A Comprehensive Survey of the Recently Proposed Localization Protocols for Underwater Sensor Networks

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ABSTRACT Underwater Wireless Sensor Networks (UWSNs) offer a huge number of applications, most of which require tagging the sensed data with location information. This makes localization algorithms an essential part of UWSN design. This paper presents a comprehensive survey of the recently proposed literature on localization in UWSNs. The surveyed algorithms are evaluated based on a wide-ranging set of parameters which constitute the elementary features of a localization algorithm. Moreover, in order to familiarize the readers with the basic design of the surveyed algorithms, brief description of the mode of operations of each algorithm is presented along with its strengths and weaknesses. The algorithms are divided into two categories based on their computational design i.e., centralized and distributed. Each category is further subdivided into the algorithms that consider node mobility, and those that do not. Towards the end, we present our view on the future research directions in the area of localization in UWSNs.

INDEX TERMS Localization survey, underwater sensor networks, underwater acoustic channel, underwater optical channel, target tracking.

I. INTRODUCTION

The desire to explore and exploit the potentials of the world's waters coupled with the rapid technological growth in the last few decades has driven the rapid development of Underwater Wireless Sensor Networks (UWSNs). UWSNs enable a vast array of applications. The range varies from scientific applications such as the study of marine life and geological processes; to disaster prevention such as tsunami and flood warning systems; to military applications such as intrusion detection, target detection and mine clearance [1]. Commercial applications include mineral exploration and mining, monitoring and control of underwater equipment e.g. pipe lines and marine cables, commercial fisheries and aquaculture. On the environmental front, UWSNs enable applications such as oil spill damage assessment and water quality monitoring [1]. Other areas that employ underwater sensor networks include water sports, treasure hunting etc.

Though the classes of applications are similar, the UWSNs face certain challenges that are alien to their terrestrial counterparts. Firstly, radio waves, which are the predominant medium of communication for terrestrial networks, are not a practical solution for UWSNs due to quick absorption in sea water [2]. Optical waves can achieve high data rates at short distance under water [3]. However they are subject to scattering and fast attenuation which makes them suitable only for short range communication [4]. Acoustic waves, on the other hand, can propagate longer distance and therefore are considered as the preferred medium of choice for underwater communication [5]. Nonetheless, the underwater acoustic channel poses its own challenges such as slow and variable speed of the sound waves (1500 m/s on average), limited bandwidth which depends on transmission range and frequency, multipath affect, high bit error rates [6], Doppler's shift, channel asymmetry due to moving current [6] and lack of availability of satellite positioning systems underwater. The satellite positioning systems communicate using radio waves which cannot penetrate more than a few meters deep into water thus rendering these systems useless for underwater localization [7].

Nevertheless, localization plays a pivotal role in sensor networks. In most of the sensing applications, the collected

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data can only be meaningful if it can be referenced to a geographical location [8]. For instance, in case of tsunami warning systems, location of the sensors recording seismic activity enable the experts to estimate the intensity and the time of impact at coastal areas. Similarly, pollution monitoring applications such as oil spills use locations of sensor nodes to determine the spread of the pollutants. Besides resolving the geographical coordinates of the sensed phenomena, localization may also be an essential component in the design of other protocols. For instance, geographic routing protocols rely heavily on the location information of sensor nodes in order to make smart routing decisions. Keeping in view the vital importance of node localization for underwater sensing systems, many localization protocols have been proposed for UWSNs. These protocols can be categorized based on different criteria such as mobility (static nodes, mobile nodes), computational model (centralized or distributed), medium of communication (acoustic, optical or magnetic induction), underlying technique (range based localization, range free localization) etc.

Many surveys have been published to evaluate the localization protocols for UWSNs [9]–[15] However, majority of these surveys do not focus on the recent work. Moreover, some do not discuss the localization strategies, merits and demerits of the surveyed schemes. In our view, brief description of the strategies, merits and demerits of the considered protocols is important to give the readers basic understanding of the schemes being reviewed. Therefore in this work, we survey the recently proposed localization algorithms (2017-2020) for underwater acoustic and optical sensor networks while identifying their strengths and weaknesses. Moreover, our analysis takes into account a broad set of parameters which have direct impact on the performance of a localization protocol. In addition, brief explanation of the localization tactic of each protocol is presented in order to acquaint the reader with the basic design of the protocol. The considered schemes are divided into two main categories based on whether the actual locations are computed at a centralized location (the centralized model) or computed by individual nodes (the distributed model). The protocols are further categorized based on whether or not node mobility is taken into consideration.

Figure 1 depicts general architecture of UWSNs. Sensor nodes, equipped with acoustic/optical transceivers, are deployed underwater. Based on application requirement, the sensor nodes can be fixed or mobile. As satellite positioning systems are ineffective in sea water, the underwater sensor nodes can be localized with the help of reference nodes with known locations. Reference nodes can be located on water surface in which case they obtain their absolute positions through satellite positioning system such as GPS. Alternatively, fixed underwater anchored nodes with known location or Autonomous Underwater Vehicles (AUVs), which surface periodically to refresh their location estimates, can be used as references for localization of underwater nodes.
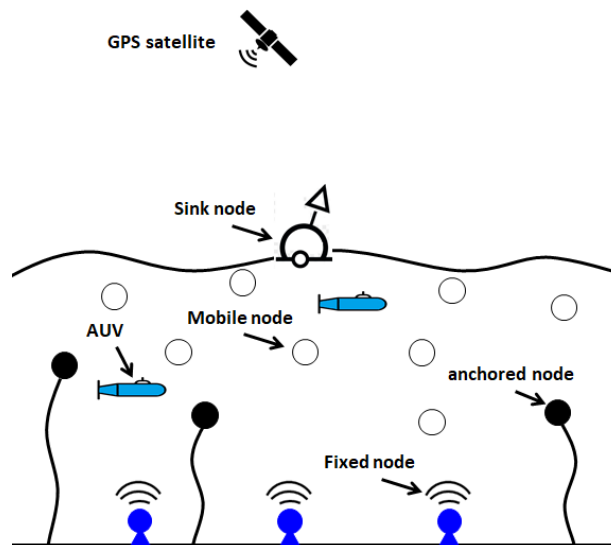

FIGURE 1. Typical architecture of UWSN.

A. PERFORMANCE OBJECTIVES
Following are some of the key performance objectives which must be considered while designing a localization protocol for UWSNs.

1) LOCALIZATION ACCURACY
Localization accuracy is the most important performance metric for a localization protocol [16]. The required localization accuracy varies depending on the application. For instance, military applications, such as target tracking and mining clearance, require highly precise location information. On the other hand, applications such as pollution monitoring, disaster prevention etc. may tolerate some degree of error in location estimates. Nevertheless, in order to be effective, an application must satisfy a minimum accuracy threshold.

2) LOCALIZATION COVERAGE
Localization coverage refers to the number of unknown nodes that a positioning scheme can localize on average. As previously mentioned, meaningful conclusions can be drawn only if the sensed data can be tallied with its geographical location. Therefore, higher localization coverage leads to bringing more meaningful data into decision making process thus improving the robustness of the system.

3) CONVERGENCE TIME
Mobility of underwater nodes with water currents coupled with slow propagation speed of acoustic waves (which are mainly used as medium of communication under water) increases the significance of the convergence time of a localization routine. If a localization protocol takes too long to converge, the measurements may go stale resulting into highly inaccurate location estimates.

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4) ENERGY CONSUMPTION

Energy consumption is a major concern in UWSNs not only because it is hard to replace and recharge batteries underwater but also due to the energy hungry nature of the underwater acoustic channel [17].

5) COMMUNICATION OVERHEAD

Communication overhead is important because it affects all the above mentioned objectives. High communication overhead may result in higher contention and thus higher number of retransmission which not only translates into higher energy consumption but also prolongs convergence time. Longer convergence time affects the accuracy of the location estimates adversely thus reducing the localization coverage.

B. EVALUATION PARAMETERS

In this subsection, we briefly explain the evaluation parameters considered in this survey.

1) UNDERLYING LOCALIZATION TECHNIQUE

Localization protocols are categorized as range based or range free protocols [18]. A range based localization protocol operates mainly by measuring distances between known reference points and unknown nodes. For instance, trilateration [19] is a range based localization method which can localize an unknown point in 2 dimensional (2D) plane based on the distance measurements between an unknown point and three non-collinearly located reference points with known locations. On the other hand, range free localization schemes, such as centroid algorithm [20], distance vector hop localization [21] etc., do not need distance and bearing measurements. Range free algorithms use topology and location information of the neighboring reference nodes to estimate locations of unknown nodes [22]. It was reported in [22] that range based schemes can achieve more accurate positioning estimates compared to range free schemes.

2) RANGING METHOD

Range based localization schemes can choose from many ranging schemes based on their performance requirements. Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA) [23], [24] and Received Signal Strength Indicator (RSSI) are some ranging methods that offer different levels of ranging accuracy and have different system requirements. For instance, TDoA can achieve better ranging accuracy as compared to RSSI, however the former requires time synchronization which is hard to achieve under water.

3) TIME SYNCHRONIZATION

Time synchronization is an important underlying requirement for certain ranging techniques, such as ToA, which uses time difference between synchronized clocks of senders and receivers to estimate distances between them.

Synchronization error in such schemes translates directly into localization error [25].

4) CENTRALIZED/DISTRIBUTED DESIGN

Based on where the location of an unknown node is resolved, localization algorithms can be classified mainly into two categories, i.e., centralized and distributed localization algorithms [9]. In the former case, locations are resolved at a centralized location such as sink node, whereas in the latter case, each unlocalized node gathers localization information and carries out location estimation procedure individually.

5) ESTIMATION BASED/PREDICTION BASED

Based on location resolution in terms of time, localization algorithms can be divided into two categories i.e. estimation based algorithms which utilize current measurements to estimate locations at the current time instant; and prediction based algorithms which use past and current measurements to predict locations in a future time instant [9].

6) MOBILITY CONSIDERATION

Underwater sensor nodes move passively with water currents [26]. Node mobility coupled with the slow speed of acoustic waves results in inaccurate location estimates. Therefore localization protocols must consider mobility in order to achieve more accurate and reliable location estimates.

7) NUMBER OF REFERENCE NODES

Reference nodes refer to the nodes with known locations. Unknown nodes can be localized using the locations of the reference nodes in conjunction with the positions of the unknown nodes relative to the reference nodes. In case of lateration, at least three reference points are required to localize an unknown node in 2D plane, where as in case of 3D at least 4 reference points are required. However the number of reference nodes may be increased based on the network sparsity and other considerations such as convergence time and accuracy.

8) COMMUNICATION PARADIGM

A localization algorithm may have active or passive communication paradigm based on whether or not the unknown nodes transmit during the localization process [27]. In case of passive algorithms, the unknown nodes only listen to the transmissions from neighboring nodes and do not transmit. Whereas the algorithms that require the unknown nodes to participate in the localization process by transmitting packets are said to have active communication paradigm.

9) PERFORMANCE OBJECTIVE

As mentioned previously, a localization protocol should be designed targeting certain performance objectives, such as accuracy, convergence time, localization coverage etc. The performance objectives of each of the protocols surveyed in this paper are presented in Table 1 and 2 in pp 6 and 10.

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In our evaluation parameters tables, the double hyphen symbol "−−" means that the value of the corresponding parameter cannot be determined based on the available information and/or the proposed localization method is open to any suitable value of the parameter.

II. CHARACTERISTICS OF THE UNDERWATER ACOUSTIC CHANNEL

A. THE SPEED OF SOUND IN WATER

The propagation speed of acoustic waves in water is influenced mainly by three factors namely depth (D), temperature (T) and salinity (S). Considering these factors, different empirical formulations have been presented to accurately estimate the speed of sound in water. One such formulation that achieves reasonable accuracy is known as Mackenzie empirical equation (1) [28].

$$c = 1449 + 4.591T - 5.304 * 10^{-2}T^2 + 2.374 * 10^{-4}T^3$$
$$+ 1.34(S-35) + 1.63 * 10^2 D + 1.675 * 10^{-7}D^2 + 1.025$$
$$* 10^{-2}T(S-35) - 7.139 * 10^{-3}TD^3 \quad (1)$$

B. ATTENUATION

The attenuation of the sound signals in the underwater acoustic channel can be represented as a function of distance d in km and frequency f in kHz (2)[29]:

$$A(d,f) = d^S . \alpha(f)^d \quad (2)$$

where $d, \alpha(f)$ and S represent distance, absorption coefficient and the spreading factor, respectively. The signal attenuation in dB is given by (3):

$$10 log A(d,f) = S.10 \log + d.10 \log \alpha(f) \quad (3)$$

The geometrical spread of an acoustic signal is given by its spreading factor (S). Usual values of S are 1, 1.5 and 2 for cylindrical, practical and spherical spreading respectively. The absorption coefficient $(\alpha(f))$ in dB/km for frequency f in kilohertz is calculated using Equation 4 [30]

$$10 \log \alpha(f) = 0.11 \frac{f^2}{1+f^2} + 44 \frac{f^2}{4100+f^2}$$
$$+ 2.75.10^{-4}f^2 + 0.003 \quad (4)$$

Equation (4) is generally used for frequencies higher than a few hundred Hertz. However, equation (5) [30] is considered more effective for lower frequencies.

$$10 log \propto (f) = 0.002 + 0.11 \frac{f^2}{1+f^2} + 0.011f^2 \quad (5)$$

Figure 2 [31] represents $\alpha(f)$ as a function of frequency f. $\alpha(f)$ increases swiftly as the frequency increases, thus resulting in a bound on the maximum usable frequency for a link between nodes with a given distance d between them.
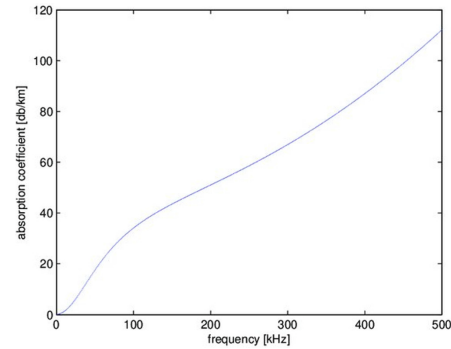

FIGURE 2. Absorption coefficient vs. frequency [31].

C. NOISE

The ambient noise in the underwater acoustic channel has four constituent factors i.e. thermal noise (6) [29] shipping activity noise (7) [29], breaking waves (8) [29], and turbulence (9)[29]. Equations (6-9) represent the power spectral density (PSD) of the constituent factors of ambient noise in dB re μPa/Hz for frequency f in kHz

$$10 \log N_{th}(f) = -15 + 20 \log f \quad (6)$$
$$10 \log N_s(f) = 40 + 20(s-0.5) + 26 \log f$$
$$- 60 \log(f+0.03) \quad (7)$$
$$10 \log N_w(f) = 50 + 7.5w^{\frac{1}{2}} + 20 \log f - 40 \log(f+0.4) \quad (8)$$
$$10 \log N_t(f) = 17 - 30 \log f \quad (9)$$

where s in (7) refer to the shipping activity factor. Value of s ranges between 0 and 1 to account for low to high shipping activity. w in (8) refers to the wind speed in m/s.

Equation (10) [5] represents the PSD of the overall ambient noise in underwater acoustic channel:

$$N(f) = N_s(f) + N_t(f) + N_w(f) + N_{th}(f) \quad (10)$$

whereas (11) represents the SNR observed at receiver.

$$SNR = SL - TL - NL + DI \geq DT \quad (11)$$

where, SL, TL and NL represent the source level, transmission loss and ambient noise respectively in dB. DI and DT represents the directivity index and detection threshold respectively. Source level (SL) is calculated using (12) [32] as follows:

$$SL = 10 \log \left(\frac{I_t}{0.67 \times 10^{(-18)}} \right) (12) \quad (12)$$

where I_t denotes the intensity. Equation (13) computes I_t in Watts/m² in shallow waters whereas (14) can be used for deep waters.

$$I_t = \frac{P_t}{2 \times \pi \times 1m \times z} \quad (13)$$
$$I_t = \frac{P_t}{4 \times \pi \times 1m \times z} \quad (14)$$

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III. LOCALIZATION PROTOCOLS FOR UWSNS

In this section we present our analysis of the localization schemes included in this survey. The basic design, operations, merits and demerits of each protocol are explained briefly. The protocols are categorized based on mode of computation i.e. centralized or distributed. Each category is further divided based on mobility consideration (figure 3).

Computational Model	Mobility Consideration	References
Centralized	Mobile	[33][34][35][36][37][38][39][40][41]
	Static	[42][43][44][45][46][47][48][49]
Distributed	Mobile	[50][51][52][53][54][55][56][57][58][59][60][61][62][63][64][65][66][67][68][69]
	Static	[70][71][72][73][74][75][76][77]

FIGURE 3. Classification of localization schemes based on computational model and mobility.

A. CENTRALIZED LOCALIZATION SCHEMES

Table 1 evaluates centralized localization schemes based on the parameters explained in section 1. In the centralized localization design, measurement are collected at a central location such as a sink node which runs a localization algorithm to compute location estimates based on the collected information. Centralized localization schemes can be divided into two categories based on mobility consideration i.e. centralized localization schemes with mobility consideration and centralized localization schemes without mobility consideration. The following section gives brief explanation of the mode of operations of each of the centralized localization schemes considered in this survey.

1) CENTRALIZED LOCALIZATION SCHEMES WITH MOBILITY CONSIDERATION

In [33], the authors propose a two stage localization scheme for partitioned UWSNs. Each node is assumed to hosts three non-collinearly positioned antennae for position estimation using trilateration. Nodes are divided into n tiers where any tier n refers to the set of nodes that are within the communication range of the nodes in the preceding tier i.e. tier n-1. Tier 0 contains only one reference node with known coordinates. The reference node initiates stage 1 by transmitting a beacon and by setting up a timer for reception of acknowledgement (ACK). Upon reception of the beacon, each tier 1 node estimates its distance from the sender and respond by transmitting a packet with transmission range higher than the calculated distance. The packet acts as acknowledgement for the sender in the preceding tier i.e. the reference node and as beacon for the nodes in the next tier i.e. tier 2. Upon reception of ACK the reference node estimates the positions of the sender relative to itself using trilateration and saves it in its table of relative location. Same steps are followed whenever a node in any tier receives a beacon or an ACK. Thus every node builds its table of relative locations which is relayed to the reference node after a certain time threshold.

The tables of relative locations from higher tier nodes arrive at tier 0 i.e. the reference node after multiple transmissions as elaborated in figure 4. The reference node can then determine relative positions of all the node with respect to itself using the received tables. In stage 2, the absolute positions of all the nodes are calculated based on their position relative to the reference node and the absolute position of the reference node at time instance t. The proposed scheme also introduces a partition handling mechanism which allows partitioned nodes to request beacons proactively after a certain threshold time. The main advantage of the proposed scheme is its ability to handle partitioned networks. However, the partition handling mechanism may solicit high number of responses in a dense network which results in high communication overhead and energy consumption.
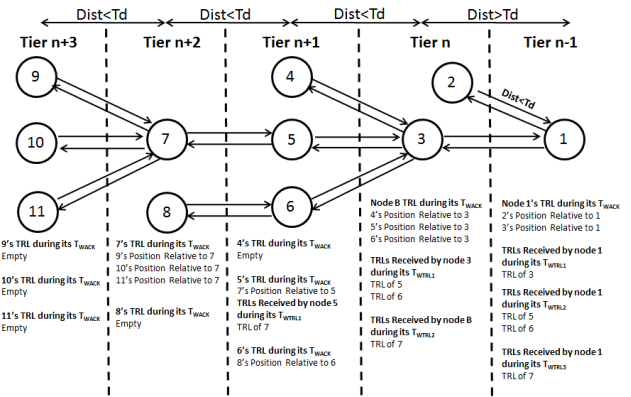

FIGURE 4. Propagation of beacon and Tables of Relative location [33].

In [34], the authors propose a localization algorithm with movement prediction for passively mobile anchored underwater sensor nodes. The nodes are divided into primary and secondary level nodes based on whether they are localized directly by the surface buoys or by the primary nodes respectively. The proposed scheme works in two stages; Time of Arrival based ranging, and movement prediction. Firstly, node positions are estimated based on the range measurements between unknown nodes and at least 3 reference nodes. Then, based on the estimated position and the node mobility model, the position and velocity of the nodes are estimated at each point of time in the prediction window (figure 5). Secondary level nodes may have higher localization error due to error accumulation. Therefore, Grey Wolf optimizer is used to minimize the accumulation error in case of secondary nodes. The protocol improves energy efficiency through reduced message exchange and by decreasing contention through backoff strategy. Moreover, error accumulation is minimized by selecting optimal first level nodes as reference points for secondary nodes using gray wolf optimizer. Even though the proposed scheme scales well for larger number of nodes, it suffers from low localization coverage for smaller number of nodes.

In [35], the authors propose a localization technique that takes Doppler's shift in the underwater acoustic channel

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TABLE 1. Evaluation Parameters (Centralized Localization schemes).

| Ref #	Time Sync Requirement	Range based?	Ranging Method	Estimation/ Prediction based	Mobility Consideration	No. of reference nodes	Communication model	Performance Objectives
[33]	No	Yes	RSSI	Estimation	Yes	One with three non-collinearly positioned antennae	Active	Localization coverage, Energy consumption, Communication overhead, error mitigation
[34]	Yes	Yes	ToA	Hybrid	Yes	3	Active	Mobility management, Localization accuracy, Energy efficiency
[35]	Yes	Yes	ToA	Estimation	Yes	4	Active	Localization accuracy
[36]	No	Yes	ToF	Estimation	Yes	-	Active	Localization accuracy
[37]	No	No	--	Prediction	Yes	One transceiver	Passive	Localization and tracking accuracy
[38]	No	Yes	RSSI	Estimation	Yes	3-12%	Active	Convergence time, Localization accuracy
[39]	Yes	Yes	ToA	Estimation	Yes	Ideally Eight, However the number may vary based on range	Active	Localization accuracy, communication efficiency, energy Consumption
[40]	No	Yes	RSSI	Estimation	Yes	-	Active	Localization accuracy, network cost
[41]	No	Yes	ToA	Estimation	Yes	One mobile ship	Active	Localization error mitigation
[42]	No	Yes	TDoA	Estimation	No	--	Active	Sound source localization
[43]	No	Yes	RSSI	Estimation	No	8-22	Active	Location accuracy
[44]	No	Yes	RSSI	Estimation	No	10	Active	Localization accuracy Energy efficiency
[45]	No	Yes	RSSI	Estimation	No	8	Active	Localization accuracy
[46]	Depends on the ranging method	Yes	Assumes that ranging information is already available	Estimation	No	4	Active	Localization accuracy Ranging error correction and outlier detection
[47]	No	Yes	RSSI	Estimation	No	10	Active	Localization accuracy
[48]	No	Yes	RSSI	Estimation	No	4	Active	Localization accuracy, Ranging error correction and outlier detection
[49]	No	Yes	RSSI	Estimation	No	3,4	Active	Error Reduction
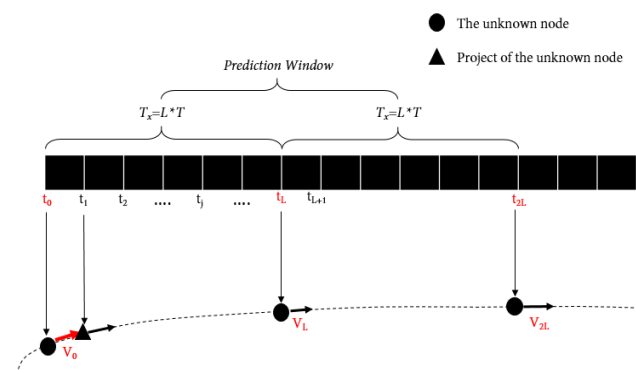
FIGURE 5. Prediction Window [34].

into consideration to calculate accurate location estimates. The estimates are further improved by employing genetic algorithm based optimization. The operations of the scheme can be divided into two distinct stages: In stages 1, upon detection of an event the respective node broadcasts a ping message. If the message is received by an anchored node, the anchored node save the time of reception of the ping message and responds by sending its ID and depth information. As soon as the response is received by the unknown node, it sends a message to the respective anchored node. Upon reception of the second message from the unknown node, the anchored node forwards the reception time of the two ping messages to the sink node along with its depth information. In total, for one unknown node the sink node receives information from four anchored nodes. Based on the received information, it runs stage 2, in which it uses the time information, depth of the anchored nodes and the speed of the underwater current to estimate the Doppler's shifts for each of the four anchored nodes. Then taking the estimated Doppler's shifts into consideration, the position of

the unknown node is determined using multilateration. The sink node further improves location estimates by employing genetic algorithms. The proposed technique improves accuracy by taking into consideration the often ignored factor of Doppler's shift and by using genetic algorithms to improve the estimates further. However the overhead generated by the three way communication between sink and anchored nodes, and the resultant contention can diminish energy efficiency.

In [36] aiming at minimizing localization errors, the authors propose a target localization and tracking method which takes into consideration the influence of underwater environment, such as variation in the speed of sound and the resultant curved trajectory of the transmitted signals. The authors use real sound speed measurement data in the ocean environment and calculate time of flight (ToF) using the underwater sound speed profile. The target position is estimated through particle swarm optimization based tracking using ToF and angle information. Data fitting is used to further improve the accuracy. This method reduces localization error by considering the actual sound propagation characteristics in the oceanic environment i.e. sound speed variation, which, if not considered, translate directly into estimation error. However, issues, such background noise and variation in target velocity which may affect the performance of localization protocols significantly, are ignored.

In [37] authors propose a novel deep learning based target localization and tracking scheme. The proposed scheme uses a convolutional denoising auto-encoder (figure 6) which takes a noisy image (that represents the time delay matrix of the signal) as input. The output is a denoised image/matrix which highlights only the path of the target. The propose scheme is scalable to the number of targets as it carries out detection and tracking per sample in the time delay matrix.
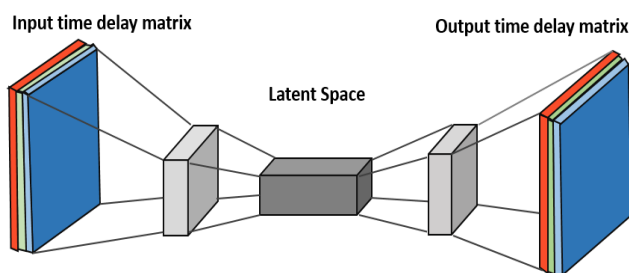

FIGURE 6. Convolutional Denoising Auto encoder [37].

In [38], the authors propose a received signal strength based localization method for underwater acoustic sensor networks. Firstly, a practical path loss model is presented. For a given area, RSS data is collected dynamically while taking into consideration measurement noises, correlation between the measurement noises and mobility of the randomly deployed anchored nodes with waves. For a transmitter-receiver pair, their geometric distance from each other is approximated based on a linear regression model. Thus quick access is obtained for the range information, while

achieving low communication overhead, localization error and response time. Moreover a method for mitigating noises in distance estimation is also presented.

In [39] the authors propose a target localization scheme for under water sensor networks with challenging communication conditions. Firstly a support vector machine based strategy is devised for selecting a set of nodes with relatively smaller distances to the target nodes to partake in the sensing process. Secondly, in order to deal with the sensing noise in the raw data collected by the selected sensor nodes, a learning based model is built to acquire precise observations in the presence of sensing noises. Moreover to acquire accurate location estimates, a likelihood function is formulated for updating the particle weights while avoiding particle degeneracy. The merit of the proposed scheme lies in cutting out unnecessary transmissions by allowing only those nodes to partake in the sensing process which are within a certain distance threshold from the target node thus saving energy and reducing sensing noise. However this is achieved by incorporating complex processing.

In [40], the authors propose a compressive sensing based positioning method for UWSNs. The sensing area is divided into cubic units. The cubic unit based sparse localization is converted to compressive sensing based node positioning problem by means of the energy relationship between the unlocalized sensor nodes and the mobile anchored node. The anchored node initiates the localization process by sending N pieces of information which is followed by reception of signals from unlocalized nodes. The signal strength of the received singles is calculated and sent to the fusion center which applies a compressive sensing based algorithm to locate the specific position of the unlocalized sensor nodes in the grid. The positioning error is further reduced by applying the centroid algorithm. The use of cube lattice positioning method (that requires the mobile node to traverse the whole cubic module using basic path models such as layered scan and random way point models) reduces complexity by avoiding the complex path planning that is required to achieve collinearity in case of trilateration. However, the proposed scheme is not scalable to the number of unlocalized nodes as the localization error increases with increase in the number of unlocalized nodes.

In [41] authors propose virtual node assisted static and dynamic localization algorithms for static and mobile environments respectively. Nodes are divided into four roles; a surface mobile beacon node, underwater auxiliary node, underwater virtual nodes and unlocalized nodes. The surface mobile beacon and the unlocalized node use Time of Arrival (ToA) to determine the distance of the unlocalized node from the mobile beacon. The mobile beacon and auxiliary node communicate to find the ToA error. A quarter circle of radius R centered at the mobile beacon is drawn where R is the distance between the mobile beacon and the auxiliary node. Virtual nodes are assumed to be located on the circle and are used to find the distance between the virtual and the unlocalized nodes.

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2) CENTRALIZED LOCALIZATION SCHEMES WITHOUT MOBILITY CONSIDERATION

In [42], the authors propose a sound source localization algorithm using the time difference of arrival of multiple instances of a signal transmitted by a sound source. Sensor nodes use compressed sensing to determine the time delay spread of the received multipath signal. To determine the search area, an adaptive OMP algorithm is proposed which facilitates expanding or shrinking the search area based on the value of the edge of the search area in terms of Euclidian metrics. The target localization is achieved by a three step weighted least square algorithm. In step 1, a rough estimate of the target position is made using least square approach. Step 2 determines the noise parameters from the polynomial equations for accurate estimation of the target position. Lastly, step 3 further refines the results obtained in the first two stages.

In [43], the authors propose target positioning techniques for known and unknown target transmission power cases. General target positioning cases based on the maximum likelihood (ML) criterion are formulated initially. However the non-convex nature of the formulated ML estimators increases the complexity of finding global optimum solution. Therefore, in order to achieve efficient solution, these estimators are converted into a Generalized Trust Region Sub-problems or GTRS framework. The localization accuracy is enhanced in case of unknown transmit power by a three step procedure which involves finding initial position estimates, finding the corresponding maximum likelihood estimate of transmission power and finally using the estimated transmission power to transform the unknown transmit power problem to the know transmit power problem. The proposed scheme attains good levels of accuracy by approaching Cramer Rao Lower bound in some cases. However, it does not consider node mobility which may have considerable adverse impact on the performance of the proposed scheme.

In [44] the authors propose an RSSI based localization method for energy harvesting wireless underwater optical sensor networks. In order to deal with the limited energy constraint, a framework for energy harvesting is introduced which enables the low energy nodes to harvest ambient energy and be active again upon harvesting sufficient amount of energy (figure 7). For location estimation, distances are estimated by the active nodes based on RSS subject to the impairments of the optical underwater channel. This is followed by computing block kernel matrices for the RSS distance estimates. The error in the estimation of shortest paths in the block kernel matrices is mitigated through a matrix completion procedure. Upon completion of block kernel matrices, nodes are localized by employing a closed form location estimation procedure. The proposed scheme includes energy harvesting which makes it robust thus achieving longer network life time. However, it does not consider the effect of node mobility on localizability of nodes which may result into highly erroneous estimates keeping in view the use of light as medium of communication.
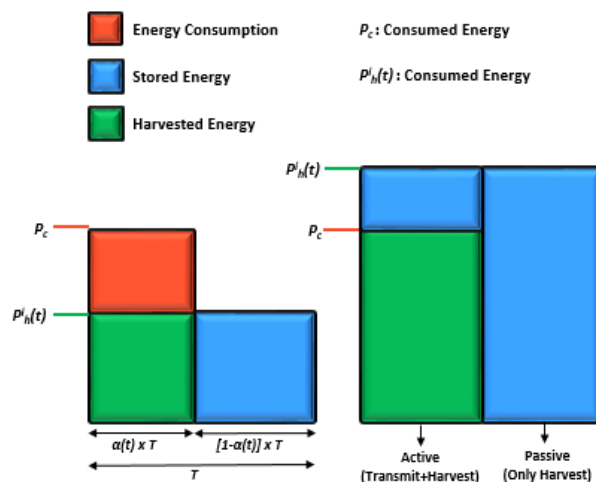

FIGURE 7. Illustration of time slotted operation of sensor nodes [44].

In [45], the authors propose a method for accurate location estimation of selected smart objects in a three dimensional underwater Internet of Things. The authors argue that in certain scenarios, data collected from a certain group of underwater smart objects is more important than others. Therefore the more important objects should be more accurately localized. To achieve this, a four step solution is presented. In step one a pairwise distance matrix is built using RSSI to measure distances between smart objects. In step 2, using a graph partitioning method, the network is divided into disjoint sub graphs each of which represents a set of smart objects (figure 8). This is followed by disintegrating the distance matrix, computed in step 1, into sub graph level distance matrices. Lastly positions of anchored nodes are optimized to achieve further improvement in localization accuracy. Due to its modular nature, the proposed solution is scalable and can be applied to small and large scale networks. However the localization accuracy may vary depending on the density of sensor and anchored nodes, ranging errors etc.

In [46], the authors propose a robust 3D location estimation scheme for optical UWSNs. The authors assume that noisy range measurements between nodes are available. Given the noisy range measurements, the distance matrix (which represents pairwise distance among sensor nodes, relay nodes and anchored nodes) may have some missing distances and outliers thus resulting into a partially connected network. A low rank matrix approximation technique is thus proposed in order to calculate accurate estimates of the missing distances. Moreover the outliers are accommodated through a closed form convergent iterative solution. Due to range limitations the localization may be carried out over multiple hops. Initially relative positions are estimated which are then transformed to absolute position estimates. The proposed scheme successfully reduces ranging errors and solves outlier problem. However, it uses multihop approach that may amplify errors due to error accumulation.

In [47], the authors propose a node localization method for underwater optical sensor networks with limited
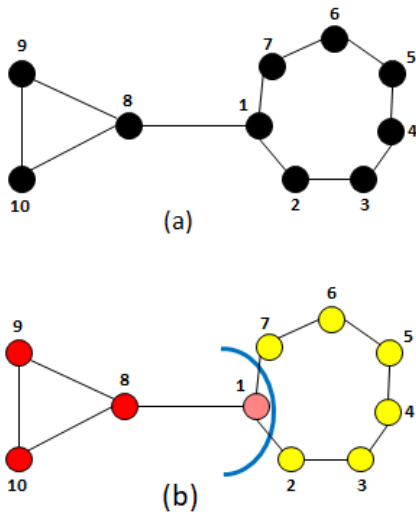
FIGURE 8. a) Graph with associated vertices and links, b) Graph after partitioning into two subgraphs [45].

connectivity. The proposed method operates on the RSSI based noisy distance estimates embedded in a high dimensional space and estimates locations in a low dimensional space. Based on the neighborhood information a weighted graph is created that contains distance estimates of the one hop neighborhood. Missing distance information in the kernel matrix is completed and helmert transform is applied to achieve further reduction in location estimation errors. The proposed technique reduces root mean squared positioning error and achieves Cramer Rao Lower Bound. However it does not considers mobility of nodes with currents which can drastically degrade the performance of an underwater localization scheme when the medium of communication is light.

In [48], the authors propose a localization scheme for partially connected 3D Underwater Optical WSNs aiming at improving localization accuracy by optimizing anchored node placement and accommodating outliers. The pairwise distances between nodes are estimated using RSSI. However due to the impairments of the underwater optical channel, the distance matrix may not be complete. The authors frame the problem of outliers and the missing pairwise distances in the pairwise distance matrix as an optimization problem and solve it using half quadratic minimization. Moreover, in order to improve accuracy, the optimal anchored node placement problem is studied. The problem is expressed as a combination of Fisher information matrices for the nodes where the D-optimality condition is satisfied. The proposed scheme successfully reduce ranging errors and outliers problem.

In [49] the authors propose a RSSI based localization method for optical-acoustic hybrid underwater sensor networks. The proposed method consists of three steps. In step 1, sensor nodes estimate ranges from neighboring nodes using optical communication. As optical channel enables only short range communication, acoustic channel is used in step 2 to measure distances from the nodes located farther away.

In step 3, the range information acquired during step 1 and step 2 is communicated to a centralized node which combines the optical and acoustic range estimates and computes a pairwise distance matrix. Finally, weighted multiple observation dimensionality reduction is applied to estimate node locations while suppressing noisy observations. The proposed method offers multiple advantages. On one hand, the use optical channel for short range communication improves data rate while on the other hand the use of acoustic communication for longer distances improves connectivity. Moreover, the hybrid approach divides the communication domain which enables collision free communication as transmissions in one communication medium do not collide with the transmission of the other medium. Furthermore, the proposed scheme also implements energy harvesting to improve the energy efficiency of the system. On the downside, assumption of a fully connected network is somewhat unrealistic. Node mobility, energy drainage and node malfunction introduce connectivity holes and partitions in the network, in which case the performance of the proposed scheme may be compromised.

B. DISTRIBUTED LOCALIZATION SCHEMES

In case of distributed localization schemes, sensor nodes collect location estimation related data and run positioning algorithms individually to estimate their positions. Table 2 evaluates distributed localization schemes based on the parameters explained in section 1. Distributed localization schemes can be divided into two categories based on mobility consideration i.e. those which consider node mobility and those which do not consider node mobility. The following section gives brief explanation of the mode of operations of each of the distributed localization schemes considered in this survey.

1) DISTRIBUTED LOCALIZATION SCHEMES WITH MOBILITY CONSIDERATION

In [50], the authors propose a cluster based distributed localization scheme with partition handling capability for mobile UWSNs. The proposed scheme consists of two stages. In stage 1 a beacon is propagated down the network. All the nodes that receive the beacon localize themselves using trilateration. However certain partitioned nodes may not receive any beacon. These partitioned nodes initiate an iterative stage two after a certain threshold time by transmitting beacon request with increased transmission power. If the beacon request is received by the reference node, it responds by transmitting a beacon which should be received by the requester within a certain time threshold. Otherwise, upon reaching the time threshold, the clusterheads (which are selected among the partitioned nodes based on random numbers included in the beacon request sent in the previous iteration) send localization request again by doubling the previously used transmission power and wait for beacon. This process continues until a beacon is received or the maximum retry limit is reached. The advantage of this scheme lies in the clustering strategy, which reduces contention and energy

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TABLE 2. Evaluation Parameters (Distributed Localization schemes).

Ref #	Time Sync Requirement	Range based?	Ranging Method	Estimation/ Prediction based	Mobility Consideration	No. of reference nodes	Communication model	Performance Objectives
[50]	No	Yes	RSSI	Estimation	Yes	One with three non-collinearly positioned antennae	Active	Localization coverage, energy efficiency, localization error reduction
[51]	No	Yes	TDoA	Prediction	Yes	3 AUVs	Hybrid	Localization accuracy, Convergence time
[52]	No	Yes	Sound Propagation loss model (centroid optimization used to refine the results)	Estimation	Yes	3, 4 and 8	Active	Error reduction, localization coverage
[53]	Yes	Yes	ToA (results refined using symmetry correction based on least square estimation)	Estimation based for first time localization, Prediction based for tracking	Yes	3	Passive	Localization error reduction
[54]	Yes	Yes	--	Estimation	Yes	4	Active	Energy efficiency
[55]	No	Yes	Based on TDoA	Estimation	Yes	3	Active	Error reduction, energy efficiency
[56]	No	Yes	RSSI	Estimation	Yes	One AUV	Active	Localization coverage
[57]	Yes	Yes	--	Estimation	Yes	--	Active	Localization accuracy
[58]	No	Yes	Two way ToA	Estimation	Yes	--	Passive	Localization accuracy, convergence time, energy efficiency
[59]	Yes	Yes	Feedback based distance estimator	Estimation	Yes	4	Active	Localization accuracy
[60]	Depends on the ranging method	Yes	Ranging method based on requirement	Estimation	Yes	>=3	Active	Localization error reduction, topology Maintenance
[61]	Yes (when ToA is used)	Yes	ToA	Estimation	Yes	--	Depends on the underlying method	Simultaneous localization of large scale mobile network, localization accuracy
[62]	No	Yes	TDoA (UPS localization scheme)	Estimation	Yes	4	Active	Localization error reduction
[63]	No	Yes	Based on TDoA	Estimation based for position estimation, Prediction based for tracking	Yes	3	Active	Localization accuracy, energy efficiency
[64]	Yes	Yes	Based on ToA (additional functionality included	Estimation	Yes	3	Passive	Localization accuracy
[65]	No	Yes	RSSI	Estimation	Yes	One mobile reference node	Passive	Convergence time, localization accuracy
[66]	No	No	--	Estimation	Yes	One AUV	Passive	Localization coverage, Localization accuracy
[67]	Yes	Yes	ToF	Estimation	Yes	>=4	Active	Localization accuracy
[68]	No	Yes	TDoA	Estimation	Yes	3	Active	Joint localization and synchronization
[69]	--	--	--	--	Yes	50 nodes/m^2	--	Availability, accuracy
[70]	No	Yes	AoA	Estimation	No	10 percent	Active	Localization accuracy
[71]	No	Yes	TDoA	Estimation	No	3	Active	Localization accuracy
[72]	Depends on ranging method	Yes	Ranging method based on requirement	Estimation	No	5 percent	--	Localization error propagation control
[73]	No	Yes	RSSI	Estimation	No	4 percent	Active	Localization accuracy
[74]	No	Yes	TDoA	Estimation	No	20 percent	Active	Detection and elimination of malicious anchored nodes
[75]	No	Hybrid	TDoA	Estimation	No	25 beacons	Active	Accuracy
[76]	No	Yes	ToA	Estimation	No	8	Passive	Time synchronization, energy efficiency, localization error reduction
[77]	--	Yes	--	Estimation	No	20 percent	--	Reduction in localization precision variation

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consumption considerably by allowing only cluster heads to request beacons of behalf of the whole cluster. Moreover, with increasing number of iterations the clusters get bigger thus resulting in fewer clusterheads and lesser traffic. Furthermore a retransmission control strategy is also introduced to further reduce the number of transmissions.

In [51], the authors propose an asynchronous localization protocol for UWSNs. The network consists of AUVs which act as reference nodes, active sensor nodes which communicate with the AUVs to estimate their positions and passive nodes which stay silent and are localized through unsolicited messages from the active nodes and/or AUVs. Node mobility is tackled through a mobility prediction algorithm which predicts the future locations of the nodes. The algorithm solves the optimization problems using least squares estimators. The proposed scheme reduces noise and interference through short distance communication as AUVs can come in short distance to sensor nodes. Reduction of noise and short distance communication improves accuracy and energy efficiency. On the downside, the protocol does not define any mechanism to localize those passive nodes which may drift away from the rest of the network and therefore are unable to receive localization messages from AUVs or active nodes. As the passive nodes do not request localization proactively, they may remain unlocalized if they do not receive localization messages.

In [52], the authors propose an anchored nodes assisted target localization scheme. The proposed scheme consists of 3 stages (Figure 9). The target node initiates stage 1 by transmitting start instruction. Upon reception, the anchored nodes estimate their distance from the target node and measure environmental parameters such as absorption coefficient and spreading characteristics of the channel. In stage 2, the anchored nodes send localization messages to the target node. Upon reception, the target node estimates transmission loss for each of the received messages. In stage 3 the target node uses the transmission loss information to measure its distance from each anchored node. Based on the measured ranges, the target node estimates its location using triangulation. The estimates are further optimized using centroid algorithm. The proposed scheme has a simple, low power and effective design which, unlike its counterparts, does not need additional clock information and can achieve similar accuracy with smaller communication cost.

In [53], the authors focus on the inaccuracy in position estimation caused due to inaccurate estimation of sound velocity as it changes non-linearly with increasing depth. The authors propose Symmetry Correction Least Square Estimation. I's a two-step process. In the first step traditional Least Square Estimation (LSE) is used to obtain initial position estimates. The authors argue that the actual target node has a symmetry relation with these estimates obtained using the LSE. Step two improves the accuracy of the first estimation by using the symmetry of the actual target node and the estimates obtained during step1. The major advantage of the proposed method is its insensitivity to the deviation of the estimated speed
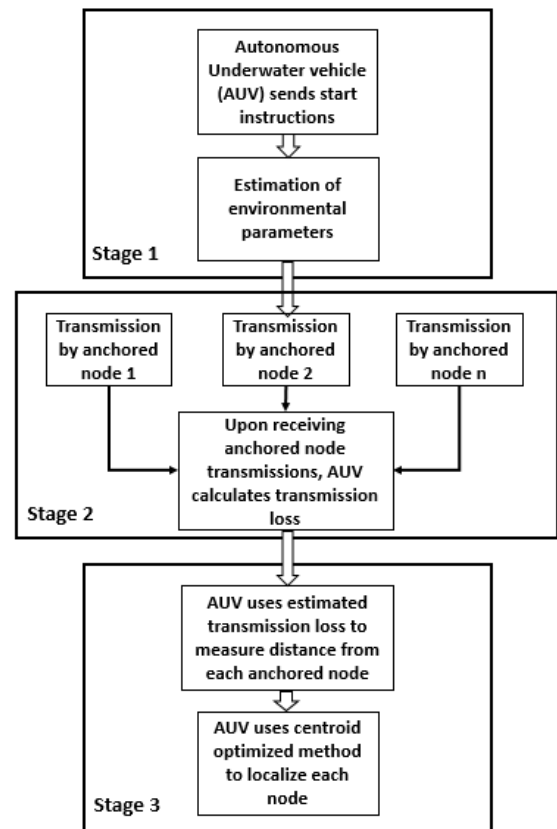

FIGURE 9. Flow chart of the proposed localization method [52].

of sound from the original speed of sound which enables it to achieve similar or more accurate location estimates at different speeds of sound.

In [54], the authors propose an energy efficient localization algorithm that aims at achieving optimum tradeoff between energy consumption and localizability by devising strategies for sensor and anchored nodes to choose optimal transmission power levels for their transmissions. The scheme uses Stackelberg game theory based approach. The sensor nodes, which act as leader, send request message using certain transmission power. Anchored nodes within the range act as followers and respond to the request by choosing an optimal transmission power. With the aim of minimizing their energy consumption, the sensor nodes localize themselves after receiving enough beacon locations. In order to improve localizability, sensor nodes can send requests with higher transmission powers to increase chances of receiving responses from multiple anchored nodes. Moreover authors also introduce a mechanism to find two hop anchored nodes if one hop anchored nodes can't produce the required results (figure 10). The proposed scheme successfully conserves energy thus prolonging network life time while not compromising on the localizability of nodes. Moreover the scheme is scalable showing increase in localization coverage with increase in number of nodes while achieving almost constant energy cost per sensor node irrespective of the number of nodes. However energy
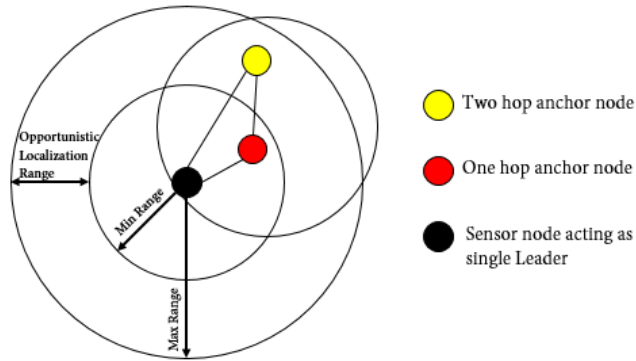
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FIGURE 10. An Example of 2-hop transmission power calculation [54].

cost per anchored node increases non-linearly with increase in the number of sensor nodes.

In [55], the authors propose a two phase technique for joint localization and tracking of Autonomous Underwater Vehicle (AUV). The first phase, called self-localization, deals with estimation of the position of AUV while taking stratification effect and lack of time synchronization into account. This phase tries to save energy by dividing the time into multiple measurement windows. Phase two deals with tracking of the AUV using a reinforcement learning (RL) based tracking controller which uses the position estimation of the first phase. By employing joint design for localization and tracking the proposed scheme improves energy efficiency significantly. Moreover consideration of stratification effect and asynchronous clock improve localization accuracy. Furthermore use of reinforcement learning improves tracking by reducing the impact of uncertainty in parameters due to ocean currents. The scheme assumes that accurate position of the surface buoys is pre-known. However the buoys move with surface currents and may affect the accuracy of tracking if a fixed pre-known position is assumed.

In [56], the authors propose an AUV based localization scheme for UWSNs subject to passive mobility. The authors assume deployment of a high speed AUV, which transmits localization beacons periodically as it traverses the network on a pre-defined path. Sensor nodes that receive the beacons estimate their position using trilateration. In order to improve localization coverage, the deployed sensor nodes disseminate neighborhood information by transmitting 'info' messages. The neighborhood information is actively shared with the AUV upon its arrival. Based on the received neighborhood information, the AUV may adaptively increase its range to reach out to more nodes thus improving localization coverage. The proposed scheme improves localization coverage; however, the improvement is achieved at the cost of the energy consumed to carry out the neighborhood information dissemination phase. Moreover, the relationship between the speed of AUV and the mobility of nodes is not defined. This relationship is important because if the AUV is not fast enough, the measurement may go stale which may result in very high localization error.

In [57], the authors focus on cooperative localization in case of multiple AUVs networks in UWASNs (figure 11). Taking into account the constraint of cooperative structure, they develop two measurement schemes for rough location estimation methods. The first scheme, which is based on isotropic transmission in the underwater acoustic medium, assumes that the ranging inaccuracies estimated from the concurrent omni-directional responses originating from the same source are correlated. Similarly, the second scheme which is based on the common observation environment, also assumes that the observation environment has correlation. The correlation that exists among errors is used for coarse estimation followed by application of an appropriate filter to fuse the coarse estimation with dead reckoning estimation in order to improve the accuracy of location estimates. The proposed schemes effectively suppress error consistently when tested under different noise levels and different navigation trails.
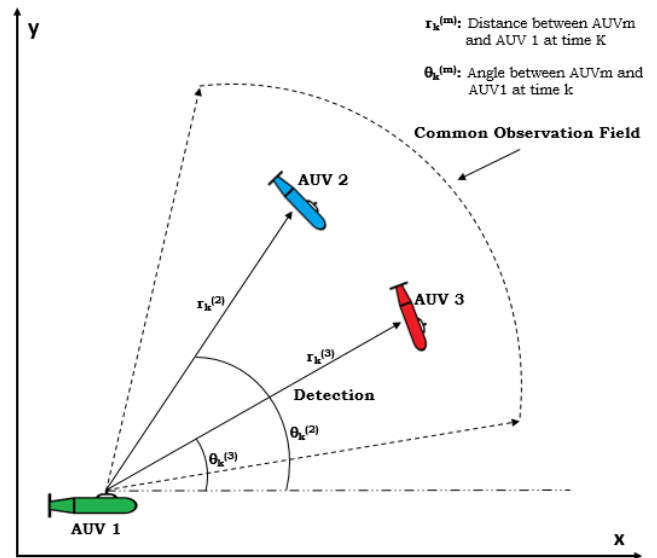

FIGURE 11. The schematic diagram of cooperative localization [57].

In [58], the authors propose a beacon free localization scheme for anchored UWSNs. The scheme achieves its objective in two stages namely maximum a posteriori (MAP) estimation and particle swarm optimization (PSO) localization. During MAP estimation stage, nodes, which are within each other's communication range, form clusters. Nodes within a cluster communicate with other nodes in their cluster to measure distance using two way time of arrival. The analysis of the mobility patterns of nodes in the first stage sets ground for localization in stage 2 by combining the distance and the priori localization info to derive posterior probability distribution and weighted objective function. In stage 2, a swarm of particles is used to look for the fittest location solutions from local and global views at the same time. Furthermore, localization ambiguity (figure 12) is removed and convergence time is improved using a novel reference node selection strategy and a bound constraint mechanism
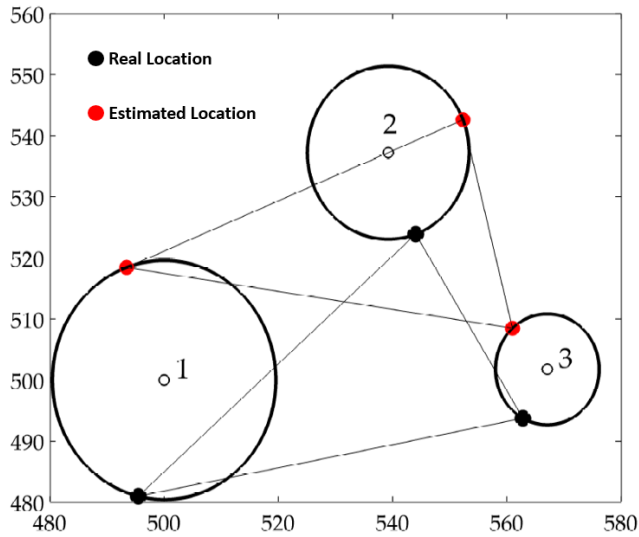
respectively. The proposed scheme takes into account different performance degradation factors such as noise, mobility and communication overhead and provides solutions in order to achieve considerable improvement in convergence time, energy consumption and location errors.

In [59], the authors propose a feedback based approach for target location estimation in UWSNs. The localization procedure is carried out in two steps. In the first step a closed loop feedback based range estimator is designed in order to estimate the distance from the target. Adequate conditions for stability are presented to demonstrate that the system can stabilize the closed loop structure. In order to localize the target, the distance information acquired in the first step is used in the second step to design a consensus based unscented Kalman filtering algorithm. The effect of malicious data is diminished by combining the direct and indirect measurements which improve the localization accuracy of the proposed scheme.

In [60], the authors propose ProLo, a distributed positioning method for mobile 3D underwater acoustic sensor networks. ProLo uses the rigidity theory and builds a virtual rigid structure using projections. The authors assume at least three beacons using which a virtual beacon plane is constructed. The 3D problem is reduced to 2D by projecting the edges of the ordinary sensor nodes onto the beacon plane. As the proposed scheme can maintain global rigidity while the nodes are in motion, the global rigidity theory is applied to enable mobile node localization. ProLo has the advantage of being able to localize nodes in 3D space using only 3 beacons. However, on the down side, it cannot handle errors in distance measurements well, which may result in high localization errors.

In [61], the authors propose a confidence based positioning scheme for mobile and large scale UWSNs. Based on the confidence value of the current positioning estimates of localized nodes, the nodes with highly precise estimated

locations are employed as reference nodes to localize their unlocalized neighboring nodes. The confidence value for each node is updated based on the expected error of the adopted positioning method. Three different positioning methods are considered namely; Trilateration based on Time of Arrival, Dead reckoning and ultra-short base line localization (figure 13). The update rules of the confidence value rely only on local information thus making the proposed method highly scalable.
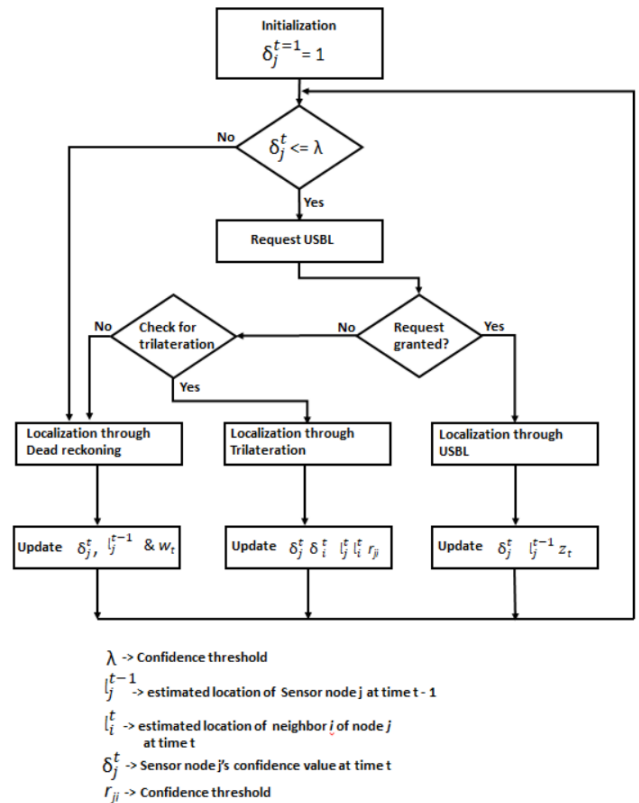
In [62], the authors propose a localization scheme that aims at improving localization accuracy by mitigating errors caused by beacon node drift and ranging. In the proposed method, the unknown nodes select four most reliable beacon nodes with in their communication range to estimate their position. Reliability is determined based on evaluation of weights of some proposed indexes using analytical hierarchy process method (figure 14) which is followed by calculation of the grey correlation grades which represent reliability of every beacon node. A set of two possible locations of the unknown node is calculated using three beacon nodes. Then one of the two possible locations that has smaller distance error from the forth beacon node is chosen as the final position estimate of the unknown node. The proposed scheme improves localization accuracy by resolving errors due to beacon node drift and ranging. However, it ignores error accumulation that is caused by using localized nodes as beacon nodes.
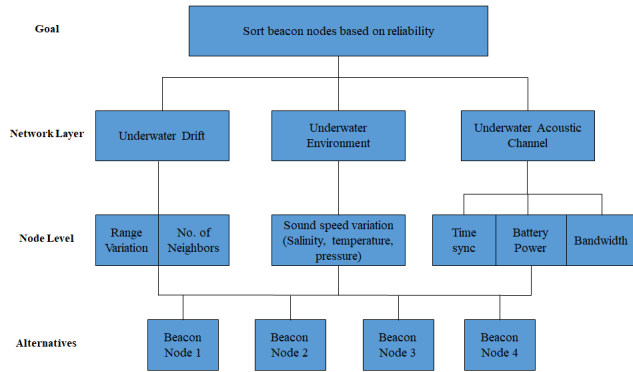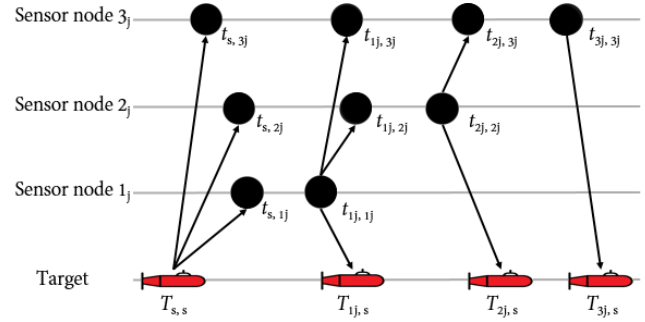
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FIGURE 14. Analytical Hierarchy Process Model [62].

Notation	Description
$T_{s,s}$	Timestamp when target sends initiator message
$T_{i,s}$	Timestamp when target receives the message from sensor i
$t_{s,i}$	Timestamp when sensor i receives initiator message
$t_{m,i}$	Timestamp when sensor i receives message from sensor m
$t_{i,i}$	Timestamp when sensor node i sends its message

FIGURE 15. Example of the localization process [63].

In [63], the authors propose energy efficient target localization and tracking scheme subject to constraints such as noisy measurements, asynchronous clocks and power limitations. The proposed scheme consists of two phases. In phase 1, which deals with position estimation of the target, an asynchronous position estimation method is developed based on the relationship between propagation delay and position (figure 15). In phase 2, in order to facilitate persistent tacking, a consensus oriented Bayesian filter is designed based on the localization results of phase 1. Specifically, longer network life time and improved tracking accuracy is achieved by jointly adopting duty cycle mechanism and the consensus fusion approach. One of the advantages of the proposed scheme is that it does not require clock synchronization which is hard to achieve in the harsh underwater environment. Moreover the possible adverse effects of lack of synchronization on position estimation are handled smartly by acquiring reception and transmission time stamps of communicating entities and using them in a least square method to acquire positions. On the downside, adverse effects of the underwater channel and environment such as mobility of sensor nodes, lack of availability of communication links etc. are ignored.

In [64], aiming at improving localization accuracy, the authors propose a passive localization scheme that considers and utilizes the multipath nature of the underwater acoustic channel. The scheme considers two types of anchored nodes; S-anchors that are deployed on or near the water surface and U- anchors which are deployed underwater. In case of S-anchors only direct path between the anchored nodes and the unknown nodes is considered whereas in case of U-anchors both direct and surface reflected paths are considered (figure 16). Nodes are localized by running optimization procedure given in (15). Once the horizontal ranges between the underwater ordinary node and S-anchors and U-anchors have been calculated, the passive localization problem of the underwater ordinary node can be formulated as an optimization problem as follows:

$$V^o = argmin \begin{bmatrix} \sum_{i=1}^{Ns} |\rho_i - ||(V^o, Z^o) - S_i||| \\ + \sum_{j=Ns+1}^{Ns+NU} |\rho_j - ||(V^o, Z^o) - U_j||| \end{bmatrix} \quad (15)$$
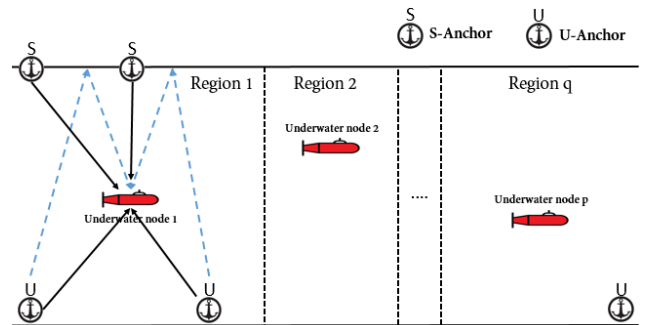

FIGURE 16. Architecture of a passive localization system [64].

where S_i, U_j, V^o represent the coordinates of the surface anchored node i, underwater anchored node j and the underwater ordinary node respectively; ρ_i, ρ_j represent horizontal ranges between the unlocalized node and the anchor nodes i and j respectively. NS, NU denote the number of surface anchor nodes and the number of underwater anchor nodes respectively. The proposed scheme considers the variations in the speed of sound due to underwater characteristics such as pressure, salinity and temperature which is an important consideration often ignored in many previously proposed designs.

In [65], aiming at improving localization accuracy and convergence time, the authors propose a mobile reference node and RSSI based localization method. The proposed method comprises four steps. Step 1 deal with defining the trajectory of the mobile reference node and estimation of RSSI values by sensor nodes. Step 2 deals with designing a support vector regression based interpolation system that processes the estimated RSSI values in order to find the projection of sensor nodes on the reference node trajectory. Step 3 develops a curve matching technique that processes the RSSI values to find the perpendicular distance between underwater sensor

nodes and the trajectory. Finally, step 4 estimates node locations by geometrically processing the available information. The proposed method reduces localization error considerably. Moreover unlike some of the existing methods in which the anchored node is required to travel two trajectories at minimum, the proposed method requires only one time trajectory to localize a node.

In [66], the authors propose an AUV based localization algorithm for distributed localization of sensor nodes. The authors study the impact of the time interval of beacon transmission and AUV traversal path on energy consumption and localization coverage. The study finds appropriate time intervals for beacon transmission when the AUV traverses the network over a layered rectangular path. As the beacons, transmitted by the AUV from different locations, are received by an unlocalized node, it estimates its position by the computing the innermost intersection body through the geometric intersection of the received signals. The proposed method saves energy by employing a passive localization approach in which sensor nodes do not transmit. Secondly, time synchronization, which is very hard to achieve underwater, is not required. On the downside, the localization coverage of the scheme depends heavily on the beacon interval. Larger beacon intervals, which may save energy, bring down the localization coverage considerably.

In [67], the authors argue that in AUV centric localization schemes the deployment geometries of anchored nodes and AUVs, which include their deployment pattern and ranges, have considerable impact on the localization accuracy of the AUV. Therefore, aiming at finding efficient deployment geometries, the authors study the impact of deployment configuration of anchored nodes and underwater autonomous vehicle on location estimation process. Firstly, Jacobian matrix of the measurement inaccuracies at the true position of the AUV is derived and used to quantify the Cramer Rao Lower Bound (CRLB) with Time of Flight measurement using an isogradient sound speed profile. Then an optimization problem is formulated which minimizes the CRLB's trace bounded by the range and angle constraints to realize the AUV-anchor geometric configuration which, being non-linear and multivariate, is hard to deal with. This multivariate problem is therefore transformed into univariate optimization problem that results in formulating an AUV-anchor geometric configuration that achieves satisfactory localization estimates and is easy to implement. The proposed scheme considers variation in the speed of sound in the underwater environment which, if not considered, will result in inaccurate distance estimates leading to inaccurate location estimates. However the authors use an isogradient sound speed profile, whereas in real world scenarios the speed varies nonlinearly. Therefore in real deployment scenarios the inaccuracies may still persist.

In [68] the authors propose Robust Joint Localization and Synchronization (RJLS) scheme which is an iterative technique to carry out simultaneous localization and synchronization in underwater sensor networks. The proposed technique

considers the inherent stratification affect in the underwater environment and tries to compensate it. The technique consists of five phases (figure 17). Phase 1 is the message exchange phase in which ordinary nodes acquire timestamp information of the reference nodes. In phase 2, the acquired time stamps are used in conjunction with the least square and weighted least square estimation to estimate the clock skew, offset and location of the ordinary nodes. Phase 3 takes the locations of the anchored and ordinary nodes as input and estimates the propagation delay by compensating the stratification affect. In phase 4, the distance between the ordinary node and the anchored node calculated based on the position information (determined in phase 2) is used in conjunction with the propagation delay between the two nodes (calculated in phase 3) to determine the speed of sound. In phase 5, the output of phase 4 is input back into phase 2 in order to run iterations so that the location accuracy and time synchronization can be improved. The advantage of the proposed scheme
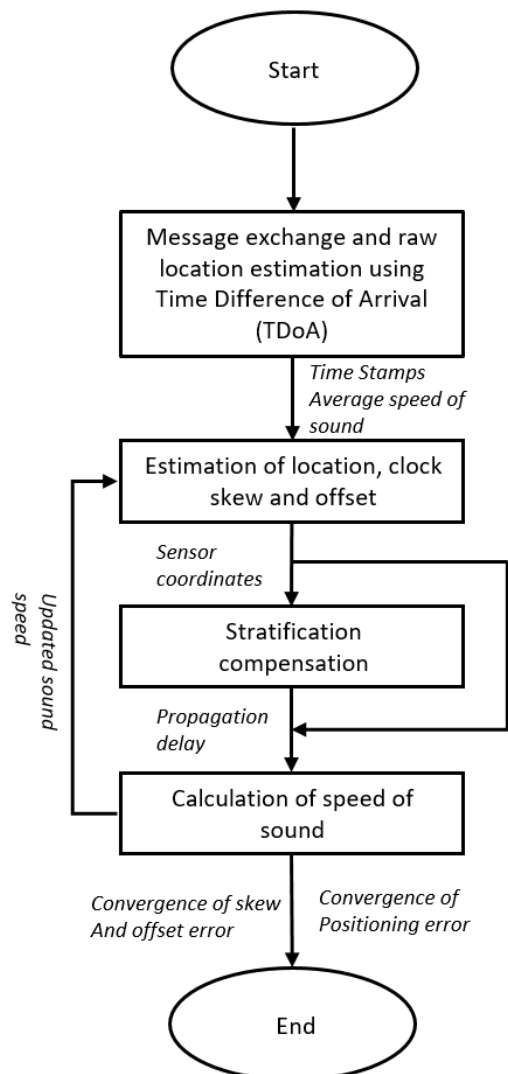

FIGURE 17. RJLS workflow [68].

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lies in the compensation of the stratification effect which, if left uncompensated, increases localization error. Moreover, the proposed technique improves location estimations and time synchronization through iterative method.

In [69], the authors propose a fuzzy decision support system (figure 18), called Best Suitable Localization Algorithm (BSLA), for selecting one or more of the available localization methods in order to achieve improved localization coverage and accuracy. BSLA assumes n underwater localization techniques each of which can localize a sensor node with certain accuracy as the node descends from the ocean surface to the ocean floor. Each sensor node runs a fuzzy inference system which evaluates the feasibility of the available localization methods for that node based on four input variables namely, Ultra Short Base Line (USBL) availability, operational depth of the node, node's battery level and the number of localized neighbors of the corresponding node. Based on the output of the fuzzy inference system, the node may select a single localization method or alternatively combine two or more methods to achieve improved localization covered and accuracy. On the high side, USBL improves localization coverage and accuracy by combining different localization methods. However, this is achieved at the cost of increased computational complexity due to the implementation of fuzzy decision support system.
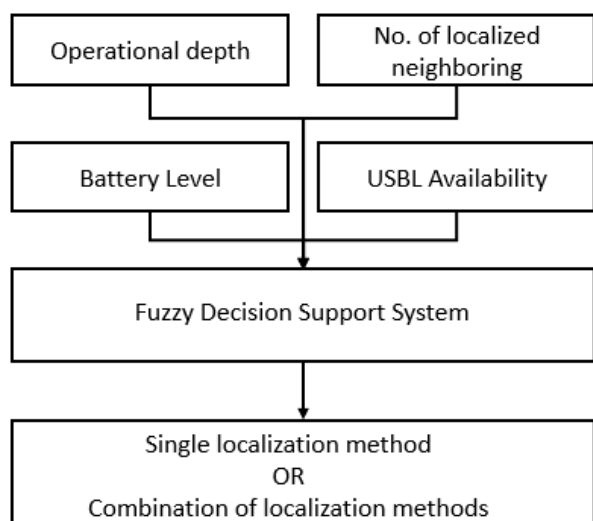

FIGURE 18. Fuzzy decision support system.

2) DISTRIBUTED LOCALIZATION SCHEMES WITHOUT MOBILITY CONSIDERATION

In [70], the authors propose a two stage localization scheme which carries out localization in sparse UWSN by estimating Euclidean distances between anchored and sensor nodes using Angle of Arrival (AoA) measurement. In stage 1, all nodes N measure their distance from anchored nodes using AoA measurements. In the second stages, trilateration is used to localize nodes based on the measured distances. Moreover, in order to minimize error, a weighted Least Square estimator

is used if distances to more than the required number of anchored nodes are available. One of the demerits of the proposed scheme is the inherent accumulation of ranging and positioning errors due to the design of the scheme. Moreover, the scheme does not consider mobility due to currents. Therefore, the error may be even more amplified. However the authors try to optimize by using weighted LS optimization if multiple least hop count paths are available.

In [71], authors propose an unscented transform based localization method that takes into account stratification effects (such as sound speed variation) and lack of time synchronization among nodes. It reduces linearization errors by computing Jacobian matrix through employing unscented transform. Particularly, ray-tracing method is used to model stratification in the underwater channel. The authors derive the Cramer Rao Lower Bound (a lower bound on error variance) for the proposed scheme and show that the proposed method diminishes the root mean square errors in the estimated positions closer to Cramer Rao Lower Bound thus achieving improved localization accuracy.

In [72], the authors propose a patch and stitch localization scheme for the sparse three dimensional UWSNs that lack enough number of common nodes among patches. The authors solve the merging problem by developing the conditions for the unique merger of two sub networks. The proposed solution treats the translation parameters as unknowns and derives a set of equation which can uniquely solve the unknowns. Moreover, in order to merge the adjacent patches, the proposed scheme uses both connecting edges and common nodes among the patches which increases the chances of the successful merger. The proposed scheme achieves higher localization coverage in even very sparse 3D networks as compared to previously proposed solutions in the given scenario. Moreover it can achieve higher localization accuracy by reducing error accumulation by calculating optimum component merger parameters.

In [73] the authors propose a received signal strength based localization algorithm for asynchronous UWSNs while accounting for the inhomogeneous nature of the underwater acoustic channel. Firstly, the authors derive the transmission loss of the acoustic signal as it travels from source to destination in the inhomogeneous underwater environment. Then, an oversampled match filter based method for measuring received signal strength is proposed. For the channels subject to flat fading, an improved oversampled match filter based received signal strength measurement method is proposed. Build on these underlying models, an iterative scheme for location estimation based on Gauss-Newton method is developed. The proposed scheme can achieve high localization accuracy at lower bandwidth. Moreover when flat fading is low it can achieve accurate results. However with high flat fading, the performance of the proposed methods degrades. The proposed RSS methods are appropriate for localization in environments with low bandwidth and where it is very hard to achieve synchronization.

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In [74] taking presences of malicious anchored nodes in consideration, the authors propose a cooperative localization scheme. The study assumes that a certain ratio of the anchored nodes is malicious and can generate incorrect ranging information to attack the localization process. The proposed scheme works in two phases. In the first phase, which deals with distance estimation, one hop neighbors of anchored nodes measure distance from the anchored nodes using ToA. Based on the difference in the distances from neighboring anchored nodes, the sensor nodes cast reputation votes. The number of votes decides whether anchored node should be considered honest or malicious node. After elimination of malicious nodes, an MMSE based iterative localization algorithm ensues in which localized nodes may act as reference nodes for unlocalized nodes. The malicious node detection and elimination mechanism of the proposed scheme is energy efficient as it does not involve any additional transmissions. On the downside, the effect of node mobility due to water currents is ignored. Ignoring such an important factor compromises the accuracy of the location estimates. Moreover, error accumulation due to relegating the role of reference node to localized sensor nodes is also ignored.

In [75] the authors propose a Two Phase Time Synchronization Free Localization Algorithm (TP-TSFLA) using mobile beacons (figure 19). The network consists of two types of nodes: mobile beacon nodes whose location are known and static sensor nodes with unknown location. In the first phase, Time Synchronization Free Localization (TSFL) is used to obtain ranges measurements between the mobile beacon nodes and the unknown sensor nodes. Then particle swarm optimization is employed to localize the nodes with known range estimates. However, some of the nodes, which could not receive beacon during phase 1, are not localized. All such unlocalized nodes initiate phase two by transmitting beacon requests. The already localized nodes act as reference nodes and respond to the requests by sending back their coordinate information. Based on the received response, every unknown node localizes itself proactively using Circle based Range Free Localization Algorithm (CRFLA). The accuracy of CRFLA based location estimates is further improved using a coordinate adjustment scheme. The proposed scheme does not need time synchronization to carry out localization which makes it more practical solution as time synchronization is hard to achieve underwater.

In [76] the authors propose a Gauss Newton method based joint localization and synchronization technique for underwater sensor networks. The major challenges addressed in this work are: 1) stratification effect in the marine environment and, 2) lack of synchronization between anchored and sensor nodes. Stratification effect is modelled using ray tracing method. Moreover, in order to achieve simultaneous localization and synchronization, the stratification effect, sensor node locations and clock imperfections are formulated into an integrated framework. The system model and the resultant Maximum Likelihood (ML) estimator are derived. Due to the nonconvex and nonlinear nature of the ML estimator, Gauss
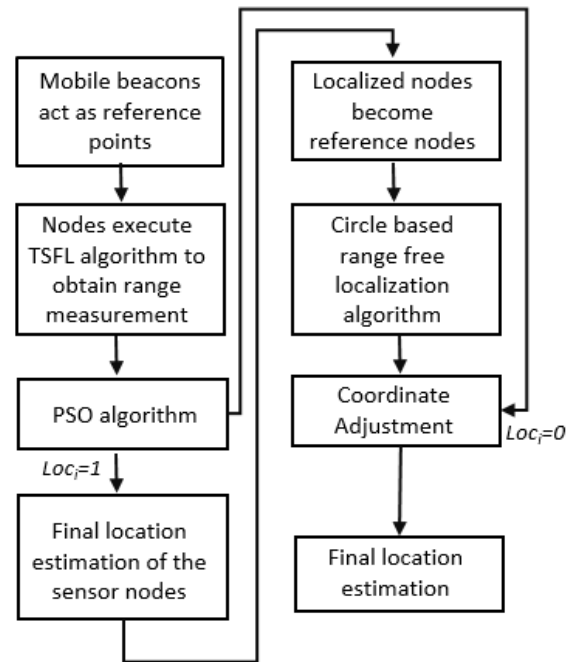

FIGURE 19. TP-TSFLA work flow.

Newton method is employed to resolve the original problem using a roughly estimated initial point. The proposed scheme employs one way messaging to save energy and reduce communication overhead. However, on the downside, the nodes positions are assumed fixed during message exchange. Considering the slow speed of the acoustic waves underwater, the assumption may not be realistic for longer distances.

In [77] the authors point to the inconsistency in the positional precision of individual nodes in the process of network positioning and propose an error control adjustment method to readjust the position estimates in order to achieve consistent localization precision. The proposed method establishes a mathematical model using the range information between nodes. Accurate range information is obtained using time delay measurements in conjunction with actual sound speed profile and ray tracing model. After processing, the positioning accuracy of sensor nodes can be enhanced with the same level of network positioning accuracy. The proposed technique tries to improve variation in estimation errors and therefore can prove beneficial for applications, such as aided navigation, data fusion and signal processing where variation in localization precision may have adverse effects on the performance of these applications.

IV. FUTURE RESEARCH DIRECTIONS
A. MOBILITY AND NETWORK PARTITIONING
Most of the existing literature on underwater localization assumes limited or no mobility of sensor nodes. Nevertheless, certain applications such as observation of the changing characteristics of the underwater streams, determination of the spread of certain pollutants or minerals in the sea

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water etc., may require untethered mobility. Consideration of such scenarios gives rise to certain challenges. For instance free mobility may introduce network partitioning in which case a set of nodes may not be able to receive localization beacons/neighborhood information and therefore will remain unlocalized. Partition handling mechanisms [33], [50], must be investigated to cope up with such situations. Moreover, the prevalent network architectures, which mostly assume fixed reference nodes and limited range, stand useless when underwater nodes are unable to communicate with the fixed reference nodes as they move away due to free mobility. Some new network architectures for such scenarios are proposed in [33], [50]. However research is required to further refine the solutions.

B. SECURITY

Many schemes have been proposed to secure the localization process [78]–[80] in terrestrial wireless sensor networks. However these solutions are not applicable underwater due to the unique characteristics of the underwater acoustic channel. Security aspects are often ignored in the localization schemes proposed for UWSNs. An attack on the localization infrastructure can compromise the integrity of the whole sensing mission by relating sensed data to wrong locations. For instance a malicious node can impersonate a reference node and jeopardize the location estimation process by transmitting wrong reference locations. Therefore, there is a need to incorporate robust authentication techniques that are appropriate for underwater localization systems. Location privacy is another major concern for certain underwater systems such as military application in which leak of location information can have dire consequences. In order to be localized, sensor node must reveal certain information that can be eavesdropped and lead to privacy holes [81]. Therefore proper confidentiality mechanisms must be researched and incorporated to design fool proof underwater localization systems. Moreover, as underwater sensor nodes have limited energy, the security related mechanism must be energy efficient.

C. SOUND SPEED VARIATION

Acoustic waves are the preferred medium of choice for underwater communication. Mostly, constant speed of sound (i.e. 1500 m/s) is assumed by localization algorithms. However, the speed of sound underwater is not constant and varies with changes in depth, temperature and salinity. Thus, assumption of a constant speed results in inaccurate range estimates which leads to error in location estimation [15]. For accurate location estimates, localization algorithms should incorporate mechanisms that measure changes in the velocity and direction of sound waves as they propagate from transmitter to receiver. Alternatively accurate sound speed profiles can be used.

D. SYNCHRONIZATION

Node time synchronization is important for certain ranging techniques such as TDoA and ToA. Most of the researches using these techniques assume time synchronization among nodes. However, in practice it is hard to achieve time synchronization underwater due to harsh channel characteristics. Some schemes have been proposed in [82]–[84]. However they require extensive communication among nodes, which may lead to high energy consumption.

E. BEYOND ACOUSTICS

Though acoustic waves are a preferred medium of choice due to their long range communication ability in UWSNs, optical waves can support high data rates over shorter distance. Therefore hybrid cluster based mechanisms such as [85] that use optical waves for short range intra cluster communication and acoustic waves for long range inter cluster communication should be investigated. Using two different mediums improves the performance by reducing contention and by improving data rate.

F. CROSS LAYER APPROACH

Although ignored in many localization algorithm designs, consideration of lower layer constraints, such as mac layer contention, is important. The contention may increase convergence time which may cause some of the information to go stale and therefore result in inaccurate location estimates. Moreover, consideration of lower layers may increase the communication overhead and energy consumption drastically and may render an otherwise feasible solution totally infeasible.

V. CONCLUSION

In this paper we presented a survey of the recently proposed localization algorithms for underwater acoustic and optical sensor networks. The algorithms are scrutinized based on parameters which cover most of the basic characteristics of a localization algorithm. Additionally, the methods adopted by each algorithm are also explained briefly along with their merits and demerits. The surveyed algorithms have been divided primarily into two classes, which are: a) Centralized Localization schemes which compute location estimates at a centralized location such as sink node and b) Distributed Localization algorithms which enable individual sensor nodes to compute their location based on received information. Each of the two classes is further divided based on mobility consideration.

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