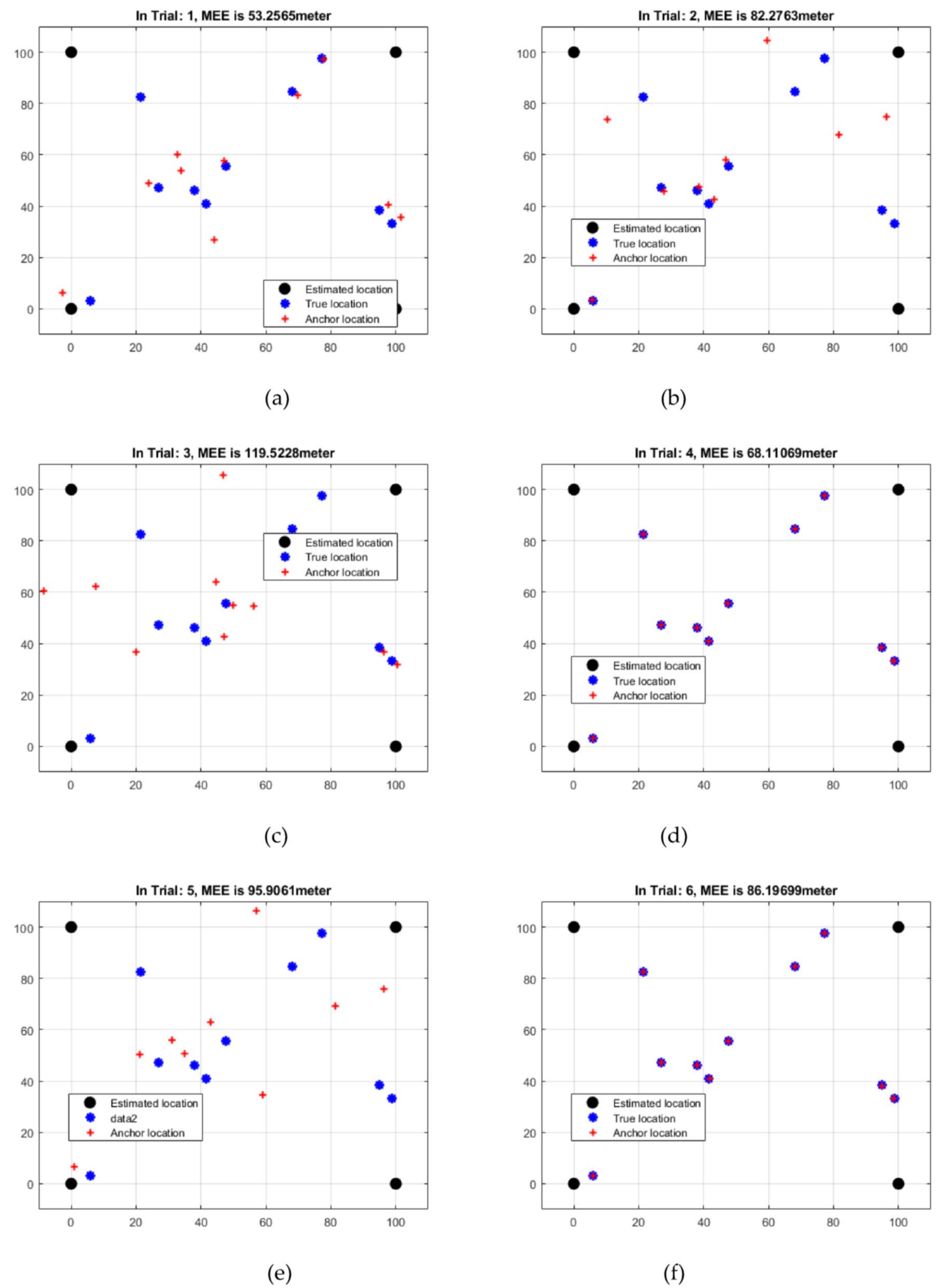


Figure 10. Measurement based on angle mean estimation errors for 12 trials.

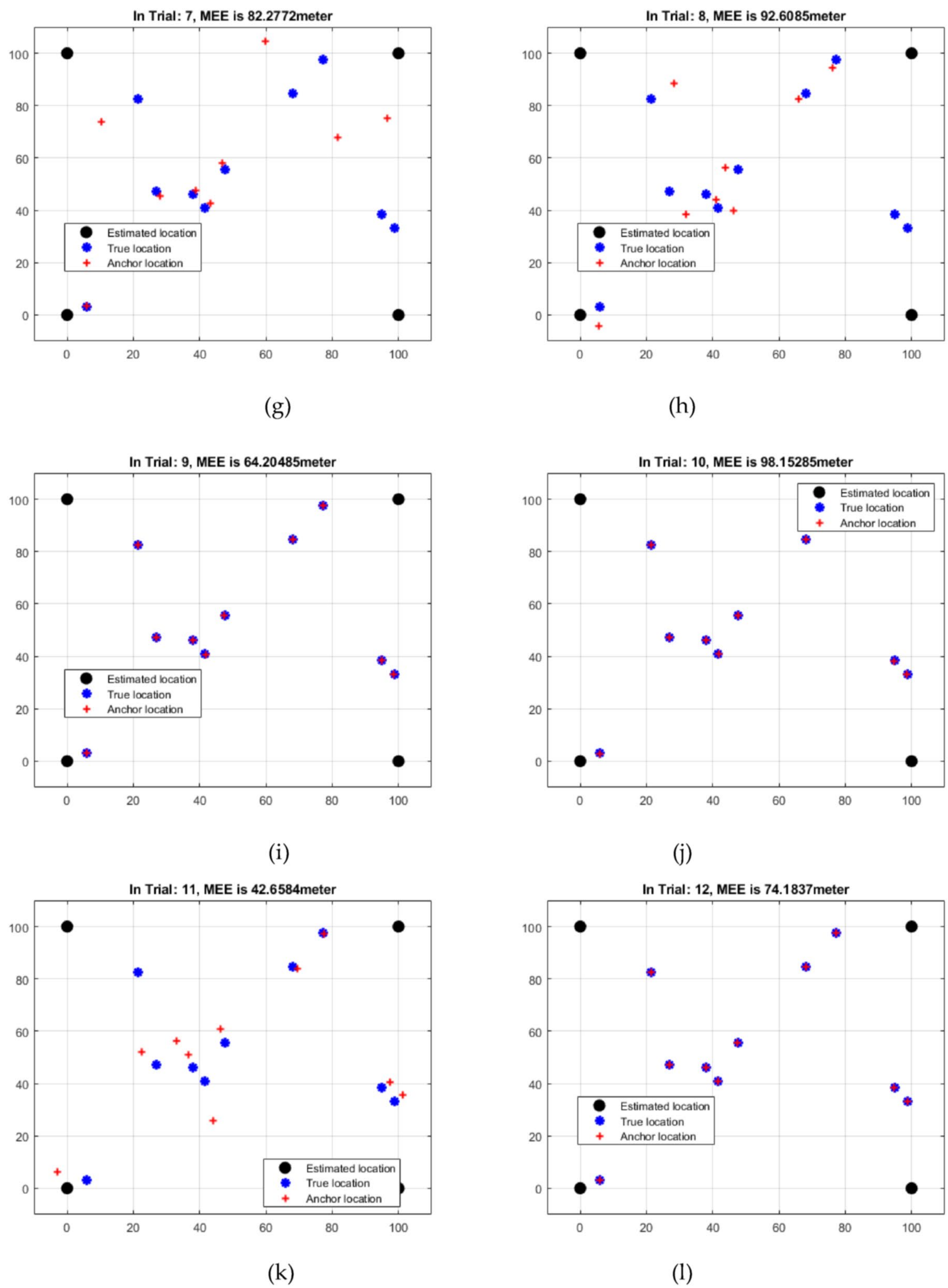


Figure 10. (Continued)

z_obj = 0 // Assuming the object is at the same depth as the Sensor nodes

8. Refine the object position using triangulation:
   Repeat until convergence:
   a) Calculate the distances from the object to each Sensor nodes:
      distances = []
      for $i = 1$ to N:

      distances[i] = sqrt((x_obj − Sensor nodes _positions[i].x)^2
      + (y_obj − Sensor nodes _positions[i].y)^2 + (z_obj − Sensor nodes _positions[i].z)^2)

   b) Calculate the weights for each Sensor nodes based on the inverse of the distances:
      weights = []
      for $i = 1$ to N:

      weights[i] = 1 / distances[i]

   c) Normalize the weights:
      total_weight = sum (weights)
      for $i = 1$ to N:

      weights[i] = weights[i]/ total_weight

   d) Calculate the updated object position:

      x_obj_new = sum(weights[i] ∗ Sensor nodes _positions[i].x) for i = 1 to N

      y_obj_new = sum(weights[i] ∗ Sensor nodes _positions[i].y) for i = 1 to N

      z_obj_new = sum(weights[i] ∗ Sensor nodes _positions[i].z) for i = 1 to N

   e) Update the object position:

      x_obj = x_obj_new

      y_obj = y_obj_new

      z_obj = z_obj_new

9. Output the precise underwater object localization:

   Print(″Object Position : (″, x_obj,″,″, y_obj,″,″, z_obj,″)″)

10. End

This hybrid algorithm combines the TDoA and AoA techniques to estimate the distance and AOA of the underwater object. It then utilizes triangulation to refine the object position based on the estimated distance and angle information. The refinement step iteratively updates the object position until convergence, similar to the previous algorithm.

Table 7
Measurement Based on Angle Mean Estimation Errors for 12 Trials

Trail number	Angle measurement (mts)
Trail no. 1	53.2565
Trail no. 2	82.2763
Trail no. 3	119.5228
Trail no. 4	68.1106
Trail no. 5	95.9061
Trail no. 6	86.1969
Trail no. 7	82.2772
Trail no. 8	92.6085
Trail no. 9	64.2048
Trail no. 10	98.1528
Trail no. 11	42.6584
Trail no. 12	74.1837

5. Simulation Results and Discussions

The efficiency of the proposed distance and angle-based measurements was validated by research conducted underwater, providing strong evidence for their use. Two fundamental methods were utilized to accomplish the primary goals of underwater localization and MEE estimation, respectively. Both tactics are an improvement over the methods that have come before them

Table 8
Measurement Based on Distance and Angle Mean Estimation Errors for Four Trials

Trail number	Distance measurement (mts)	Angle measurement (mts)
Trail no. 1	2.1218	93.6701
Trail no. 2	2.2994	84.2154
Trail no. 3	2.6501	93.8275
Trail no. 4	2.5632	88.7431

because, first, they precisely localize the sensor nodes, and then, second, they calculate the MEEs.

5.1. Measurement Based on Distance

Measuring distance is utilized in localizing a network by determining the distance between the sensor and anchor nodes. According to this strategy, the length of the boundary between each node in the network is set at 80 m, which results in the network being in the shape of a square. Sensing nodes are not permanently installed in any one location; as a result, mobile sensor nodes are free to move around wherever they like inside this zone. There are a total of 10 wandering nodes, along with four stationary nodes in the network. Each of the sensor nodes in the network can communicate with one of the four anchor nodes, which are positioned at each of the network's four corners. The schemes have an error ratio in the calculation of distance that is 0.1 m, which equates to an accuracy in the calculation of distance that is 90%. The precision of one m, approximately 0.1, is a good illustration of this concept. Before measuring the actual distances that separate the sensor nodes, it is first necessary to use a calculation to identify a non-uniform distribution of the sensor nodes. After the location of the sensor nodes has been determined, the procedure is analyzed through several iterations, and MEEs are acquired. Many trials of this process are carried out here; four, eight, and 12 trials are considered. The MEEs tend to move back and forth between the ranges of 2.1218 and 2.6501 m for four trials, 2.0604 and 3.1748 m for Eight trials, and 0.0669 and 0.2074 m for 12 trials, as can be seen in Figure 5 and the results of the trials that are presented in Table 2 for four trials, Figure 6 and the results of the trials that are presented in Table 3 for Eight trials and Figure 7 and the results of the trials that are presented in Table 4 for 12 trials.

5.2. Measurement Based on Angle

Measurement based on angles yields results comparable to those derived from measuring distances in terms of the range and the number of sensor nodes.

The network is dispersed 100 m by 100 m, and each of its 10 mobile nodes and four anchor nodes has been selected with care. The cardinal points are home to each of the four anchor nodes that make up the network. After selecting a random pair of nodes, P and Q, as the starting point, the next step is to compute their respective locations and angles. The MEEs can be computed once the nodes have been found in the network. This angular measurement has used four, eight, and 12 trials. The MEEs tend to move back and forth between the ranges of 84.2154 and 93.8275 m for four trials, 61.2256 and 92.7956 m for Eight trials, and 42.6584 and 119.5228 m for 12 trials, as can be seen in Figure 8 and the results of the trials that are presented in Table 5 for four trials, Figure 9 and the results of the trials that are presented in Table 6 for Eight trials and Figure 10 and the results of the trials that are presented in Table 7 for 12 trials.

Table 9
Measurement Based on Distance and Angle Mean Estimation Errors for Eight Trials

Trail number	Distance measurement (mts)	Angle measurement (mts)
Trail no. 1	2.2699	72.2491
Trail no. 2	2.2895	75.2378
Trail no. 3	2.26693	72.3617
Trail no. 4	3.1748	78.3824
Trail no. 5	2.0604	92.7956
Trail no. 6	2.965	85.1724
Trail no. 7	2.8694	61.2256
Trail no. 8	2.4301	68.838

Comparatively, the distance-based measurement is more accurate and time-efficient than the proposed angle-based measurement. When put next to the angular measurement, this is quite striking. The MEEs values obtained from distance measurements are smaller than those obtained from angle measurements. Compared to distance measurements, angular measurements are more challenging to take underwater due to the existence of impediments created by water currents. Depending on the measurement angle, MEEs can range from 42.6584 to 119.5228 m, whereas MEEs, based on distance, can swing from 0.0669 to 3.1748 m. The outcomes comparison of the data sets is provided in Table for Four trials, Table 9 for eight trials, and Table 10 for 12 trials.

Table 10
Measurement Based on Distance and Angle Mean Estimation Errors for 12 Trials

Trail number	Distance measurement (mts)	Angle measurement (mts)
Trail no. 1	0.1721	53.2565
Trail no. 2	0.2001	82.2763
Trail no. 3	0.1761	119.5228
Trail no. 4	0.1514	68.1106
Trail no. 5	0.2074	95.9061
Trail no. 6	0.1573	86.1969
Trail no. 7	0.1460	82.2772
Trail no. 8	0.0669	92.6085
Trail no. 9	0.1768	64.2048
Trail no. 10	0.1766	98.1528
Trail no. 11	0.1356	42.6584
Trail no. 12	0.1322	74.1837

6. Conclusion

The approaches of localization that are distance-based and angle-based are both covered in this article. After the locations of the subsea nodes have been determined, the MEEs are calculated. To perform distance-based measurements, a total network field of 100 m × 100 m in which mobile sensor nodes are permitted to roam has been established. There are 10 wandering nodes in the network, with the anchor nodes situated in the four corners of the network. When taking a reading of the MEE, the position of a sensor node is picked at random. After the random placements of the sensor nodes have been picked, different trials are applied; however, in the initial scenario, only a tiny subset of those trials are considered. The MEEs are computed after assessing six distinct combinations of the number of trials. The MEEs tend to move back and forth between the ranges of 2.1218 and 2.6501 m for four trials, 2.0604 and 3.1748 m for Eight trials, and 0.0669 and 0.2074 m for 12 trials, as can be seen in Figure 5 and the results of the trials that are presented in Table 2 for four trials, Figure 6 and the results of the trials that are presented in Table 3 for Eight trials and Figure 7 and the results of the trials that are presented in Table 4 for 12 trials. The network size for angle-based measurement is also 100 m × 100 m, which provides the mobile sensor nodes significant space to move. In each of the four corners of the square field, there is a total of 10 sensor nodes and four anchor nodes that have been placed. After angle estimations between sensor nodes have been determined, the MEEs can be computed. The MEEs can be computed once the nodes have been found in the network. This angular measurement has used four, eight, and 12 trials. The MEEs tend to move back and forth between the ranges of 84.2154 and 93.8275 m for four trials, 61.2256 and 92.7956 m for Eight trials, and 42.6584 and 119.5228 m for 12 trials, as can be seen in Figure 8 and the results of the trials that are presented in Table 5 for four trials, Figure 9 and the results of the trials that are presented in Table 6 for Eight trials and Figure 10 and the results of the trials that are presented in Table 7 for 12 trials. As seen in Tables 8–10, the measurements based on distance tend to produce more accurate findings than those based on the angle.

Abbreviations

UWSN	Underwater Wireless Sensor Networks
RF	Radio Frequency
AoA	Angle of Arrival
TDoA	Time Difference of Arrival
MEE	Mean Estimation Error
EM	Electromagnetic Waves
ISI	Inter-Symbol Interference
TWSN	Terrestrial Wireless Sensor Networks
GPS	Global Positioning System
RFID	Radio Frequency IDentification
WSNs	Wireless Sensor Networks
DAS	Distributed Antenna Systems
ToA	Time of Arrival
RSSI	Received Signal Strength Indicator
AUVs	Autonomous Underwater Vehicles
MVM	Minimum Variance Method
WSF	Weighted Subspace Fitting
ESPRIT	Estimation of Signal Parameters via Rotational Invariance Techniques
CRLB	Cramer-Rao Lower Bound
GCC	Generalized Cross-Correlation
EKF	Extended Kalman Filter

TOF	Time of Flight
ICP	Iterative Closest Point
WMDS	Weighted Multidimensional Scaling
RMSE	Root Mean Squared Error

Data Availability Statement

No data was used in this manuscript.

Acknowledgments
Dr. Mohammad Alibakhshikenari acknowledges support from the CONEX-Plus programme funded by Universidad Carlos III de Madrid and the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No. 801538. Additionally, the authors sincerely appreciate funding from Researchers Supporting Project number (RSP2023R58), King Saud University, Riyadh, Saudi Arabia. Besides above, the Article Processing Charge (APC) was afforded by Universidad Carlos III de Madrid (Agreement CRUE-Madroño 2023).

References

Almutairi, A., & Mahfoudh, S. (2017). Deployment protocol for underwater wireless sensors network based on virtual force. *International Journal of Advanced Computer Science & Applications*, *8*(11), 241–249. https://doi.org/10.14569/ijacsa.2017.081132

Awan, K. M., Shah, P. A., Iqbal, K., Gillani, S., Ahmad, W., & Nam, Y. (2019). Underwater wireless sensor networks: A review of recent issues and challenges. *Wireless Communications and Mobile Computing*, *2019*, 6470359. https://doi.org/10.1155/2019/6470359

Bagadi, K., Ravikumar, C. V., Sathish, K., Alibakhshikenari, M., Virdee, B. S., Kouhalvandi, L., et al. (2022). Detection of signals in MC-CDMA using a novel IBDFE. *Institute of Electrical and Electronics Engineers (IEEE Access)*. https://doi.org/10.1109/access.2022.3211392

Bian, T., Venkatesan, R., & Li, C. (2009). Design and evaluation of a new localization scheme for underwater acoustic sensor networks. In *GLOBECOM 2009-2009 IEEE Global Telecommunications Conference* (pp. 1–5). IEEE.

Biao, W., Chao, L., Zhihui, Z., & Qingjun, Z. (2015). DOA estimation based on compressive sensing method in micro underwater location platform. *Applied Mathematics & Information Sciences*, *9*(3), 1557.

Carroll, P., Domrese, K., Zhou, H., Zhou, S., & Willett, P. (2014). Localization of mobile nodes in an underwater distributed antenna system. In *Proceedings of the 9th International Conference on Underwater Networks & Systems* (pp. 1–5).

Cheng, X., Shu, H. S. H., & Liang, Q. (2007). A range-difference based self-positioning scheme for underwater acoustic sensor networks. In *International Conference on Wireless Algorithms, Systems and Applications (WASA 2007)* (pp. 38–43). IEEE.

Choi, J., & Choi, H.-T. (2015). Multi-target localization of underwater acoustic sources based on probabilistic estimation of direction angle. In *Proceedings of the OCEANS-Genova* (pp. 1–6). IEEE.

Choi, J., Park, J., Lee, Y., Jung, J., & Choi, H.-T. (2018). Robust directional angle estimation of underwater acoustic sources using a marine vehicle. *Sensors*, *18*(9), 3062. https://doi.org/10.3390/s18093062

Diamant, R., & Lampe, L. (2013). Underwater localization with time synchronization and propagation speed uncertainties. *IEEE Transactions on Mobile Computing*, *12*(7), 1257–1269. https://doi.org/10.1109/tmc.2012.100

Emokpae, L. E., DiBenedetto, S., Potteiger, B., & Younis, M. (2014). UREAL: Underwater reflection-enabled acoustic-based localization. *IEEE Sensors Journal*, *14*(11), 3915–3925. https://doi.org/10.1109/jsen.2014.2357331

Erol, M., Vieira, L. F., Caruso, A., Paparella, F., Gerla, M., & Oktug, S. (2008). Multi stage underwater sensor localization using mobile beacons. In *2008 Second International Conference on Sensor Technologies and Applications (sensorcomm 2008)* (pp. 710–714). IEEE.

Erol-Kantarci, M., Mouftah, H. T., & Oktug, S. (2011). A survey of architectures and localization techniques for underwater acoustic sensor networks. *IEEE Communications Surveys & Tutorials*, *13*(3), 487–502. https://doi.org/10.1109/surv.2011.020211.00035

Han, G., Jiang, J., Shu, L., & Guizani, M. (2015). An attack-resistant trust model based on multidimensional trust metrics in underwater acoustic sensor network. *IEEE Transactions on Mobile Computing*, *14*(12), 2447–2459. https://doi.org/10.1109/tmc.2015.2402120

Hao, B., Zhao, Y., Li, Z., & Wan, P. (2017). A sensor selection method for TDOA and AOA localization in the presence of sensor errors. In *2017 IEEE/CIC International Conference on Communications in China (ICCC)* (pp. 1–6). IEEE.

He, C., Wang, Y., Chen, C., & Guan, X. (2018). Target localization for a distributed SIMO sonar with an isogradient sound speed profile. *IEEE Access*, *6*, 29770–29783. https://doi.org/10.1109/access.2018.2843438

Hu, K., Song, X., Sun, Z., Luo, H., & Guo, Z. (2019). Localization based on MAP and PSO for drifting-restricted underwater acoustic sensor networks. *Sensors*, *19*(1), 71. https://doi.org/10.3390/s19010071

Huang, H., & Zheng, Y. R. (2016). AoA assisted localization for underwater ad-hoc sensor networks. In *Proceedings of the OCEANS MTS/IEEE Monterey* (pp. 1–6).

Isik, M. T., & Akan, O. B. (2009). A three dimensional localization algorithm for underwater acoustic sensor networks. *IEEE Transactions on Wireless Communications*, *8*(9), 4457–4463. https://doi.org/10.1109/twc.2009.081628

Jia-Tong, L., Chen, Z., & Hong-Xin, Z. (2018). On simultaneous AUV localization with single acoustic beacon using angles measurements. In *2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)* (pp. 2372–2378).

Kouzoundjian, B., Beaubois, F., Reboul, S., Choquel, J. B., & Noyer, J.-C. (2017). A TDOA underwater localization approach for shallow water environment. In *Proceedings of the OCEANS-Aberdeen* (pp. 1–4).

Luo, H., Zhao, Y., Guo, Z., Liu, S., Chen, P., & Ni, L. M. (2008). UDB: Using directional beacons for localization in underwater sensor networks. In *2008 14th IEEE International Conference on Parallel and Distributed Systems* (pp. 551–558). IEEE.

Luo, J., Fan, L., Wu, S., & Yan, X. (2018). Research on localization algorithms based on acoustic communication for underwater sensor networks. *Sensors*, *18*(1), 67. https://doi.org/10.3390/s18010067

Mahmood, A., Shi, K., Khatoon, S., & Xiao, M. (2013). Data mining techniques for wireless sensor networks: A survey. *International Journal of Distributed Sensor Networks*, *9*(7), 406316. https://doi.org/10.1155/2013/406316

Mridula, K. M., & Ameer, P. M. (2018). Localization under anchor node uncertainty for underwater acoustic sensor networks. *International Journal of Communication Systems*, *31*(2), e3445. https://doi.org/10.1002/dac.3445

Park, S. H., Mitchell, P. D., & Grace, D. (2019). Reinforcement learning based MAC protocol (UW-ALOHA-Q) for underwater acoustic sensor networks. *IEEE Access*, *7*, 165531–165542. https://doi.org/10.1109/access.2019.2953801

Poursheikhali, S., & Zamiri-Jafarian, H. (2015). TDOA based target localization in inhomogenous underwater wireless sensor network. In *Proceedings of the 5th International Conference on Computer and Knowledge Engineering (ICCKE)* (pp. 1–6). IEEE.

Rahman, T., Yao, X., & Tao, G. (2018). Consistent data collection and assortment in the progression of continuous objects in IoT. *IEEE Access*, *6*, 51875–51885. https://doi.org/10.1109/access.2018.2869075

Ravikumar, C. V., & Bagadi, K. P. (2017). MC-CDMA receiver design using recurrent neural network for eliminating multiple access interference and nonlinear distortion. *International Journal of Communication Systems*, *10*(16), e3328. https://doi.org/10.1002/dac.3328

Ravikumar, C. V., & Bagadi, K. P. (2019). Design of MC-CDMA receiver using RBF network to mitigate multiple access interference and nonlinear distortion. *Neural Computing & Applications*, *31*(2), 1263–1273. https://doi.org/10.1007/s00521-017-3127-0

Sathish, K., Hamdi, M., Chinthaginjala, R., Pau, G., Ksibi, A., Anbazhagan, R., et al. (2023). Reliable data transmission in underwater wireless sensor networks using a cluster-based routing protocol endorsed by member nodes. *Electronics*, *12*(6), 1287. https://doi.org/10.3390/electronics12061287

Sathish, K., Hamdi, M., Chinthaginjala Venkata, R., Alibakhshikenari, M., Ayadi, M., Pau, G., et al. (2023). Acoustic wave reflection in water affects underwater wireless sensor networks. *Sensors*, *23*(11), 5108. https://doi.org/10.3390/s23115108

Sathish, K., Ravikumar, C. V., Ab Wahab, M. N., Anbazhagan, R., Pau, G., & Akbar, M. F. (2023). Underwater wireless sensor networks performance comparison utilizing telnet and superframe. *Sensors*, *23*(10), 4844. https://doi.org/10.3390/s23104844

Sathish, K., Ravikumar, C. V., Rajesh, A., & Pau, G. (2022). Underwater wireless sensor network performance analysis using diverse routing protocols. *Journal of Sensor and Actuator Networks*, *11*(4), 64. https://doi.org/10.3390/jsan11040064

Sathish, K., Ravikumar, C. V., Srinivasulu, A., & Gupta, A. K. (2022). Performance analysis of underwater wireless sensor network by deploying FTP, CBR, and VBR as applications. *Journal of Computer Networks and Communications*, *30*, 1–30. https://doi.org/10.1155/2022/7143707

Siddiqi, T. R., Ning, H., Ping, H., & Mahmood, Z. (2017). DPCA: Data prioritization and capacity assignment in wireless sensor networks. *IEEE Access*, *5*, 14991–15000. https://doi.org/10.1109/access.2016.2630118

Thulasiraman, P., & White, K. A. (2016). Topology control of tactical wireless sensor networks using energy efficient zone routing. *Digital Communications and Networks*, *2*(1), 1–14. https://doi.org/10.1016/j.dcan.2016.01.002

Ullah, I., Chen, J., Su, X., Esposito, C., & Choi, C. (2019). Localization and detection of targets in underwater wireless sensor using distance and angle based algorithms. *IEEE Access*, *7*, 45693–45704. https://doi.org/10.1109/access.2019.2909133

Ullah, I., Liu, Y., Su, X., Esposito, C., & Kim, A. P. (2019). Efficient and accurate target localization in underwater environment. *IEEE Access*, *7*, 101415–101426. https://doi.org/10.1109/access.2019.2930735

Ullah, I., Ming-Sheng, G.-M., Kamal, M. M., & Khan, Z. (2017). A survey on underwater localization, localization techniques and its algorithms. In *Proceedings of the 3rd Annual International Conference on Electronics, Electrical Engineering and Information Science (EEEIS 2017)* (pp. 252–259). Atlantis Press.

Valente, J. F., & Alves, J. C. (2016). Real-time TDOA measurements of an underwater acoustic source. In *Proceedings of the OCEANS MTS/IEEE Monterey* (pp. 1–7).

Wilding, T., Grebien, S., Miihlmann, U., & Witrisal, K. (2018). AoA and ToA accuracy for antenna arrays in dense multipath channels. In *Proceedings of the 8th International Conference on Localization and GNSS (ICL-GNSS)* (pp. 1–6). IEEE.

Yang, G., Dai, L., & Wei, Z. (2018). Challenges, threats, security issues and new trends of underwater wireless sensor networks. *Sensors*, *18*(11), 3907. https://doi.org/10.3390/s18113907

Yang, J., Fei, Z., & Shen, J. (2015). Hole detection and shape-free representation and double landmarks based geographic routing in wireless sensor networks. *Digital Communications and Networks*, *1*(1), 75–83. https://doi.org/10.1016/j.dcan.2015.01.001

Yin, J., Wan, Q., Yang, S., & Ho, K. C. (2016). A simple and accurate TDOA-AOA localization method using two stations. *IEEE Signal Processing Letters*, *23*(1), 144–148. https://doi.org/10.1109/lsp.2015.2505138

Zandi, R., Kamarei, M., & Amiri, H. (2013). Underwater acoustic sensor network localization using four directional beams. In *Proceedings of the 21st Iranian Conference on Electrical Engineering (ICEE)* (pp. 1–6). IEEE.

Zarar, S., Javaid, N., Zaki, S. M., Ejaz, M., Khan, Z. A., Qasim, U., & Hussain, S. (2016). Increased throughput DB-EBH protocol in underwater wireless sensor networks. In *2016 30th International Conference on Advanced Information Networking and Applications Workshops (WAINA)* (pp. 571–576). IEEE.

Zhang, B., Hu, Y., Wang, H., & Zhuang, Z. (2018). Underwater source localization using TDOA and FDOA measurements with unknown propagation speed and sensor parameter errors. *IEEE Access*, *6*, 36645–36661. https://doi.org/10.1109/access.2018.2852636

Zhang, H., Huang, Q., Li, F., & Zhu, J. (2016). A network security situation prediction model based on wavelet neural network with optimized parameters. *Digital Communications and Networks*, *2*(3), 139–144. https://doi.org/10.1016/j.dcan.2016.06.003