Review Article

A Review on Optimal Placement of Sensors for Cooperative Localization of AUVs

Xu Bo, Asghar A. Razzaqi, and Ghulam Farid

College of Automation, Harbin Engineering University, Harbin 150001, China

Correspondence should be addressed to Asghar A. Razzaqi; asghar.abbas.razzaqi@gmail.com

Received 13 May 2019; Revised 2 July 2019; Accepted 16 July 2019; Published 30 July 2019

Academic Editor: Jaime Lloret

Copyright © 2019 Xu Bo et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Self-positioning of submerged Autonomous Underwater Vehicles (AUVs) is a challenging task due to nonavailability of GPS signals. One of the most recent solutions for this is the use of surface vehicles (sensors) for cooperative localization of the underwater vehicles (targets) by measuring their relative positions. However, correct placement of the surface sensors is very critical as their geometric configuration affects their observability and hence availability of their relative positions information to the targets. In this paper, a comparative survey of sensors’ optimal formation techniques for cooperative localization of AUVs has been presented. Introduction to the basic cooperative localization techniques and background theory of optimal sensor placements have been provided. This paper can also serve as a fundamental reading material for students and researchers pursuing research on optimal sensor placement for cooperative localization.

1. Introduction

Since their introduction in 70s [1], Autonomous Underwater Vehicles (AUVs) have remained the focus of research for about four decades in order to improve their size, efficiency, operating time, and area, etc. With the development of sophisticated sensors and reliable underwater communication equipment, it is now possible to use AUVs in many complex and extended military as well as civil applications which were previously not possible. Few examples of AUVs application are bathymetric surveys [2, 3], inspections of underwater gas, oil, or other installations [4–6], search of wreckages of missing airplanes [7], rescue of men or material from underwater [8], marine research [9, 10], and mine countermeasure operations and surveillance for military purpose [11–14]. Beside other challenges of an AUV’s operation, self-localization is extremely difficult task due to severe attenuation of Radio Frequency (RF) waves and nonavailability of Global Positioning System (GPS) signals in water [15]. One suitable option for localization and navigation of AUVs is to use inertial sensors and/or magnetic compass. However, it is an established fact that inertial sensors accumulate error with time, resulting in unbounded error in localization of the AUVs. To limit the localization error for longer operations of AUVs, inertial navigation is being augmented by various techniques like frequent surfacing of AUVs for GPS feed [16], surface or bottom tracking using Doppler velocity log (DVL) [17, 18], and predeployment of surface beacons for acoustic baseline system [19, 20]. Although these methods have been proved effective for some of the underwater applications, these either require expensive preinstallations of surface beacons or need the AUVs to temporarily halt the operation and go for the GPS fixes. Moreover, these methods also limit the operating area of AUVs.

To overcome the limitations of traditional localization methods, a new technique, called cooperative localization, is being studied recently [20–25]. In this method, few autonomous vessels (known as master or sensors) are either positioned on water surface or frequently leave the operation area for getting GPS signals. So, accurate positions of the sensors are known at all times. The remaining AUVs, operating underwater (known as slave or targets), maintain their accurate position by taking reference from the sensors at regular intervals. The relative position of the targets can be estimated by using the principles of intersection of different lines and the proper geometric formulation. Time difference of arrival (TDOA), received signal strength (RSS), time of arrival (TOA), and angle of arrival (AOA) are the four available
methods used in cooperative localization to calculate the target’s position using lines and angles. At the cost of only few extra vessels (sensors), cooperative localization method provides a sustainable and accurate localization solution for many modern-day applications.

Cooperative localization of underwater vehicles is much complex and challenging task compared to that of aerial or ground autonomous vehicles. This is because of the fact that, for above water, range can be easily measured using RF or Laser signals. It is also easy to relate RSS of RF or laser to range of the target for above water measurements. It has been shown by [26] that autonomous vehicles can estimate their position accurately, even without GPS, by sharing their attitude and relative position data with each other. On the other hand, RF waves are strongly attenuated in water and, therefore, acoustic waves are the only option for range measurement as well as for communication. Transmission of sound waves in water is very lossy and is severely affected by complex and uncertain characteristics of underwater environment. Thus, underwater range measurement is harshly affected by the noise and underwater communication is limited to low data rate only. Moreover, defining accurate inverse function to extract the distance upon transmission loss is also very difficult due to time varying propagation loss and multipath effect [15]. Although factors related to underwater environment characteristics such as multipath affect, varying speed of sound, and bathy conditions are uncontrollable, accuracy of the cooperative localization can still be optimized using suitable estimation algorithm and by maximizing the observability of the sensor vessels by keeping them at maximum observable location (called optimal formation of the sensor vessels).

Extensive research has been carried out in the field of cooperative localization and different estimation algorithms and techniques have been proposed. However, optimal formation of the sensors for cooperative navigation is relative new field and only few research papers are available. The lack of a review paper in this field is also one of the bottlenecks of wider acceptance of the idea. In this paper, we will briefly provide a comparative survey of sensors’ optimal formation techniques for cooperative localization of AUVs. First we have given a brief overview of the techniques and methods used for cooperative localization of AUVs in Section 2. Background theory of optimal sensor formation and the problem statement is discussed in Section 3. In Section 4 we have reviewed the methods and techniques proposed in literature for optimal sensor formation. In Section 5, the research challenges associated with optimal sensor placement and future trends are explained in detail. Finally the paper is concluded in Section 6.

2. A Brief Overview of Cooperative Localization Techniques for AUVs

To better understand the problem of optimal formation, this section provides a brief overview of various techniques used for cooperative localization of AUVs that is at the core of the paper at hand. As already mentioned in previous section, in cooperative localization, target AUVs are localized by taking reference from the sensor AUVs whose accurate positions are known. A general form of cooperative localization of AUVs is graphically shown in Figure 5. Angle of Arrival (AOA), Time of Arrival (TOA), Time Difference of Arrival (TDOA), and Received Signal Strength Indicator (RSSI) are the four standard techniques used in cooperative localization. Every technique has its advantages and limitations and is suitable for particular scenarios/applications. Table 1 compares the localization techniques and summarizes the advantages/disadvantages associated with them.

Table 1: Analysis and comparison of cooperative localization techniques.

| Localization techniques | Advantages | Disadvantages | Applicable conditions | In literature of optimal sensor placements (Ref number) |
|-------------------------|------------|---------------|----------------------|--------------------------------------------------------|
| Time of Arrival         | High accuracy which is not much affected by range; significant literature available | Time synchronization between sensors and targets required | Suitable for long range, NLOS operations | [27–35] |
| Angle of Arrival        | Clock synchronization not required between targets and sensors; Smaller number of sensors required | Accuracy decreases with range; High accuracy directional antennas are to be installed, additionally | Suitable for short ranges when there is limitation on number of sensors | [36, 37] |
| Time Difference of Arrival | High accuracy even at long ranges; No time synchronization between sensors and target required | Larger number of sensors required as compared to other methods | Best option for long ranges operations when larger number of sensors are available | [38] |
| Received Signal strength | Does not need to install extra hardware in both, targets and sensors | Severely affected by multipath, NLOS and other underwater environmental conditions | Suitable for short ranges and LOS communication only | None |

2.1. Angle of Arrival Based Localization. By measuring the angle of the received signal at target from a reference sensor, we can draw a straight line in that direction. Using multiple reference sensors, we can get multiple straight lines crossing each other at a common intersection point which is the
estimated position of the target. AOA based localization problem is explained in Figure 1, where \( N_1(x_1, y_1) \) and \( N_2(x_2, y_2) \) are the known positions of \( i_{th} \) and \( j_{th} \) sensors and \( T(x, y) \) is the estimated position of the target using AOA.

Let \( \theta_i \) and \( \theta_j \) be the measured bearing of the target from the respective sensors which are given as

\[
\theta_i = \tan^{-1} \left( \frac{x - x_i}{y - y_i} \right), \\
\theta_j = \tan^{-1} \left( \frac{x - x_j}{y - y_j} \right)
\]  

At least two sensors are required for 2D localization and three sensors are required for 3D target localization. With two sensors, \( N_1 \) and \( N_2 \), the target position in 2D, \( T(x, y) \), can be calculated as follows:

\[
y = x \tan \theta_2 + (y_2 - x_2 \tan \theta_2) \\
x = \frac{y_2 - y_1 - x_2 \tan \theta_2 + x_1 \tan \theta_1}{\tan \theta_1 - \tan \theta_2}
\]  

AOA method does not require any sort of clock synchronization between target and sensors as it is required in the case of TOA. Moreover, fewer sensors are required for position estimation as compared to TDOA method. However, AOA measurement requires costly antennas with high directional arrays to precisely measure the target bearing. Its accuracy is also decreased with the increase of target range. Therefore, AOA is complex and is difficult to implement for underwater localization especially for longer ranges due to sound wave propagation properties.

2.2. Time of Arrival Based Localization. The time of arrival (TOA) method relies on the propagation time of a signal from the sensors to the target. In this method, one-way or two-way propagation time is determined and the range of sensors from target is estimated. Multilateration principle is used to estimate the target position as shown in Figure 2.

In Figure 2, \( N_i(x_i, y_i) \) is the \( i_{th} \) sensor whose accurate position is known and \( d_i \) is the target range from \( i_{th} \) sensor. Assuming constant speed of sound and in absence of any noise, target range is calculated from measured TOA, \( T_i \), as follows:

\[
d_i = C \times T_i
\]  

where \( C \) is the speed of sound in water.
If we draw arcs of radii $d_i$ from the sensor $N_i$, the three arcs will intersect each other at $T$, which is the estimated position of the target. In absence of any measurement noise, the target position can be calculated as follows:

$$y = \frac{x_2^2 + d_1^2 - d_2^2}{2 \times x_2}$$  \hspace{1cm} (5)$$
$$x = \frac{x_3^2 + y_3^2 + d_1^2 - d_3^2 - 2 \times x \times x_3}{2 \times y_3}$$  \hspace{1cm} (6)$$

This method is suitable for longer ranges as compared to RSS and AOA method. However, accurate time synchronization is required between reference nodes and the target which is a challenging task. AOA localization method has mostly been considered in the past literature of sensors placement for cooperative localization due to its less complexity and ease of implementation.

2.3. Received Signal Strength Based Localization. If path loss propagation model is known, range of the transmitter can be estimated by measuring the strength of the received signal. After measuring the range of a target from different sensors, its position is estimated utilizing multilateration technique as shown in Figure 3. Each sensor is considered to be located at the centre of a circle whose radius is the estimated range of the target from the sensor. The target lies on the circumference of the circle. The intersection of the circumferences is the location of the target node. At least three or more sensors are needed to estimate the target’s positioning in 2D while four or more sensors are required in the case of 3D position estimation.

Estimating the target range based on RSS measurement is complicated for underwater environment. However, various underwater transmission loss models have been proposed in the past which may be utilized for this purpose [40, 41].

In noise-free environment, the received power, $P_i$, at the target from $i_{th}$ sensor at range $d_i$ is given as [40]

$$P_i = K_0 \times P_{ti} \times d_i^\alpha$$  \hspace{1cm} (7)$$

where $K_0$ is reference path loss, $\alpha$ is path loss exponent, and $P_{ti}$ is the transmitted power of $i_{th}$ sensor.

RSS based localization method offers some advantages; i.e., no extra hardware is required to be installed in sensors or in target except power detector. Moreover, time synchronization between the target and the sensors is also not required. However this method is difficult to implement for underwater localization especially for longer ranges due to sound wave propagation properties. Consequently, RSS based cooperative localization of AUVs has not been much explored by the researchers yet.

2.4. Time Difference of Arrival Based Localization. TDOA method depends on the time difference of two signals that are generated from two sensors when arriving to the target. Each TDOA measurement determines that the target should lie on a hyperbolic curve with constant range difference between the two transmitting reference sensors as shown in Figure 4. At least two pairs of sensors are needed to estimate the location of a target in 2D and three pairs of sensors are required for 3D localization. Contrary to TOA method, The TDOA method can be implemented without clock synchronization.

As TDOA method depends upon sensor pairs, it is important how the sensor pairs are made for these measurements. Two types of sensor pair strategies have been presented in the past literature, i.e., Centralized Sensor Pairing (CSP) and Decentralized Sensor Pairing (DSP). In CSP, one of the sensors is declared as reference sensor and all other sensors make pair with common reference for TDOA measurement. Hence, for CSP, maximum possible sensor pairs are $M-1$, where $M$ is the total number of sensors in the system, while in DSP, no sensor is declared as reference and any two sensors make pair with common reference for TDOA measurement. Although CSP is commonly used and widely studied technique due to ease of implementation, it has observability constraint due to power, bandwidth, and communication range limitations.
3. Background Theory and Problem Statement

3.1. Problem Statement. Consider that \( m \) number of target AUVs are operating underwater and their depths can be accurately measured using depth sensors. The position of the \( j \)th target is given as \( q_j = [x_j, y_j, z_j]^T \) where \( j = 1, 2, \ldots, m \). To achieve cooperative localization of the target AUVs, \( n \) sensor AUVs are deployed on the water surface. The accurate positions of the sensors are known using GPS or other reliable positioning methods. The position of the \( i \)th sensor is denoted as \( p_i = [x_i, y_i, z_i]^T \) where \( i = 1, 2, \ldots, n \). The minimum number of sensors required for cooperative localization of the targets depends upon the number of targets and the technique used for cooperative localization. A typical scenario of cooperative localization of AUVs is shown in Figure 5.

In order to estimate the position of a target AUV, its relative position with respect to the sensor AUVs is measured using acoustic waves with the help of techniques mentioned in Section 2. Once the relative position of a target w.r.t. the accurate sensors’ positions is known, its position can be estimated using different estimation algorithms proposed in the research literature [1, 42–46]. However, measurement of this relative position in water is a challenging task due to inconsistent and unpredictable underwater environment. Moreover, it is also an established fact that accuracy of the relative position measurement also depends upon the positions of the deployed sensors [47–49]. Therefore, despite all the underwater environment effects, optimal sensor placement will ensure that relative position information for the targets is maximized.

For any cooperative localization problem, the optimal sensor configuration depends strongly on the constraints imposed by the problem itself, i.e., the maximum number of available sensors and limitation of the area where sensors can be placed. For example, for cooperative localization of AUVs, the sensors are mostly placed on water surface to enable them to achieve GPS feed. In fact, a poor sensor configuration may incorporate large positioning errors irrelevant of the positioning technique used. The optimal sensor configuration for any cooperative localization system can be computed by analyzing the corresponding CraméRao lower bound (CRLB) or Fisher information matrix (FIM). FIM and CRLB can be defined in terms of position coordinates of the sensors and the optimal sensor configuration is estimated by maximizing FIM or minimizing CRLB.
3.2. Cramer-Rao Lower Bound (CRLB). CRLB or, alternatively, FIM has been utilized in most of the previous literature for estimation of optimal sensor positions for cooperative localization. For any particular experiment, the observations recorded at different time are different in a certain way. The variance of the estimator is obtained by the weighted summation of the variances at different times. It can be found that, regardless of the weight distribution, the variance of any unbiased estimator can only approach a lower limit infinitely, and not below that limit. This lower limit of achievable variance is called CRLB.

The cooperative localization process is actually a state prediction process. The positioning error covariance is the quantity used for evaluation of its performance. CRLB gives estimation of minimal achievable variance for unbiased estimator, i.e., maximum achievable positioning accuracy in this case. Therefore, CRLB can be used to analyse the influence of sensor formation on positioning accuracy. Consider that unbiased estimation of the target’s position \( \tilde{T}_k \) is \( \hat{T}_k \); the CRLB is given as

\[
E\left\{ (\tilde{T}_k - T_k)(\tilde{T}_k - T_k)^T \right\} \succeq F_k^{-1}
\]

where \( F_k \) is the value of FIM at time \( k \). It describes the amount of information available for the minimum variance estimation in the prediction process. It reflects the accuracy of the position estimation in cooperative localization. As the value of \( F_k \) increases, the estimation covariance becomes smaller and more accurate estimation can be obtained [50].

4. Literature Review

The idea of finding the optimal geometric configuration for surface-deployed sensors for localization of a submerged target was initially presented in 1990 by Zhang [48], where a method was devised to determine the optimal sensor placement in two dimensions for localization of an underwater robot. One of the scenarios that were considered in [48] was the localization of underwater vehicle using the acoustic sensors that are constrained to lie on water surface only.

In most of the past literature of sensor placement for cooperative localization of AUVs, CRLB or FIM has been used as an indicator of accuracy of the estimated positions. The history of usage of CRLB/FIM as accuracy indicator for sensor placement goes back to [47] where geometric interpretation of CRB was developed and was used for calculation of sensor positions that minimize the CRB variance.

Now we will discuss all the significant research papers available in research literature relevant to sensor placement for cooperative localization of AUVs. In [28], optimal placement of n-sensors on water surface for positioning of single underwater target was discussed keeping in view the range-dependent measurement noise. The details of the paper developments are as follows:

(i) Geometric representation of FIM was defined based on maximum likelihood function. Determinant of the FIM was calculated and was solved for its maximum value to estimate the optimal positions of the sensors.

(ii) Initially, the case of 3 sensors and zero mean Gaussian measurement noise with fixed variance was studied. Moreover, there was no constraints on placement of the sensors; i.e., sensors could be placed anywhere in 3D coordinates. It was analytically concluded that if the target was positioned at the origin of inertial coordinates and sensor 1 was placed on x-axis (\( y_1 = z_1 = 0 \)), then optimal formation of sensor 2 and sensor 3 would be in YZ plane (\( x_2 = x_3 = 0 \)) and there would be no restriction on \( x_1, y_2, y_3, z_2, \) and \( z_3 \). Moreover, optimal FIM for 3 sensors’ cooperative localization with fixed measurement variance was estimated as

\[
FIM_{opt} = \frac{1}{\sigma^2} I,
\]

where \( \sigma \) is the measurement noise covariance and \( I \) is the identity matrix.

(iii) The case of 3 sensors and 1 target was again studied keeping in view the distance dependent measurement noise, modeled as

\[
\omega = (I + \eta \phi(r)) \omega_o,
\]

where \( r \) is the range and \( \eta \) is the modeling parameter for distance dependent noise component. It was shown that, in this case, optimal formation would be given as equilateral triangle centered on the target while size of the triangle would be proportional to the depth of the target (z) and the amount of measurement noise (\( \omega \)). The optimal radius \( R \) of the circle was calculated as

\[
1 + z^2 ((3 + 6 \eta R)/R^2 (-4 \eta R - 1)) = 0.
\]

(iv) Finally, the general case of n-sensors was discussed. In this case, the optimal formation was estimated as symmetrical distribution of all the sensors around the target at the same distance \( R \), which would be the function of the distance dependent noise variance and the target depth.

In [39], the authors have extended the work of [28] to the scenario of simultaneous localization of multiple targets. To estimate optimal positions of all the targets simultaneously, a recursive algorithm was introduced in which sensors’ positions were updated in very cycle of algorithm until the optimal formation was achieved. The simulation examples demonstrated that the optimal sensor location depends on the size of the area in which the targets operate and the type of measurement noise. Moreover, the case of targets with different Pareto weights (where some targets had higher localization importance than others) was also discussed and illustrated through examples. Finally, solution was also presented for the case where targets’ positions were only known with uncertainty. [28, 39] presented analytical solutions for the sensors placement considering most of the real world issues, i.e., distance dependent noise, multitargets multisensor scenario, and computation complexity, etc. However, it was assumed that sound waves travel in straight path with a constant speed. The assumptions are clearly far from real scenarios and might induce errors in the final results.

In [37], optimal sensor placement was studied for single underwater target localization using bearing measurements instead of the range measurements. The measurement noise was considered to be distance dependent and was modelled as

\[
\omega_1 = (\omega_{\alpha_1}, \omega_{\beta_1})^T = (\omega_{\alpha_0}(1 + \eta \gamma_1), \omega_{\beta_0}(1 + \eta \gamma_1))^T,
\]

where \( \alpha \) and \( \beta \) are the azimuth and elevation angles of the
target and $\omega_{ij}$ and $\omega_{ji}$ are the measurement noises associated with these angles, respectively. Analytical solution for optimal positions of $n$-sensors was calculated using CRB trace minimization criteria. It was concluded that the optimal formation of sensors would be obtained by placing the sensors on the circumference of a circle centred at the target projection to sea surface and its radius would be dependent on the noise model and the target depth.

A preliminary literature reviewer in the field of optimal sensors placement for underwater target positioning was presented in [29]. Moreover, brief introduction of the relevant principles and methods available in the literature were also given in the paper for understanding and motivation of the readers about this challenging research topic.

In [36], the optimal configuration of sensors network was studied in order to maximize the bearing related information for underwater target positioning system. The measurement noise was assumed to be corrupted by distance dependent Gaussian noise. The trace of CRB was used as criteria for estimating optimal sensor positions. Analytical results were obtained and were supported by various simulation examples. It was concluded that the optimal formation of sensors would be obtained by placing the sensors on the circumference of a circle centred at the target projection and its radius would be dependent on measurement noise model and the depth of target. In both [36, 37], the authors presented analytical solutions of sensors formation for cooperative localization of AUVs using AOA method. However, similar to [28, 39], sound waves propagation was assumed to be in a straight line with constant speed which is unrealistic. Although speed of sound does not much affect the solution for AOA based method, assuming straight line propagation of sound waves will clearly induce some bearing error (particularly at long ranges) and may ultimately affect the solution for sensors configuration.

An interesting case of underwater target localization with only single surface sensor using range measurements was studied in [30]. Using determinant of FIM criteria, optimal geometric trajectory was estimated for the moving sensor such that the available range related information for the target positioning would be maximized during the whole trip of the sensor. Two approaches for estimation of the optimal trajectories were presented by the authors. The first approach involved the computation of only the next sensor position that would maximize the current FIM determinant. The second approach focused on estimating the complete optimal trajectory for the number of range measurements considered. It was concluded that the optimal trajectory of the sensor would depend upon its velocity, the sampling time, and the number of measurements obtained for the FIM calculation. Subsequently in [31], the work of [30] was extended to trajectory estimation of the surface sensor for positioning of a moving underwater target.

Another research similar to [31] was carried out by [32] in which trajectory planning of a moving surface sensor was estimated using Empirical Gramians for positioning of an underwater robot. Simulation examples of different scenarios, like stationary or moving target, were presented for estimating the optimal trajectory of the sensor. Although different estimation techniques were used in this paper, the results obtained were similar to the one obtained in [30, 31] which also proved the authenticity of the proposed methods. The optimal path of the surface sensor was found to be a circular path around the target projection on the surface.

In [33], the methods of cooperative navigation of AUVs and optimal sensor placement were combined for path planning of surface sensor for underwater target localization. Unlike all the previous research of optimal sensor placement, where underwater target position was assumed to be known in advance (at least with some uncertainty), it was assumed that the position on the underwater target was unknown. Using range measurements, the sensor had to first estimate the target’s position and subsequently compute its own optimal path using the estimated position of the target. The methods used for target’s position estimation and sensor’s trajectory estimation were Extended Kalman filter and Empirical Gramians, respectively.

In [34], the localization of a single target AUV was studied with range measurements from a moving beacon. The optimal trajectory for the moving beacon was proposed for maximizing the range related information while also considering minimization of energy spent by the moving beacon. The determinant of FIM was used as performance criteria to achieve the optimal trajectory.

A very detailed research on 3D optimal sensor placement for cooperative localization of underwater targets using range measurements was presented in [27]. The analytical solutions for multiple sensors system were derived and were supported with simulation examples. The obtained optimal sensor configurations were shown to depend on the number of range measurements, target depth, and the probability distribution function that defines the uncertainty in the target location. Another important conclusion was drawn for the case that when two disjoint sets of $m$ and $n$ sensors each were placed optimally, the resulting formation of $m + n$ sensors would also be optimal. Therefore, higher order optimal formations can be obtained by combining two or more optimal configurations.

In [35], underwater targets’ localization and tracking was performed by optimally placing two surface sensors. Both static and moving underwater targets were considered and analytical solutions were derived for various situations.

Finally, in [38], optimal configuration of multiple surface sensors was studied for cooperative localization of multiple targets simultaneously. The technique considered for cooperative localization of AUVs was Time Difference of Arrival (TDOA). An evaluation function based on FIM was derived as measure of accuracy of sensors’ configuration. The effect of distance-dependent measurement noise, variable speed of sound in water, and travel of a sound wave along a curved path instead of a straight line was considered while deriving the evaluation function. An iterative stepping algorithm was followed for solving the evaluation function and obtaining the optimal positions of the sensors to bound computation complexity and time. A more practical scenario, when the target position would only be known with uncertainty, was also discussed and the solution was presented. The paper provides the sensors configuration solution considering most of
the real world constraints relevant to underwater localization. However, numerical solution was only provided instead of analytical solution.

Table 2 presents an easy and clear comparison of all the research papers available in the literature of sensor placement for cooperative localization of AUVs. The "*" in the table represents positive points in the paper and "#" indicates limitations with respect to research challenges considered in the paper. As can be observed from the table, TOA and AOA localization techniques have mostly been considered in the past while there is only one paper in which optimal sensor formation has been presented for TDOA based cooperative localization. Moreover, it can also be seen that RSSI based localization has not been studied yet for optimal sensors placement.

5. Research Challenges and Future Research Directions

In this section, various research challenges associated with the field of optimal formation estimation for cooperative localization of AUVs are discussed and future work is suggested.

5.1. Constraints of Sensor Placement. For localization of sensor nodes in wireless sensor networks (WSN), the sensors can be placed anywhere around the node in 3D. However, for cooperative localization of AUVs, the sensor AUVs have to operate on water surface in order to receive the GPS signals. On the other hand, target AUVs operate underwater at various depths. Therefore, targets are operating underwater and are to be localized in 3D while sensors can only be placed on water surface in 2D as shown in Figure 6. In most of the previous research, sensors as well as targets were considered to be placed in 2D [51–54]. In the cases where 3D localization of the targets was considered, it was assumed that both sensors and targets can be located anywhere in 3D [27, 55]. However, only few researchers have assumed the real scenario as discussed above [38, 56].

5.2. Distance Dependent Measurement Noise. Acoustic waves are used for measuring the relative position of targets with respect to the sensors. These measurements are plagued with noise that depends on multiple factors relating to propagation properties of acoustic waves in water, for example, (1) speed of propagation of sound in water which is depth and bathy condition dependent, (2) multiple-path effect, (3) ambient noise, and (4) degrading signal-to-noise ratio with the increase of distance travelled. Therefore, the value of measurement noise depends upon the range between target and the sensor and is to be modelled accordingly in order to achieve realistic results. However, in most of the previous research, measurement noise is assumed as zero mean Gaussian noise with constant covariance [48, 56, 57]. Clearly, realistic modelling of measurement noise is a challenging task in this field which can be explored in the future. Few researchers have considered the noise as zero-mean Gaussian process with a distance dependent added term [36, 38]:

\[
\omega_{ij} = \sigma \left( 1 + \eta d_{ij}^{\gamma} \right) \tag{9}
\]

where \(\omega_{ij}\) is the measurement noise between and \(d_{ij}\) is the range between \(i\)th sensor and \(j\)th target, respectively. Moreover, \(\sigma\) is zero mean Gaussian process and \(\eta\) and \(\gamma\) are the constant modelling parameters related to distance.

5.3. Varying Speed of Sound Propagation in Water. It is an established fact that speed of sound in water varies with the depth mainly depending upon temperature, pressure, and salinity. Moreover, in water, acoustic waves follow a curved propagation path instead of straight one. These characteristics of sound propagation make it very difficult and challenging for the sensors to estimate accurate relative position of the targets, no matter which of the techniques of cooperative localization is being used. However, in research literature of
| S No. | Reference No. | Cooperative Localization technique used | Sensor-target configuration | Optimality criteria for sensor placement | Experimental verification | Targets type | Moving | Research challenges considered | Targets position uncertainty considered | Optimality criteria | Underwater Sound Speed | Underwater sound propagation | Measurement noise | Solution type | Remarks |
|-------|---------------|----------------------------------------|----------------------------|----------------------------------------|--------------------------|--------------|--------|-------------------------------|------------------------------------------|-----------------|----------------------|---------------------------|----------------|---------------|---------|
| 1.    | [27]          | ToA                                    | Multi-sensors Multi-targets | Determinant of FIM                    | ×                         | ST           | ×      | ×                            |                           | ×               | ×                     | ×                     | ×             | Numerical   |         |
| 2.    | [38]          | TDOA                                   | Multi-sensors Multi-targets | Evaluation function based on FIM      | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Analytical  |         |
| 3.    | [36]          | AoA                                    | Multi-sensors Single-target  | Trace of CRB matrix                  | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Numerical   |         |
| 4.    | [28]          | ToA                                    | Multi-sensors Single-target  | Determinant of FIM                   | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Analytical  |         |
| 5.    | [39]          | ToA                                    | Multi-sensors Multi-targets | Determinant of FIM                   | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Numerical   |         |
| 6.    | [37]          | AoA                                    | Multi-sensors Single-target  | Trace of CRB matrix                  | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Numerical   |         |
| 7.    | [29]          | ToA                                    | Multi-sensors Single-target  | Determinant of FIM                   | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Numerical   |         |
| 8.    | [30]          | ToA                                    | Single-target Single-sensor   | Determinant of FIM                   | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Numerical   |         |
| 9.    | [31]          | ToA                                    | Single-target Single-sensor   | Determinant of FIM                   | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Numerical   |         |
| 10.   | [32]          | ToA                                    | Single-target Single-sensor   | Empirical Gramians                  | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Analytical  |         |
| 11.   | [33]          | ToA                                    | Single-target Single-sensor   | Empirical Gramians                  | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Analytical  |         |
| 12.   | [34]          | ToA                                    | Single-target Single-sensor   | Determinant of FIM                   | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Analytical  |         |
| 13.   | [35]          | ToA                                    | Multi-targets two-sensors     | Determinant of FIM                   | ×                         | ST           | ×      | ×                            | ×                          | ×               | ×                     | ×                     | ×             | Analytical  |         |

**Remarks:**
- Target position was assumed to be unknown and was estimated using range measurements in each step.

**CS:** Constant  
**VR:** Varying with the depth  
**ST:** Propagation along straight path  
**CR:** Modeled as propagating along curved path  
**DD:** Distance dependent noise variance
cooperative localization and sensor placement, sound speed was mostly taken as constant and sound wave was considered to be travelling in a straight line. One of the exceptions is in [38], where sound speed was taken as a function of depth as follows:
\[ v(z) = az + b \] 
where \( z \) is the depth, \( a \) is the steepness of sound speed profile (SSP), and \( b \) is the sound speed at surface. Moreover, it was considered that sound waves travelled in a curved path instead.

There are many underwater sound propagation models available in research literature [58, 59]. One of the future challenges is the integration of these models in the field of sensor placement for cooperative localization to achieve more accurate and realistic results.

5.4. Reduction of Computational Time. With the advancement in technology, AUVs are now being utilized for more complex and sophisticated operations. In most of the modern-day applications of AUV, multiple AUVs are being operated together. As the number of target AUVs increases, the corresponding sensors AUVs are to be increased accordingly. In such situation, all sensors are to be placed in a formation that is optimal for the entire target AUVs. Therefore, the optimal position of all the sensors is to be computed simultaneously for all the targets. When the number of targets/sensors increases, the corresponding computation complexity and time increase drastically. Few researchers have proposed some optimization algorithms to ensure fast and achievable calculations [50, 51] but the research area can further be explored in future.

5.5. Experimental Verification. Although adequate research has been carried out in the last decade in the field of sensors placement for cooperative localization of AUVs, main focus of the research remained theoretical recommendations and simulation analysis. There has not been any experimental verification of any of the proposed methods, yet. Theoretical results supported by mathematical verifications have their importance, but experimental verification will not only enhance researchers’ confidence on the proposed theories but also allow improving the proposed methods by addressing the shortcomings highlighted by the experiments. Therefore, experimental verification is also a potential future research area in this field.

6. Conclusions

Optimal sensor placement is a challenging research task in the field of cooperative localization of AUVs. Adequate research has been carried out in the area in past decade, but there remain many challenges associated with it which require further and detailed investigation. In this paper, a comprehensive review of the past research has been presented. The future research challenges associated with the field have been highlighted and discussed in detail. The basic theories, methods, and techniques associated with cooperative localization and optimal sensor configuration have also been presented. Although it has been almost a decade since the initiation of research in the field of sensor placement for cooperative localization of AUVs, the lack of a review paper is one of the bottlenecks of wider acceptance of the idea. The paper is expected not only to seek researchers’ attention towards this promising future research area but also to provide the basic reading material for the students.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] I. Paul, S. Saeedi, M. Seto, and H. Li, “AUV navigation and localization: a review,” IEEE Journal of Oceanic Engineering, vol. 39, no. 1, pp. 131–149, 2014.
[2] J. Rendas, “Mapping ocean bathymetry using an AUV equipped of an altimeter: a terrain-driven approach,” in Proceedings of the Oceans 2003, vol. 2, p. 955, San Diego, Calif, USA, 2003.
[3] B. McCarter, S. Portner, W. L. Neu, D. J. Stilwell, D. Malley, and J. Minis, “Design elements of a small AUV for bathymetric surveys,” in Proceedings of the 2014 IEEE/OES Autonomous Underwater Vehicles (AUV ’14), pp. 1–5, Oxford, Miss, USA, 2014.
[4] M. Jacobi, “Autonomous inspection of underwater structures,” Robotics and Autonomous Systems, vol. 67, pp. 80–86, 2015.
[5] Y.-H. Lin, S.-M. Wang, L.-C. Huang, and M.-C. Fang, “Applying the stereo-vision detection technique to the development of underwater inspection task with PSO-based dynamic routing algorithm for autonomous underwater vehicles,” Ocean Engineering, vol. 139, pp. 127–139, 2017.
[6] N. Hurtós, N. Palomeras, A. Carrera, and M. Carreras, “Autonomous detection, following and mapping of an underwater chain using sonar,” Ocean Engineering, vol. 130, pp. 336–350, 2017.
[7] S. Venkatesan, “AUV for Search & Rescue at sea - an innovative approach,” in Proceedings of the 2016 IEEE/OES Autonomous Underwater Vehicles (AUV), pp. 1–9, Tokyo, Japan, November 2016.
[8] A. Murphy, M. Landamore, and R. Birmingham, “The role of autonomous underwater vehicles for marine search and rescue operations,” Underwater Technology, vol. 27, no. 4, pp. 195–205, 2008.
[9] M. Ludvigsen, S. M. Albrektsen, K. Cisek et al., “Network of heterogeneous autonomous vehicles for marine research and management,” in Proceedings of the OCEANS 2016 MTS/IEEE Monterey, pp. 1–7, Monterey, Calif, USA, 2016.
[10] H. Yoshida et al., “A working AUV for scientific research,” in Proceedings of the Oceans ’04 MTS/IEEE Techno-Ocean ’04 (IEEE Cat. No.04CH37600), vol. 2, pp. 863–868, Kobe, Japan, November 2004.
[11] J. Ferrand, J.-P. Malkasse, N. Le Bouffant, and F. Florin, “Automatic mine counter measure mission control For AUV Systems,” IFAC Proceedings Volumes, vol. 40, no. 17, pp. 7–12, 2007.
[12] M. S. Wijg, T. R. Krogsstad, and Ø. Midtfjord, “Autonomous identification planning for mine countermeasures,” in Proceedings of the 2012 IEEE/OES Autonomous Underwater Vehicles (AUV), pp. 1–8, Southampton, UK, 2012.
[47] J. Abel, “Optimal sensor placement for passive source localization,” in Proceedings of the International Conference on Acoustics, Speech, and Signal Processing, Albuquerque, vol. 5, pp. 2927–2930, 1990.

[48] H. Zhang, “Two-dimensional optimal sensor placement,” IEEE Transactions on Systems, Man, and Cybernetics, vol. 25, no. 5, pp. 781–792, 1995.

[49] D. Jourdan and N. Roy, “Optimal Sensor Placement for Agent Localization,” in Proceedings of the 2006 IEEE/ION Position, Location, And Navigation Symposium, pp. 128–139, Coronado, Calif, USA, 2006.

[50] B. Xu, X. Wang, A. A. Razaqi, and X. Zhang, ”Topology optimization method for multiple AUV cooperative localization formation based on acoustic measurement network,” IET Radar, Sonar & Navigation, vol. 13, no. 6, pp. 927–936, 2019.

[51] D. Moreno-Salinas, A. M. Pascoal, and J. Aranda, ”Optimal sensor placement for multiple target positioning with range-only measurements in two-dimensional scenarios,” Sensors, vol. 13, no. 8, pp. 10674–10710, 2013.

[52] K. Doğançay and H. Hmam, “On optimal sensor placement for time-difference-of-arrival localization utilizing uncertainty minimization,” in Proceedings of the 17th European Signal Processing Conference, Glasgow ’09, pp. 1136–1140, 2009.

[53] M. Hamdollahzadeh, S. Adelipour, and F. Behnia, “Optimal sensor configuration for two dimensional source localization based on TDOA/FDOA measurements,” in Proceedings of the 17th International Radar Symposium (IRS), pp. 1–6, Krakow, Poland, 2016.

[54] W. Meng, L. Xie, and W. Xiao, ”Optimal TDOA Sensor-Pair Placement With Uncertainty in Source Location,” IEEE Transactions on Vehicular Technology, vol. 65, no. 11, pp. 9260–9271, 2016.

[55] D. Jourdan and N. Roy, “Optimal Sensor Placement for Agent Localization,” in Proceedings of the 2006 IEEE/ION Position, Location, And Navigation Symposium, pp. 128–139, Coronado, Calif, USA.

[56] D. Moreno-Salinas, A. M. Pascoal, and J. Aranda, ”Multiple underwater target positioning with optimally placed acoustic surface sensor networks,” International Journal of Distributed Sensor Networks, vol. 14, no. 5, 2018.

[57] F. Mandić, N. Mišković, and Z. Vukić, ”Range-only navigation - Maximizing system observability by using extremum seeking,” IFAC-PapersOnLine, vol. 28, no. 16, pp. 101–106, 2015.

[58] J. M. Hovem, Modeling and Measurement Methods for Acoustic Waves and for Acoustic Microdevices, chapter 23, InTech, 2013.

[59] C. Paul Etter, ”A review of recent developments in underwater acoustic modeling,” The Journal of the Acoustical Society of America, vol. 129, no. 4, 2011.
