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Efficient and Accurate Target Localization in Underwater Environment

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ABSTRACT Localization is the basic feature of wireless sensor networks (WSN) and estimating the time difference of arrival (TDoA), and angle of arrival (AoA) is the most used schemes for localization. Underwater wireless sensor network (UWSN) is extensively used for data collection in an underwater environment for both military and civilian applications. Nevertheless, efficient and accurate localization algorithms are essential for the UWSN because of the dynamical property of the underwater surrounding. Also, data management, collection, and processing for WSNs have become a more active topic nowadays in computer science, such as database system and data mining. The objective of deploying the WSNs applications is to collect the real-time data, which has very challenging due to the capacity of communication and high data generated by WSNs. For this purpose, the time and location are the basic aspects when a sensor collects data, especially for the case of location-aware data. Many researchers have studied the underwater sensor nodes localization and they have considered the sensor location where the data is collected and most of them focused on the fixed sensor nodes. In this research work, energy efficient and accurate localization schemes are presented named as distance-based and angle-based schemes for the underwater environment with relatively less energy consumption and mean estimation errors (MEEs). The proposed schemes mainly focus on the localization of underwater nodes and especially on the MEEs in localization. The extensive simulation is performed to compare the proposed schemes with other counterpart schemes. The results show that the proposed schemes outperform other counterpart schemes in terms of MEEs of localization and energy consumption.

INDEX TERMS Underwater wireless sensor networks (UWSNs), underwater localization, underwater acoustic sensor networks (UASNs).

I. INTRODUCTION

Water has covered 70 % of the land surface; basically, water is an infrequent substance that characterizes just 0.05 % of the land entire mass. However, water always plays an important role in the appearance of life on earth and especially for the living organism. The earth would be considered as a dead planet without the existence of water. The Underwater environment is still not well explored and researched for the betterment of human being life. Nowadays underwater communication technology has become an important part of our daily life and attracted more attention due to its broad applications in underwater. Those applications include control systems, environmental monitoring, navigation and many more. Underwater Acoustic Sensor Networks (UASN) knowledge delivers novel openings to discover the underwater environment and as a consequence it expands our understanding of the environmental problems that we face in daily life, such as climate changes, animals life in oceans and the continuous changes in the inhabitants of coral reefs [1]. UASN function is prevalent expertise for the wide range of applications such as tsunami forewarning, naval surveillance, ocean monitoring, oil platform monitoring, and climate monitoring. For the achievement of these applications different type of sensors are used in UASN, such as Autonomous Underwater Vehicle (AUV) and Unmanned Underwater Vehicle (UUV). To collect data from these sensor and vehicles surface beacons and ships are used [2]. However,

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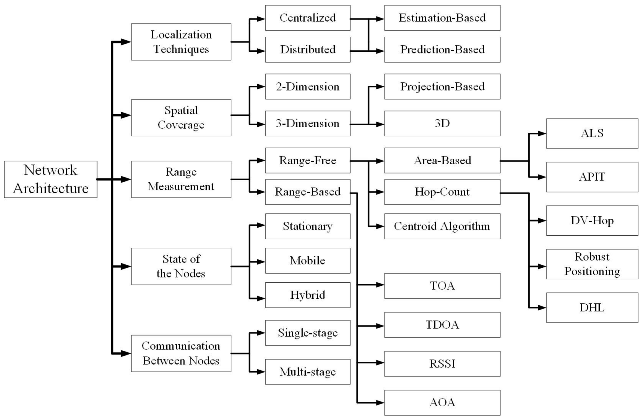

FIGURE 1. Network architectures of UASNs.

the harsh characteristics of the ocean environment, which include limited bandwidth, high propagation delay, spreading, etc., make the underwater localization more challenging task. Figure 1 represents the network architecture classification of UASNs.

A different number of applications manage the sensed data based on Underwater Wireless Sensor Networks (UWSNs) with various requirements. The sensor node can be found in different states such as standing, dynamic or hybrid, which sends the data by a connected wireless network. Currently, WSNs and several other technologies have offered Global Positioning System (GPS) and Radio Frequency (RF) for the terrestrial localization. However, in underwater RF signals attenuate highly and the frequency for RF signals which are appropriate for UWSNs are ranging from $30Hz - 300\ Hz$. Also, it's a requirement that the power of transmission is high or the size of the antenna is large. The features of Underwater Sensor Networks (USNs) are basically diverse from that of Terrestrial Sensor Networks (TSN). Acoustic channels in underwater are considered by the harsh physical layer surroundings with rigorous limitations of bandwidth. Similarly, the optical signals in an underwater environment also suffer from scattering and high attenuation [3]–[5]. As a result, these both technologies are not desirable for underwater communication. But, fortuitously acoustics waves are the most promising mode of communication for UWSNs. Acoustic frequency is lower, which is lying between $10\ Hz - 1\ MHz$, provide a small bandwidth but a long wavelength. The following Table 1 present an approximate time-scale unit for recording various type of waves.

Furthermore, during the last decade, we have observed a keen improvement in UWSNs. UWSNs introduce a lot of applications, some of them are warning system (tsunami and earthquake), underwater military surveillance, ocean exploration, navigation, ecological application (biological water quality), pollution control, etc., [6]. But the variable speed of sound in underwater and the motion of sensor nodes because of the shipping activities and water current produce a unique set of problems and challenges for localization in an underwater environment. More challenges in an underwater environment include node deployment, variation in signal strength, time synchronization, sound speed variation, acoustic wave characteristics, etc. There are still a lot of issues in USN like energy efficiency, localization and routing protocols which required to be solved. Localization of nodes is important because detected data is only meaningful when we localize a sensor node [7]–[9]. Many localization techniques are proposed for WSNs but these cannot be applied directly to UWSNs because of its varying characteristics form WSNs.

TABLE 1. Estimated time-scale units for recording various kinds of waves.

Wave Type	Material Type	Time Units
Acoustic wave	Air	1 millisecond
Acoustic wave	Water	1/2 millisecond
Acoustic wave	Rock	1/10 millisecond
Electromagnetic (EM) wave	Vacuum, Air	1 nanosecond

USNs field has seen a keen interest in approaching wireless communication network through Distributed Antenna Systems (DAS). This disagree from the shared Central Antenna System (CAS), in that various antennas are spread out all over a WSN and plugged in by some external links, whichever wiring or in the case of UANs an exterior link which links up sensor nodes through radio [10], [11]. DAS rewards in term of coverage area, outage performance, throughput, and other characteristics are well studied. The impression of fusing data from various antennas in the wireless network to empower nearest instantaneous location measurement for vastly mobile sensor network factors such as gliders, quickly traveling AUV and other non-confined sensor nodes in comparatively sparse sensor networks. A DAS may be positioned indoors (iDAS) or outdoors (oDAS). It can also be employed by utilizing inactive feeders and splitters or sometimes the vigorous repeater amplifiers can be involved to control the sufferers of the feeder. In networks where equalization is utilized, it may be suitable to acquaint hold spread in the area of overlapped coverage, allow quality development through the diversity of time.

In the ocean, anchor nodes are deployed to accumulate information from sensor nodes in 2D underwater sensor network environment. These anchored nodes utilize acoustic links to connect with each other or with underwater sinks. The sinks are accountable to collect all the information from the sensor nodes and transfer this information to the offshore BS station through the surface station. Therefore, the sinks are provided which is accompanied by vertical and horizontal transceivers. The vertical transceiver is utilized to transfer data to BS station and the horizontal transceiver is communicating with the nodes for the collection of data and supply commands to those sensor nodes. Because the underwater environment is deep, so vertical transceiver has enough range [12]. The links on the surface which is equipped with the acoustic transceivers having the ability to control the parallel communication through the multiple sinks in underwater. The surface sinks then communicate with the offshore sinks by the extensive range RF transmitters.

Generally, the localization algorithms are grouped into two categories such as Rang-based and Range-free algorithms [13]. In range-based algorithm sensor nodes use angle or distance information and anchor sensor nodes for localization. For the achievement of this information, Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA) and Received Signal Strength Indicator (RSSI) can be used. Also, range-free localization uses the connectivity information for the localization of sensor nodes. Range-free localization doesn't need angle or distance estimation to the sensor nodes. Several algorithms are presented, where a mobile sensor node e.g. AUV work as a impart sensor node for the collection of information from the other sensor nodes [14], [15]. In such techniques, mobile sensor nodes use a particular trajectory named as ''tour-path'' to travel through the network. During the traveling time, it stops at some particular positions named as ''tour-point'' for the collection of collected information from the sensor nodes in their vicinity. These schemes are capable to minimize the energy ingestion. The systems turn out to be inefficient in case of large scale sensor networks, where the mobile sensor node trajectories are big; consequently, operational costs and data-gathering latency are increasing. Furthermore, the restraint of the onboard energy incomes, the mobile sensor node functional time is not unlimited, resultantly the coverage area is reducing. Operational issues which are confronted by mobile sensor node can be considered if various mobile sensor nodes are utilized in the network, where every mobile node travel the network on a specific trajectory. The mobile sensor nodes may organize in a constant interconnection to stay with each other's, which enable a multi-hop communication through the reporting area. However, the achievement of constant communication between the AUVs is difficult because of the inconstant nature of underwater surrounding and the mobility of AUVs.

Furthermore, an autonomous data collection approach is presented in [16], [17], which analyze the planning path problem for an AUV to collect data from an USN. They equipped sensor nodes with acoustic modems which provide a range limited and noisy communication. AUV is deployed in such a way that maximizes the collected data while minimizing the fuel expenses or traveling time. In this case, the communication constrained data collection is more practical with an AUV. Also, in [18], [19] a clustered based AUV aided data collection scheme is presented for UWSN. The scheme consists of three phases such as Discovery, Clustering and Data Collection. During the discovery phase of AUV, the neighbor sensor data is interchanged and then collected, which is used in the clustering to find the members and cluster heads. In this case, the tour of AUV is organized that all the cluster heads are visited while decreasing AUV tour length. For the sensor clustering and to cover the sensor heads with the shortest tour, an optimal technique is proposed to find the global optimal solution and then an efficient technique is proposed to achieve the near optimal solution in a lower computational time. The scheme is applicable in both connected and disconnected wireless networks.

A data mining in WSNs is basically the action of extracting the application-oriented and patterns with a possible accuracy from a rapid, continuous and non-ending flow of data stream from a sensor network. In such conditions, the overall data cannot be saved and required quick processing [20], [21]. Therefore, data mining has to be faster for the processing of arriving high-speed data. Conventional data mining techniques are utilized to manage static data. For this purpose, use the multistep and multi-scan algorithms to analyze the data-sets of static data. Consequently, the conventional data mining algorithms are not applicable for managing the high dimensionality, high quantity, and distributed nature data which is generated by WSNs.

Based on the motivation, we aim to design two efficient localization schemes for USNs, named as distance and angle-based measurements. The proposed schemes first localize the sensor nodes in underwater. After the localization of nodes, the most important task is to measure the MEEs in localization and detection of targets in the underwater environment. The whole localization process is divided into two basic parts: sensor nodes localization and the measurement of MEEs in localization. Simulation results show that the localization algorithms can greatly reduce the MEEs in localization, consequently reducing the communication cost and present a high level of accuracy.

The rest of the paper is structured as follows. In Section II, related work is described, background information, including various localization algorithms in an underwater environment and communication technologies for UWSNs. In Section III, the proposed localization schemes are presented. Further, in Section IV, the performance of the proposed schemes are evaluated through several simulations. Finally, in Section V, the proposed schemes are concluded and recommended some future works.

II. RELATED WORK

As discussed in the above section, GPS-free sensor node localization scheme is required due to the deficiency of GPS signals in an underwater environment. Most of these schemes required ranging measurements between the communicating sensor nodes in the shape of TDoA, ToA, AoA, and RSSI or at least the alignment of two methods. In recent years localization of sensor nodes in underwater has attracted more attention. In almost all the proposed localization schemes, a pre-defined reference sensor node is required. Because without the deployment of reference nodes, localization is almost impossible [22]. But a major hindrance and drawback of this scheme is the requirement of multiple reference sensor nodes in a large and wide network. Therefore, in most underwater fields it is not practicable to place multiple reference sensor nodes because of energy consumption, communication cost, and other requirements. In [23], the authors consider a UASN that consists of multiple sensor nodes placed at the network field. For the reduction of the network cost, the sensor node has limited computational capability and lower-complexity with energy constrained. Due to the dynamical nature of underwater, the sensor nodes continuously move with the water current and shipping activities. Therefore, due to these issues, the localization process should be finished in a short duration, otherwise, if the sensor nodes travel from one location to another, the estimated locations will become absolute. Hence, it is important to organize energy efficient and fast localization algorithm to give a real-time localization in a resource-constrained sensor network. As a result of the continuous sensor nodes mobility, some sensor nodes may roam out of the network operational field, which resultantly increments the problems of network sustentation and recycling.

Underwater localization faces an extensive and variable propagation delay problems. The acoustic waves propagation in underwater is nearly $1.5 \times 10^3 m/s$, which is five orders lesser than the radio speed in the air which is $3 \times 10^8 m/s$. Also, in underwater the wave speed is altered by various factors such as brininess, temperature, ocean deepness, which is calculated below [24]:

$$V1 = 1449.2 + 4.6T + 0.055T^2 + 0.00209T^3 + (1.34 - 0.01T)(S-35) + 0.06D \tag{1}$$

$$V2 = 1449 + 4.6T + 0.055T^2 + 0.003T^3 + (1.39 - 0.012T)(S-35) + 0.017D \tag{2}$$

$$V3 = 1449.2 + 4.6T - 0.055T^2 + 0.00029T^3 + (1.34 - 0.01T)(S-35) + 0.016D \tag{3}$$

$$V4 = 1448.96 + 4.591T - 0.05304T^2 + 0.0002374T^3 + (1.34 - 0.0102T)(S-35) + 0.0163D + 1.675 \times 10^{-7}D^2 - 7.139 \times 10^{-13}TD^3 \tag{4}$$

$$V5 = 1492.9 + 3(T - 10)4.6T - 0.006(T - 10^{-2}) - 0.04(T - 18)^2 + (S-35)(1.39 - 0.01T) + D/16 \tag{5}$$

where V is the speed of an acoustic wave in m/s, T is the temperature in degree Celsius, S is the salinity of water in parts per thousand and D is water deepness in a meter. From the analysis, it is assumed that the water temperature and salinity are constant. Using the above equations, we can get different acoustic waves speed. Unluckily, near rivers or in coastal areas, generally, these premise is not valid making the speed of acoustic waves variable.

In [25], the authors presented two schemes for target localization in underwater, named as Nonlinear Weighted Least Squares-based Underwater Target Localization (NWLS-UTL) and Space-Alternating Generalized Expectation Maximization-based Underwater Target Localization (SAGE-UTL). These algorithms perform the localization of target using the data gathered by a distributed star receiver network. The network is considered is one of the main receiver and various normal receivers. The corresponding network is considered to be anchored in underwater depth and an iso-gradient SSP is also assumed. As the temperature and salinity mostly not remain constant, therefore, the iso-gradient SSP supposition is sensible for the underwater field. The authors consider time delay as an explicit function w.r.t the target localization with the iso-gradient SSP. All the receivers are not time-synchronized, so it is problematic for all the receivers in the underwater environment to keep all the clock time-synchronized. Moreover, a closed-loop problem (where the estimation of distance is served as a response variable) is investigated for underwater target localization [26], which deem the moving and high noise physical characteristics of the underwater field. Accordant with the control theory, proportional integral reckoner is made for sensor nodes to collect the distance information via indirect estimations. The authors presented a consensus-based unscented KF algorithm along with distance information for the collection of target information.

Furthermore, [27]–[29] investigated the TDoA and ToA localization algorithms. A closed form solution is considered by constructing a connection between the unknown source location and hybrid estimations and to discover the most suitable sensor nodes association, respectively. Both of them consider the Cramer-Rao Lower Bound (CRLB), which can narrate the accuracy of localization, is the lowest bound of any unbiased estimator. The MEE matrix is derived under the small error condition. But it is impossible to achieve its true value in real. Therefore, a closed structure localization scheme is considered and utilizing its error covariance matrix to estimate the CRLB. An optimization problem is developed to find which nodes association should be used and they converted this non-convex problem into convex by relaxing the condition of constraint.

Based on the accurate sound travel time, a Self-Localization scheme with precise Sound Travel Time Solution (SL-STTS) is presented for the superficial underwater field. SL-STTS is considered as a time-synchronization free algorithm. The fluctuating precision is dependent on the exact estimation of time and it is approachable in a microsecond (ms) resolution with transceivers in the lowest part of the sea. The position of the transceiver is already defined in advance. Basically, the two-way travel time (TWTT) between the transponder and AUV is divided into the one-way travel time (OWTT), which is the acoustic wave propagation delay from the transceivers to AUV or vice versa. The AoA and AUV orientation for acoustic waves from the transponders are examined to estimate the OWTT. Unfortunately, the error estimation of OWTT in millisecond (ms) induce the error of distance measurement in meters (m), which directly affect the accuracy of localization. Therefore, it is necessary to work on a better sound travel time solution for localization. A Levenberg-Marquardt algorithm (LMA) is presented in [30], to improve distance measurements. The time-synchronization free algorithm is demonstrated which save energy for two-way packet trade-off and a sound travel time solution is demonstrated which meliorate the localization and ranging precision.

A localization algorithm under anchor node uncertainty for UASNs is presented [31], which deals with the sensor node localization issues in the existence of uncertainty in the anchor position. The network environment is prone to inauspicious the effects of water current, as a result, cause the non-negligible mobility of the anchor in underwater. If an anchor node has uncertainty, then it is more challenging to do localization in a well-organized manner. The underwater environment ray-bending property is considered for the accurate location measurements, because of the sound speed in underwater. Ray equations are applied to sit the way followed by the acoustic rays in underwater. Maximum likelihood (MML) is utilized to measure the location of the target sensor node with the uncertainty in anchor locations. It is compared with the other schemes; those have precise information about the anchor node location. CRLB is also derived for the target location estimation with anchor node uncertainty. Basically, USNs is a combination of a variable of sensor nodes which are designed to jointly monitor oceanic operations. For the achievement of these objectives, sensor nodes self-organize to autonomous networks that can accommodate the description of an underwater environment. The most important objectives for USNs are its relative ease of outfit and lower expenses, as they do not require cabling underwater and without intervening with shipping operations. The distinct characteristics of USNs have demanded a modern review of many issues related to localization operations. Often tend to intensify, motion-induced Doppler shift, multi-path interference, propagation delays, and limited bandwidth, etc., provide many antecedently proposed results inaccurate.

A Variety of underwater localization schemes have been presented by researchers, some of them are already discussed in the above sections. Most of them focused on the localization of sensor nodes and target localization or sometimes on the time synchronization of sensor nodes in underwater. Similarly, some schemes focused on the dynamic nature and the movement of sensor nodes in underwater which is basically caused by the dynamic nature of the ocean field. But, unfortunately still underwater localization faces a lot of challenges and need to be researched in a precise manner. The most important task is the precision and efficiency in the localization schemes. Therefore, this paper addresses the solution of underwater localization using different schemes. In the proposed schemes the authors not only focused on the simple underwater localization or only on the target localization in an underwater environment. In the proposed distance and angle-based measurements, the authors first localize the underwater target nodes and then find the MEEs in localization. The purpose of the above approaches is to present a more accurate and efficient scheme for underwater localization and estimation of mean errors in localization. To the best of our knowledge, the proposed underwater localization schemes (distance and angle-based) are novel and more accurate as compared to the previous localization schemes.

III. PROPOSED METHODS

This section presents the proposed schemes for localization in an underwater environment, which is initially computed to accomplish underwater target localization. After the localization of target, MEE is estimated. It is based on the existing distance and angle-based measurements. The estimation of the MEE is performed by first localizing a sensor node, and then estimate the MEE in localization of a target.

A. DISTANCE-BASED MEASUREMENT

In an underwater environment, the sensor data is typically interpreted with the location of a sensor node, such as target tracking, physical condition monitoring or reporting of an event. As mentioned before, underwater localization is more challenging as compared to the terrestrial because the RF signals attenuate highly in underwater, resultantly GPS is also not feasible for underwater. Different localization schemes presented a variety of techniques for localization which consider a variety of factors such as device capabilities, the propagation speed of the signal, energy, etc. Most localization schemes consider the location of a sensor node in the network field, and the nodes whose position is known is referred to as anchor sensor node. An approach for target localization basis on the estimation of TDoA in an inhomogeneous underwater field is presented in [32]. Due to the inhomogeneity of the underwater environment, the waves in underwater travel over a curved path. Resultantly, making the TDoA localization more challenging as compared to the terrestrial localization. In this approach, a TDoA based localization is considered utilizing the iterative algorithm. The approach is converging to the CRLB, outperform the line-of-sight (LoS) TDoA by considering the localization of an asynchronous target and accuracy of localization.

Related algorithms with distance-based measurements can be found in [33], a system which estimates the TDoA between different arriving signals from underwater beacons. The time synchronization of beacons with the receivers is not required for the proposed system allowing propagation termination prejudice in underwater. Therefore, the TDoA estimation is associated with the beacon sensor node position. The demonstration of the problem leads to a set of hyperbolic equations and the theoretical position of the node is then at the crossing of this set of hyperbolas. Though, the comprehensive cross-correlation betwixt the signals is a typical method for finding the TDoA. Underwater field brings together numerous distortions in amplitude and received wave phase due to the reflections reverberation. Another alternative scheme to estimate the TDoA, comprising in the exploration of the primary portion of received signals to determine a serial of comparable zero-crossing periods for the identification of their establishment and measuring the time difference between them. The technique is implemented in a configurable system-on-chip, bonding to an embedded ARM processor, a custom design digital signal processor setup [34]. The scheme has been studied in a tank and in open field.

The scheme is able to compute in real-time 2D of an underwater acoustic spreader, and merging the various directions, subsequent from the comparative motion between the location of the acoustic sources.

A matching scheme which basis on a metric named as Hausdorff distance [35] as an expense function to be decreased, in order to accomplish localization. The data set for this localization was gathered at the time of DGA crusade in ALMA 2015. The localization was performed at the southern beach of France in a shallow water field. The acoustic information was estimated over a 10 m vertical linear array which is comprised of total 64 hydrophones. The 2D localization, in-depth and range is accomplished by coordinating the shape of TDoA, between the respectively discovered succession. Different variants of Hausdorff distance are utilized, independently in every hydrophone and then joined to increase the precision of localization by minimizing the uncertainty both in range and depth.

The proposed scheme for localization which is based on distance measurement is applied in such a way that first of all an 80 $m \times 80$ m area is considered for the network field. The 80 $m \times 80$ m area is the field in which the underwater sensor nodes can ramble freely. At the first case, the area is limited only up to 80 $m \times 80$ m, later on, in the next coming sections, the scheme is also applied in a large field to check the distance effect on localization and accuracy of localization. Four anchor nodes are considered which are positioned at the four apexes of the localization network field. A number of mobile nodes are selected, here for the first case, only 10 number of mobile nodes are selected. The mobile nodes are moving in the 80 $m \times 80$ m network field. For the measurement of MEEs, a nonuniform position of a sensor node is selected. After the setting of random position for a sensor node, various iterations are applied, but for the case, first, only a limited number of iterations are considered. For this case, six number of iterations are considered and the MEEs are calculated. The reason of why choosing only six iterations is that, because the MEEs are mostly ranging in between those six iterations see Figure 2. For the measurement of distance betwixt the mobile sensor node and beacon node, the beacon sensor nodes are interconnected to the comparative antenna. In our previous study [36], a Doppler speed estimation is applied, assuming N number of active antenna nodes such as x_n, y_n, and z_n, where $n = 1, 2, 3 \ldots N$ and vector:

$$\Theta(k) = \left[x(k), \acute{x}(k), y(k), \acute{y}(k), z(k), \acute{z}(k)\right] \tag{6}$$

Zero mean Gaussian additive noise for the active node s at locations x_s, y_s and z_s is:

$$\begin{aligned}\Theta(k) &= Arg_{\theta(k)} min \frac{1}{2(c\sigma_t)^2} \sum_{n=2}^{N} \left[c\delta\hat{t}_{n,1}(k) - (d_{sn}(k) - d_{s1}(k))\right]^2 \\ &+ \frac{1}{\sigma_v^2} \sum_{n=1}^{N} \left(\hat{v}_n(k) - \sqrt{\acute{x}(k)^2 + \acute{y}(k)^2 + \acute{z}(k)^2} V_n(k)\right)^2\end{aligned} \tag{7}$$

Here $V_n(k)$ is:

$$V_n(k) = \left(\frac{x(k) - x_n}{r_n(k)} + \frac{y(k) - y_n}{r_n(k)} + \frac{z(k) - z_n}{r_n(k)}\right) \tag{8}$$

and $r_n(k)$ is:

$$r_n(k) = \sqrt{\left(x(k) - x_n\right)^2 + \left(y(k) - y_n\right)^2 + \left(z(k) - z_n\right)^2} \tag{9}$$

Here σ_v is the estimation error (EE) standard deviation of Doppler speed, $v(k)$ is the process noise, k is the time instant, τ is the discrete model sampling interval and d_{sn} is the actual distance from sensor node s to n.

In the case of two sensor nodes, equation (9) will become: x_s, and y_s, the $r_n(k)$ become:

$$r_n(k) = \sqrt{\left(x(k) - x_n\right)^2 + \left(y(k) - y_n\right)^2} \tag{10}$$

As seen in Figure 2, the process is repeated many times but only six iterations are selected in the proposed scheme, because the MEEs are mostly ranging in between those iterations. The fluctuation of MEEs is from 2.7499 m to 3.4789 m, as the MEE is reduced highly as compared to the previous schemes, see Table 2.

TABLE 2. MEEs in distance-based measurement.

Iterations	Distance-based measurement MEEs (in meters)
Iter. no. 1	2.7494 m
Iter. no. 2	2.7712 m
Iter. no. 3	3.0705 m
Iter. no. 4	3.1536 m
Iter. no. 5	3.3941 m
Iter. no. 6	3.4789 m

B. ANGLE-BASED MEASUREMENT

Recent research in the field of underwater localization has shown the possibility of applying angle-based measurements. The paper [37] utilizes a scheme for the robust approximation of the AoA of an acoustic source. This scheme measures the directional angles of a stationary source in an underwater environment by means of a moving oceanic vehicle which is dually furnished with two hydrophones. By utilizing the properties of the acoustic waves in underwater, the equipment transmits signals sporadically or non-sporadically and continually. The aim of this method is assuming that an acoustic source emits a specific signal continually. The process is composed of three phases; initially, a preceding probability is estimated by utilizing the state transition model. Secondly, a Generalized Cross Correlation (GCC) is utilized to obtain the directional information from the existing acoustic signal. Finally, a remark is proved by matching the entropy of existing correlation to prior probability. But the exploration of the physical features of numerous acoustic sources which basis on their bands of frequency which is not investigated in the proposed scheme. Those physical features concentrated on

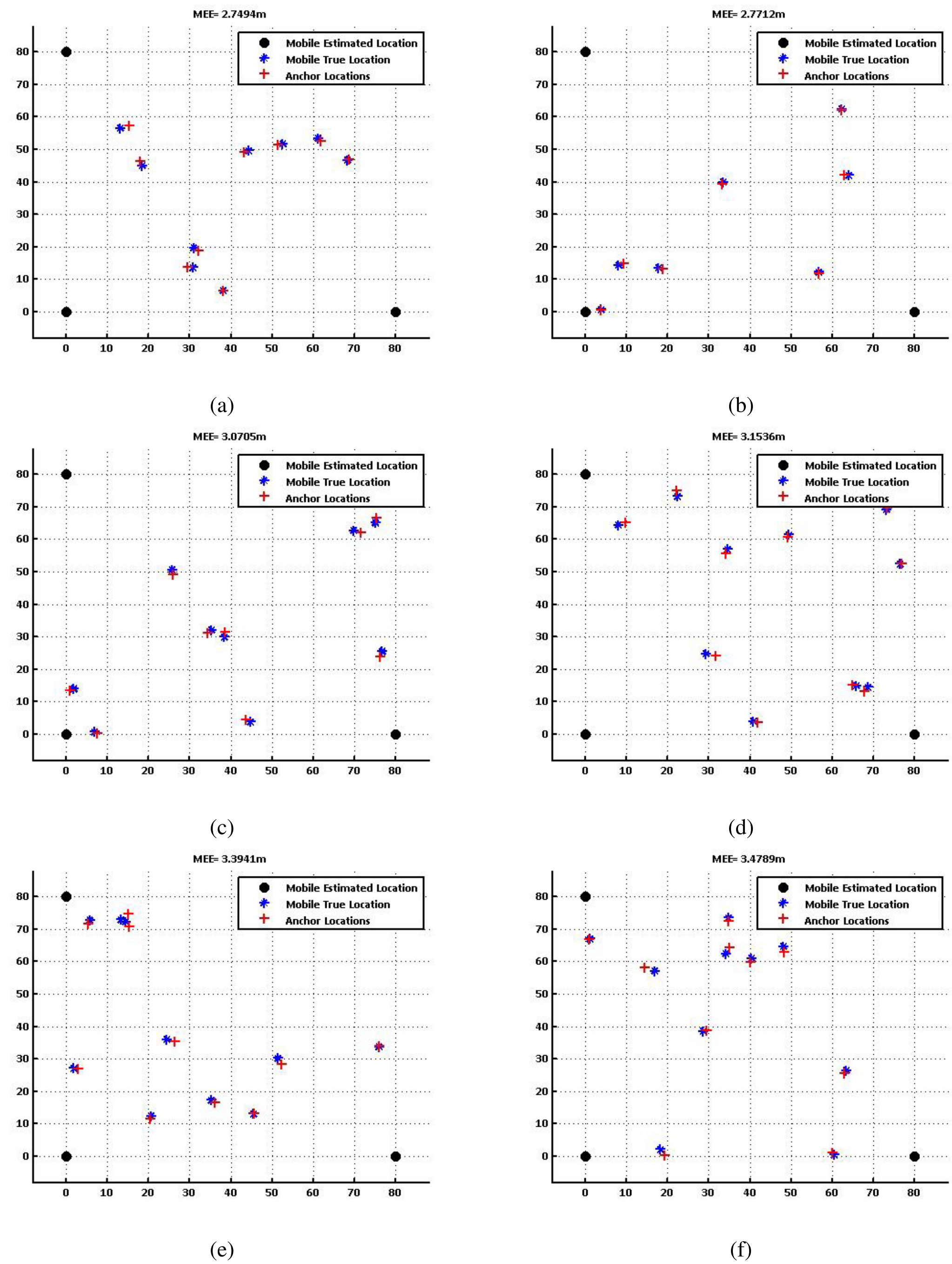

FIGURE 2. **Mean Estimation Errors (MEEs) of six iterations by employing distance-based measurement.**

the robust measurement of the acoustic sources directional angle with known evidence about the frequency band.

Furthermore, in [38]–[41] various AoA localization schemes are applied. A bearing only estimation-based algorithm for a real-time AUV localization is presented which assume the pre-define depth of beacon. The EKF is based for the scheme and a State-Space model is used considering the AUV motion with 2-DOF. Similarly, a scheme for multiple underwater sources which recognizes and extracts the acoustic target signals by applying frequency bands. The Bayesian process is used for the directional information and EKF for the direction angles developed at different positions. Moreover, an AoA aided localization scheme for underwater Ad-hoc networks in space of 2D and 3D is presented which measure the distance from anchor to sensor nodes by using multi-hop AoA estimation. When the estimation of distance is received from at least three or four anchor nodes by the sensor node, the location of a sensor node can be estimated.

In this section, the proposed angle-based measurement scheme is implemented by the following processes. First, an $80m \times 80m$ area is selected for the network field in which the mobile nodes can ramble, the same as distance-based measurement. Four anchor nodes are positioned at the four apexes of the network field and the number of mobile nodes is 10 for the network field. A nonuniform location for the mobile nodes is estimated. After the estimation of random location for nodes, the Euclidian distance is calculated. The MEEs is calculated after the computing of derivatives. In this section, the area is limited up to $80m \times 80m$ and the number of sensors is up to 10. In the next sections, we will also present the effect of area and number of sensor nodes on the accuracy of localization. For angle-based measurement, six iterations are considered in the first case, because the MEEs are mostly ranging in between those iterations. Sometimes jump above the range of these six iterations, but mostly in between these six iterations. Hence, the angle between sensor nodes are estimated and the MEEs is calculated. The MEEs is fluctuating from $91.0353m$ to $104.9208m$ as presented in Figure 3 and iteration results in Table 3. The variation in the MEEs is basically due to the vigorous property of water environments such as the water current, shipping activities, and many other issues. Resultantly, it makes the underwater localization more challenging, but still, the proposed scheme present a good level of accuracy as compared to the previous localization schemes. In [36], for estimating the distances and angles between nodes, a random position for nodes A and B are selected, which are placed at positions X_1, Y_1 and X_2, Y_2. By considering the nodes, A and B:

$$A_\circ = \sqrt{X_1 + Y_1} \tag{11}$$

and

$$B_\circ = \sqrt{X_2 + Y_2} \tag{12}$$

Distance between these sensor nodes are:

$$AB = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2} \tag{13}$$

To estimate the angle between nodes A and B:

$$\cos\theta = \frac{A_\circ + B_\circ - (AB)^2}{2A_\circ B_\circ} \tag{14}$$

rewrite the above equation as:

$$\cos\theta = \frac{X_1X_2 + Y_1Y_2}{\sqrt{X_1^2 + Y_1^2}\sqrt{X_2^2 + Y_2^2}} \tag{15}$$

and the angle θ

$$\theta = \cos^{-1}\left[\frac{X_1X_2 + Y_1Y_2}{\sqrt{X_1^2 + Y_1^2}\sqrt{X_2^2 + Y_2^2}}\right] \tag{16}$$

TABLE 3. MEEs in angle-based measurement.

Iterations	Angle-based measurement MEEs (in meters)
Iter. no. 1	91.0353 m
Iter. no. 2	97.416 m
Iter. no. 3	98.2772 m
Iter. no. 4	103.732 m
Iter. no. 5	104.6013 m
Iter. no. 6	104.9208 m

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The experiments for underwater localization were carried out to bear out the effectiveness of the proposed distance and angle-based measurements. Basically, two schemes were applied for the purpose of underwater localization and estimation of MEEs. In both schemes first, the sensor nodes are localized and then the MEEs are calculated which resultantly gives a high level of accuracy as compared to the previous implemented schemes.

In distance-based measurement, the localization process was performed using the distance estimation between sensor nodes and the anchor nodes. For this scheme, an area was specified for the whole network which has a border length of 80 $m \times 80$ m. In this area, the mobile sensor nodes can roam freely, because the sensor nodes are dynamic, not at a specific position. The quantity of mobile nodes is 10 and the number of anchor nodes is four. The four anchor nodes are positioned at the four vertices of the network in which every sensor node can communicate. For the schemes, the distance calculation error ratio is seated as $0.1m$, which means that the precision of distance calculation is 90%. For instance, the imprecision of 1 m is approximately 0.1 m. First, a nonuniform location of the sensor nodes is calculated and then the distances between those sensor nodes are measured. After the localization of sensor nodes, the process is evaluated by a number of iterations and the MEEs is measured. Here for the case, the process is repeated several times, but only six iterations are considered. Because of the MEEs are mostly fluctuating among these six iterations which are 2.7499 m to 3.4789 m as presented in Figure 2 and iteration results in Table 2. The fluctuation of MEEs is basically due to the dynamic nature of water, shipping activities and many other issues, but still the proposed scheme achieve a good level of accuracy.

For the angle-based measurement the range and number of sensor nodes are similar to distance-based measurement. An 80 $m \times 80$ m area for the whole network, 10 number of mobile nodes and four anchor nodes are selected. The four anchor nodes are positioned at the four apexes of the network field. First of all, two random nodes A and B are selected, then the location and angles between these nodes are estimated. After localizing the nodes, the MEEs is calculated. Here for the angle-based measurement, the number of iterations is six. The process is repeated several times to clarify the MEEs and achieve good accuracy, but only six iterations are considered. Because the MEEs is fluctuating among these six iterations.

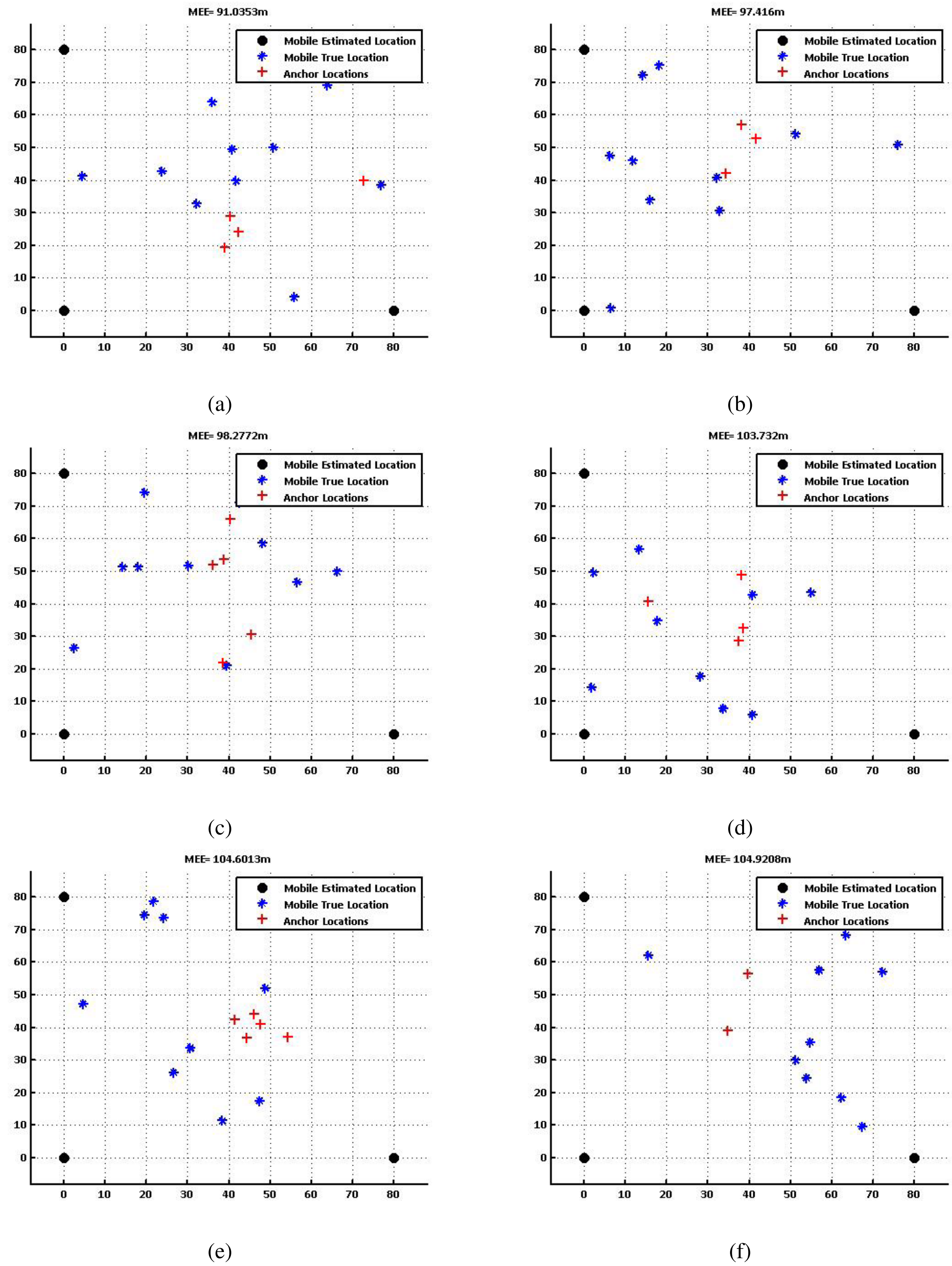

FIGURE 3. Mean Estimation Errors (MEEs) of six iterations by employing angle-based measurement.

The fluctuation of MEEs is from 91.0353 *m* to 104.9208 *m*. The fluctuation of MEEs is basically due to the water current and other obstacles in an underwater environment. The MEEs of angle-based measurements are shown in Figure 3 and the iteration outcomes in Table 3.

To compare the proposed distance and angle based measurements, distance-based measurement is more accurate and efficient as compare to angle-based measurement. The MEEs of distance-based is lower as compare to angle-based measurement. Because due to the water current and obstacle in underwater making the angle-based measurement more challenging as compare to distance-based measurement. The distance-based measurement MEEs is fluctuating between 2.7494 *m* to 3.4789 *m* and the angle-based MEEs is fluctuating between 91.0353 *m* to 104.9206 *m*. The results are shown in Figure 2, 3 and the comparison is shown in Table 4.

To evaluate the proposed scheme more in term of accuracy and efficiency, the schemes are also evaluated by varying the

TABLE 4. Distance and angle-based measurements MEEs comparison.

Iterations	Distance-based measurement	Angle-based measurement
Iter. no. 1	2.7494 m	91.0353 m
Iter. no. 2	2.7712 m	97.416 m
Iter. no. 3	3.0705 m	98.2772 m
Iter. no. 4	3.1536 m	103.732 m
Iter. no. 5	3.3941 m	104.6013 m
Iter. no. 6	3.4789 m	104.9208 m

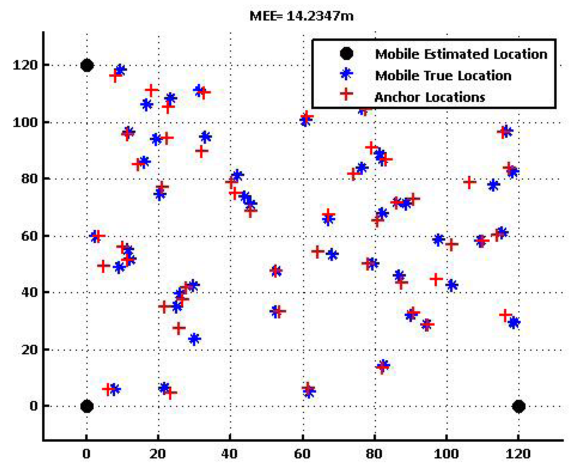

FIGURE 4. Distance-based measurement with large number of sensor nodes and cross section area.

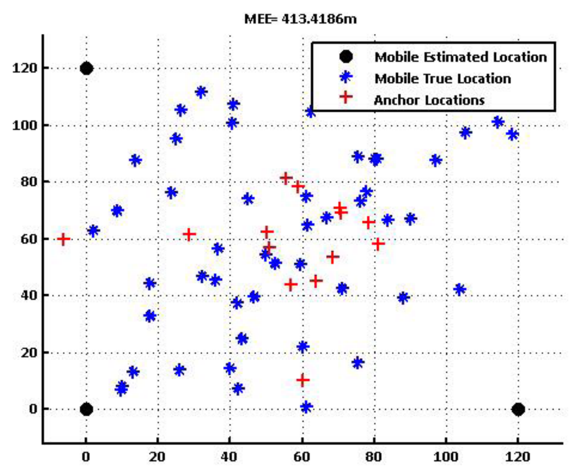

FIGURE 5. Angle-based measurement with large number of sensor nodes and cross section area.

number of mobile nodes and the network field area for the proposed networks. For the proposed schemes, the number of sensor nodes is changed from 10 to 50 and the area is changed from 80 m to 120 m. Resultantly, distance-based measurement is less affected as compared to angle-based measurement as shown in Figure 4 and 5, respectively. The proposed schemes are most feasible for a smaller number of sensor nodes and a small area as compared to a large number of sensor nodes and a large area. So, by varying these factors, directly affect the efficiency and accuracy.

V. CONCLUSION

In this paper, two localization schemes are presented named as distance and angle-based measurements. Firstly, the underwater nodes are localized and then the MEEs are calculated. For the distance-based measurement, an 80 $m \times 80$ m area is considered for the whole network field in which the mobile sensor nodes can ramble. The number of mobile nodes is 10 and the anchor nodes which are positioned at the four apexes of the network field. To measure MEEs, a random position of a sensor node is selected. After setting the random position for the sensor nodes, various iterations are applied, but for the case, first, only a limited number of iterations are considered. For this case, six number of iterations are considered and the MEEs are calculated. Because of the MEEs are mostly fluctuating among these iterations which are 2.7499m to 3.4789m as presented in Figure 2 and Table 2. For the angle-based measurement, the network size is also 80 $m \times 80$ m in which the mobile sensor nodes can ramble. The number of sensor nodes is 10 and four anchor nodes which are positioned at the four apexes of the square field. After estimating the angles between sensor nodes, the MEEs are calculated. Similarly, in angle-based measurement, six number of iterations are applied. In angle-based measurement, the MEEs are fluctuating from 91.0353m to 104.9208m as shown in Figure 3 and the iteration outcomes in Table 3. Resultantly, the distance-based measurement is more accurate as compared to angle-based measurement as shown in the comparison Table 4. The proposed schemes are also evaluated for a large number of sensor nodes and network field. The proposed schemes are not more feasible for a large number of sensor nodes and area as compared to a smaller area. The MEEs in the case of large sensor nodes and a large area is shown in Figure 4 and 5. The proposed schemes are well suitable for an area of 80 $m \times 80$ m. Therefore, the schemes give a high level of accuracy and present good efficiency as compared to the previous schemes. In the future, we will try to reduce the MEEs more and also to implement the RSSI for underwater localization.

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