

Wireless Sensor Networks for Underwater Localization: A Survey

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Abstract

Autonomous Underwater Vehicles (AUVs) have widely deployed in marine investigation and ocean exploration in recent years. As the fundamental information, their position information is not only for data validity but also for many real-world applications. Therefore, it is critical for the AUV to have the underwater localization capability. This report is mainly devoted to outline the recent advancement of Wireless Sensor Networks (WSN) based underwater localization. Several classic architectures designed for Underwater Acoustic Sensor Network (UASN) are briefly introduced. Acoustic propagation and channel models are described and several ranging techniques are then explained. Many state-of-the-art underwater localization algorithms are introduced, followed by the outline of some existing underwater localization systems.

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1 Introduction

Oceans cover about 71% of the earth's surface, but most of them have not been explored. Recently, the exploration on oceans is significantly increasing since they are rich in valuable resources. Moreover, sea is one of the most important ecological environment for human being. Therefore, many studies are undertaken to protect the ocean from being influenced [1].

Most of these marine application and investigation rely on the AUVs to accomplish the task now. The location of the AUVs is very important because the application cannot know where the data is sampled unless the location is tagged. In other words, the information is useless without the corresponding location. The AUV also requires its current position to make the decision for the control and navigation. Therefore, the localization is regarded as a basic capability of AUV if it is going to track a target [2], explore the resources [3], monitor the underwater environment, etc. Apart from the significance for AUV, the localization can also improve the performance of the system, such as the location-based routing protocol [4].

According to the used hardware, the means of underwater localization can be categorized into three types [5]:

- Inertial navigation systems. The compass, Inertial Measurement Unit (IMU), Doppler Velocity Log (DVS), etc. can be employed to estimate the position. The position calculated by twice integration of the sensed acceleration is normally better than dead-reckoning in terms of localization accuracy. However, the additional acceleration produced by the ocean current is difficult to be distinguished from the real one. Another drawback is the unbounded position error. Therefore, some new techniques are proposed to update the position using satellite navigation system [6]. Although the accuracy is improved, the AUV possibly collides with the surface vessels when it emerges from water to refine the location, especially near the coast and the port.
- Geophysical navigation. This method estimates the location by matching the measured geophysical parameter with that in the pre-built environment map. The parameters are usually the physical features of the environment, e.g. magnetic field. Now it is widely used in the submarines to achieve the accurate navigation [7]. However, it is unsuitable for the AUV because the environment should be mapped in advance and the map construction, the data searching, etc. are time- and energy-consuming.
- Communication navigation. Because the distance between the beacon and the AUV can be estimated by communication, the location can be derived by the localization algorithms without extra consumption especially for a swarm of AUVs. However, the acoustic signal is the unique suitable technique to make the underwater communication viable since the radio frequency (RF) and optical signal only propagate a very short distance in water due to the absorption, attenuation and scattering. This is also why the WSN is usually replaced by the UASN when the underwater environment is discussed.

As a new and promising approach developing in recent years, the UASN has many inherent advantages [3, 8] and attracts more attention. On the other hand, it operates under the following constraints and challenges, which are produced by the extreme features of water environment and the restrictions of the acoustic signal:

- Serious disturbance and noise. The underwater acoustic communication and channel are considerably influenced by the dynamic water environment (e.g. temperature, density and depth) and various disturbances (e.g. path loss and multi-path). All these cause the propagation path to be complicated with temporal and spatial variation. Meanwhile, the channel is subjected to man made and ambient noise, which produce uncertain perturbations to the system constantly. The detail will be discussed in Section 3.
- Poor link quality and high bit error rates. Because the communication link suffers from various disturbance and noise, the underwater acoustic channel has low link quality and the connectivity is

not reliable. Therefore, the probability of error rate is high, especially when there are some sudden noises.

- Long latency. The physical transformation of communication from RF to acoustics changes the signal propagation speed from light to sound, which indicates the propagation delay is five orders of magnitude longer under the water than in the air. Therefore, time synchronization is indispensable.
- Limited bandwidth and low data rate. The available bandwidth of the acoustic channel is limited, particularly under the long-range transmission. Hence, the data rate is very low, see Table 1.
- Others. The deployment and collection of the beacon nodes is costly due to the demand of the vessels. Therefore, the energy is so precious that it severely constrains all the parts of the UASN. Additionally, the hardware, which is more complex and expensive than terrestrial sensor nodes, should be fully protected due to the extreme underwater environment, such as marine corrosion.

Because of these difficulties, the underwater localization seriously lags behind the terrestrial and aerial counterparts, and some existing conceptions and algorithms of them cannot be migrated to underwater environment easily. Therefore, it remains a great challenge yet a good chance to investigate the underwater localization scheme using UASN. Much work has been done for UASN during the past decade, and some preliminary achievements have been summarized in [3, 9–16]. This report aims to present a survey of the recent underwater localization techniques for UASN as well as the basics.

Table 1: Data rates for underwater acoustic links with various ranges [17]

Span	Range (km)	Data rate
Short range	<1	~20 kbps
Medium range	1–10	~10 kbps
Long range	10–100	~1 kbps
Basin scale	3000	~10 bps

In the rest of this report, the categories of the architecture are introduced in Section 2. Section 3 discusses the acoustic propagation and the ranging techniques. In section 4, many state-of-the-art underwater localization algorithms are presented. The existing underwater systems are outlined in Section 5. Finally, a brief conclusion is given in Section 6

2 UASN Architectures

Nowadays, most of the UASN based localization algorithm and system can be generally divided into range-free and range-based localizations depending on how the unknown location is calculated. The range-free localization, which is simple yet needs large-scale sensor nodes, entirely relies on the proximity and connectivity between the beacon and the unknown node, e.g. MAP-M and MAP-M&N [18]. In general, there are two types of range-free localization techniques that have been proposed for sensor networks: local techniques and hop-based techniques [19], both of which require a very high density of beacons and consume excessive energy during the frequent data broadcast and transfer. Because the sensor cost and the energy value in the UASN system are much higher than terrestrial one, the range-free based localization is unsuitable for the underwater localization.

For the range-based scheme, the location of unknown node can be determined by the localization algorithm once the distance or angle between the unknown node and the beacon is measured. This approach outperforms the range-free localization in terms of the beacon number and localization accuracy. Note that the AUV can be considered as the unknown node in UASN. In this report, our attention focuses on the range-based localization.

For the different underwater architectures, the beacons can be anchored in the sea floor or attached to the floating buoy (in such case the buoy can freely drift along with the sea current or be tethered to a rude position), which dramatically influences the localization algorithm, implementation as well as the system performance. Therefore, some typical architectures are outlined in this section.

2.1 Two-Dimensional and Three-Dimensional Systems

The UASN systems can be classified as two-dimension or three-dimension according to the spatial coverage [20].

A reference two-dimensional architecture [3] is shown in Fig. 1. All the nodes are anchored to the ocean floor which is assumed to be a plain. By the horizontal transceiver, uw-sink can collect the data from the sensor nodes. Then, it relays the information to a surface station by the vertical transceiver. The surface station has RF signal to efficiently communicate with the onshore and surface sinks, where the sensed data is processed. For this scheme the uw-sink and the sensor node can be the unknown node and beacon respectively.

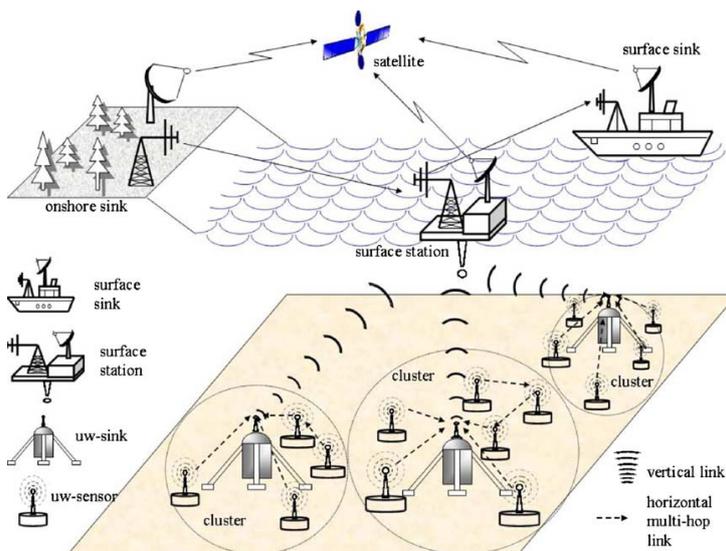


Figure 1: A two-dimensional UASN [3]

However, it is necessary to investigate the three-dimensional localization since it is much closer to our

real world and many tasks cannot be accomplished in two-dimension, such as the research on the species diversity with respect to different ocean depths. In [21], a three-dimensional architecture is discussed, see Fig. 2. Each uw-sensor node is attached to a buoy by a cable, which can also transmit data between each other. The lengths of the cables are different for the requirement of the three-dimensional localization. When the sensed data is received by the buoy, it is transmitted to the central station by RF signal. However, the buoy randomly drifts along the sea current, which may obstruct or collide with the vessels. The scheme whose sensor nodes are anchored to the bottom can overcome this [3]. As shown in Fig. 3, the sensor node floating under the water is tethered with a wire, which is fixed to the ocean floor and has the adjustable length. The AUV can shuttle in the surveillance region covered with these beacons. The communication principle is the same as the one described in Fig. 1 except that the surface station can receive the data from the sensor nodes directly.

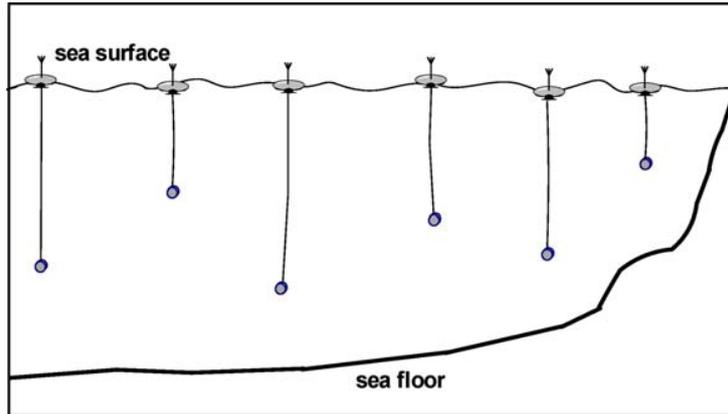


Figure 2: A three-dimensional UASN where sensors float with buoy [21]

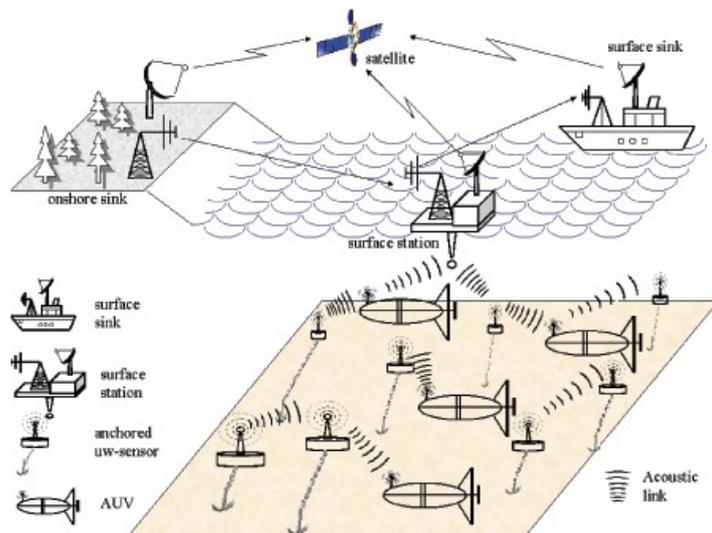


Figure 3: A three-dimensional UASN where sensors are deployed on the sea floor [4]

2.2 Long-Term NTC and Short-Term TC Systems

Cui *et al.* [22] present the long-term non-time-critical (NTC) and the short-term time-critical (TC) architectures for mobile UASN, see Fig. 4. Because the first one aims at long-term underwater applications, e.g. pollution detection and monitoring, the hardware, communication mechanism, localization algorithm etc. should be energy saving. In contrast, the short-term time-critical system regards the real-time data

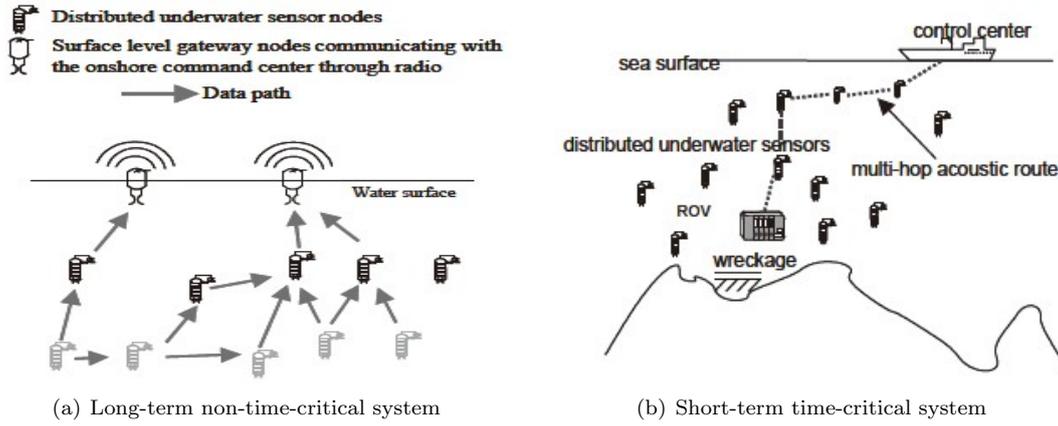


Figure 4: Architecture of mobile UASNs [22]

transfer as the most important criterion. For example, the detection of an enemy's submarine should be transferred to the headquarters as soon as possible. The nodes in these two architectures both relay data via multi-hop acoustic routes.

2.3 AUVs-based System

Because the AUVs can shuttle in the ocean, an architecture where the network connectivity relies on the AUV is proposed [10]. The AUV visits the sparsely deployed nodes periodically to collect the sensed and stored data with the aid of an optical location system. When the distance between the AUV and the destination node is short enough, the data is transmitted by acoustic communication. Although saving the energy of the node and improving the data transfer rate simultaneously are the advantages of this method, the optical location system is influenced by the scattering, beam divergence and ambient light, and it takes too much time for an AUV to collect all the data in a large region. Moreover, the system only can monitor the area where the sensors deployed since the AUV does not perceive the environment.

2.4 Summary

The existing architectures have their own characters and application areas. The architecture which highly determines the further choice of sensor, communication method, localization algorithm, implementation, etc. should be designed first according to the application environment and performance requirement.

3 Underwater Acoustic Propagation and Ranging

Because the RF signal and optical wave are unsuitable for the underwater propagation, most of the underwater systems employ the acoustic signal as the communication technique. On the one hand, the complex and uncertain characteristics of the underwater environment result in many big challenges in acoustic propagation, which is essentially sensitive to the disturbances. On the other hand, the performance, such as the accuracy, has to satisfy the various requirements of the application scenario. Therefore, the underwater acoustic channel should be studied to comprehend the characters of the acoustic signal.

The existing WSN localization generally contains two stages: measuring the geographic information from the network and computing the locations with this measured data. In this section, the basics of acoustic propagation and the solutions of ranging are briefly introduced, which is considered as the first step.

3.1 Underwater Acoustic Propagation and Channel Models

Underwater acoustic communication is seriously affected by many factors, which make the underwater propagation channel enormously complex. They can be temperature, density, path loss, noise, multi-path propagation, Doppler effect, propagation delay etc. In order to design and improve the localization algorithm with clear orientation, these disturbances and noises as the chief influences on the performance should be studied.

3.1.1 Disturbance and Noise

Underwater acoustic channel suffers from various disturbances and noises, which severely reduce the ranging accuracy. They are mainly [3]:

- Disturbance. (1) Path loss: The acoustic signal propagates under the water, working off some sound energy. One of the two reasons is attenuation. The absorption as well as the scattering and reverberation consume a great deal of energy during the propagation. The other is geometric spreading, which can be spherical or cylindrical according to the different depths. The cylindrical spreading is suitable for the shallow waters while the spherical one is for the deep sea. (2) Multi-path effect: The reflection, especially provoked by the ocean surface and floor, is the main cause of the multi-path propagation. Because the temperature and density in the varying depths of the ocean are different, reflection also exists in the liquid interface [8]. The weighted Gerchberg-Saxton algorithm (WGSA) as a solution can identify the direct path and mitigate the effects of multiple range measurements [23]. (3) Doppler effect: The Doppler effect produced by the relative movement of the transducer and the transponder is the phenomenon that the observer receives a wave with the changing frequency. The Doppler effect of UASNs is particularly serious due to the slow sound velocity.
- Time and Space Variability of Water Medium. Owing to the varying physical properties of the ocean and the constant perturbations created by the environment, the underwater acoustic channel is endowed with temporal and spatial variability, which severely affect the time synchronization and localization accuracy.
- Noise. There are two types of noise - man made and ambient noises. The man made noise is usually caused by the marine machinery, such as the offshore drilling platform and the vessel, while the ambient noise is generated by the tides, sea current, storms, wind and rain as well as the biological activities like fishes swimming etc. Some of the ambient noise is so strong that the UASN may be destroyed.

3.1.2 Mathematical Model

As described in Fig. 5, the modeling plays a key role in the experiment and analysis. In order to analyze the system and process the data, the mathematical models of the acoustic propagation, noise etc. should be developed. Because the discipline of underwater acoustics has been studied for many years, there are some available theories and models. However, the models have their own inherent advantages, disadvantages and restrictions.

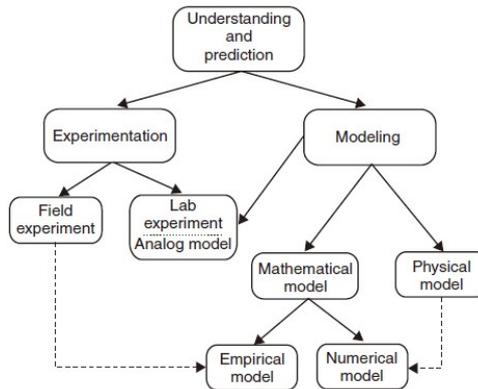


Figure 5: Schematic relationship between experiment and modeling [24]

Speed The underwater sound speed model has been developed over the years for the exact mathematical relationship between it and the ocean properties. Many models have been produced after a tremendous amount of scientific work, and some of them are summarized in Table 2. It can be seen that the temperature, salinity and pressure, which is related to the depth, are usually considered as the main factors that affect the sound speed even though the numbers of the terms are different. The model should be chosen according to the ranges of its properties and the accuracy. The expression of the formula Mackenzie (1981) of the sound speed at a particular depth is

$$\begin{aligned}
 c = & 1448.96 + 4.591T - 5.304 \times 10^{-2}T^2 + 2.374 \times 10^{-4}T^3 + 1.340(S - 35) \\
 & + 1.630 \times 10^{-2}D + 1.675 \times 10^{-7}D^2 - 1.025 \times 10^{-2}T(S - 35) - 7.139 \times 10^{-13}TD^3
 \end{aligned} \quad (1)$$

where c is the speed of sound in m/s, T is the water temperature in Celsius, S is the salinity in practical salinity units and D is the depth in meter. For the issue of determining these environment parameters, they can be easily accessed from the existing databases, such as the Bedford Institute of Oceanography (BIO), National Physical Laboratory (NPL) and the National Oceanic and Atmospheric Administration (NOAA), which are constructed using the actual data collected from the ocean.

Acoustic Propagation Model Most of the terrestrial propagation models assume that they only relate to the transmission distance, but the signal frequency also affects the underwater acoustic propagation. The acoustic propagation models can be divided into five categories according to the applied theoretical method: ray theory model, normal mode model, multi-path expansion model, fast field model and parabolic equation model. They are derived from the wave equation, Harmonic solution or Helmholtz equation, and their relationships have been summarized in Fig. 6. Each model can be further divided into many specific models, see Table 3. It can be seen that there are more than 100 established models like BELLHOP [25]. Therefore, choosing the appropriate model is quite difficult. Table 4 provides the applicable domains of these five general models, which can be used to narrow down the choices. The characters of each specific model should be referred and it can be tested in reality to compare the performance when selecting the candidate models.

Table 2: Summary of sound speed algorithms and parameter ranges [24]

Reference	Temperature range (°C)	Salinity range (ppt)	Pressure or depth range ^a	Standard error (m s ⁻¹)	Number of terms
Wilson (1960)	-4-30	0-37	1-1,000 kg cm ⁻²	0.30	23 terms
Leroy (1969)	-2-34	20-42	0-8,000 m	0.2	13 terms [complete (1st formula)]
Frye and Pugh (1971)	-3-30	33.1-36.6	1.033-984.3 kg cm ⁻²	0.10	12 terms
Del Grosso (1974)	0-35	29-43	0-1,000 kg cm ⁻²	0.05	19 terms
Medwin (1975)	0-35	0-45	0-1,000 m	~0.2	6 terms [simple formula]
Chen and Millero (1977)	0-40	5-40	0-1,000 bar	0.19	15 terms [requires correction at low temperature and high pressure (Millero and Li, 1994)]
Lovett (1978)	0-30	30-37	0-10,000 dbar	0.063	13 terms [3rd equation]
Coppens (1981)	-2-35	0-42	0-4,000 m	0.1	8 terms [Lovett's 3rd equation simplified]
Mackenzie (1981)	-2-30	25-40	0-8,000 m	0.07	9 terms

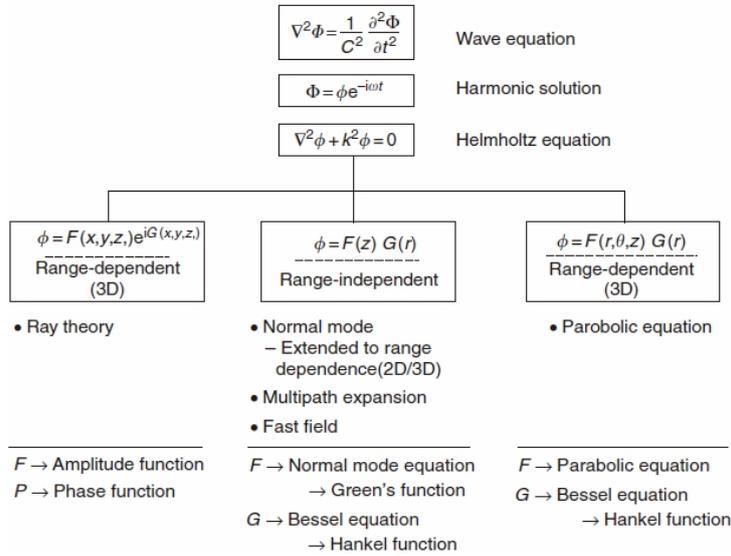


Figure 6: Summary of relationships among propagation modeling [24]

Noise Model Mathematical models of noise in the ocean can be classified into ambient-noise models and beam-noise statistics models. The noise sources of ambient model are surface weather, biologic activities, shipping and oil drilling. The beam-noise models, which can be further divided into analytic and simulation approaches, are good at the application which has low-frequency shipping noise. Some typical noise models are summarized in Table 5.

3.2 Solutions to Ranging

With the aid of the acoustic propagation models, the distance between the devices can be estimated by ranging method. The time of arrival (TOA), time difference of arrival (TDOA), received signal strength indicator (RSSI) and angle of arrival (AOA) are the four typical ranging techniques of the WSN system. The requirement and constrain on ranging hardware, measurement accuracy, energy consumption etc. should be comprehensively considered when choosing the ranging approach. The TOA, TDOA and AOA are more appropriate for the application which requires a high localization accuracy, such as resource exploration or environment monitoring, while the RSSI is better for saving energy.

Table 3: Summary of underwater acoustic propagation models [24]

<i>Technique</i>	<i>Range independent</i>		<i>Range dependent</i>	
Ray theory	CAPARAY [1] FACT [2] FLIRT [3] GAMARAY [4] ICERAY [5] PLRAY [6] RANGER [7]		ACCURAY [8] BELLHOP [9] Coherent DELTA [10] FACTEX [11] GRAB [12] GRASS [13] HARORAY [14] HARPO [15] HARVEST [16] LYCH [17]	MEDUSA [18] MIMIC [19] MPC [20] MPP [21] Pedersen [22] RAYWAVE [23] RP-70 [24] SHALFACT [25] TRIMAIN [26]
Normal mode	AP-2/5 [27] BDRM [28] COMODE [29] DODGE [30] FNMS [31] MODELAB [32] NEMESIS [33] NLNM [34] NORMOD3 [35] NORM2L [36] ORCA [37]	PROTEUS [38] SHEAR2 [39] Stickler [40]	ADIAB [41] ASERT [42] ASTRAL [43] CENTRO [44] CMM3D [45] COUPLE [46] CPMS [47] FELMODE [48] Kanabis [49] KRAKEN [50] MOATL [51]	MOCTESUMA [52] NAUTILUS [53] PROLOS [54] PROSIM [55] SHAZAM [56] SNAP/C-SNAP [57] WEDGE [58] WKBZ [59] WRAP [60] 3D Ocean [61]
Multipath expansion	FAME [62] MULE [63] NEPBR [64] RAYMODE [65]		No existing solutions	
Fast-field or wavenumber integration	FFP [66] Kutschale FFP [67] MSPFFP [68] OASES [69] Pulse FFP [70]	RPRESS [71] SAFARI [72] SCOOTER [73] SPARC [74]	CORE [75] RDFPP [76] RD-OASES [77] RDOASP [78] RDOAST [79]	SAFRAN [80]
Parabolic equation			AMPE/CMPE [81] CCUB/SPLN/CNP1 [82] Corrected PE [83] DREP [84] FDHB3D [85] FEPE [86] FEPE-CM [87] FEPES [88] FOR3D [89] HAPE [90] HYPER [91] IFD Wide Angle [92] IMP3D [93] LOGPE [94] MaCh1 [95] MOREPE [96] OS2IFD [97]	PAREQ [98] PDPE [99] PE [100] PECAN [101] PE-FFRAME [102] PESOGEN [103] PE-SSF (UMPE/MMPE) [104] RAM/RAMS [105] SNUPE [106] Spectral PE [107] TDPE [108] Two-Way PE [109] ULETA [110] UNIMOD [111] 3DPE (NRL-1) [112] 3DPE (NRL-2) [113] 3D TDPA [114]

3.2.1 Time of Arrival

Assuming the velocity of sound has already been known, Time of Arrival (TOA) uses the signal traveling time from the transmitter to receiver to measure the distance. According to the propagation theory, the distance in Fig. 7 equals to

$$Dist = V \cdot T = V \cdot (T_2 - T_1) \quad (2)$$

where V is the spreading speed, and T is the traveling time which is the time difference between the transmitting time T_1 and the arrival time T_2 . Sound is the commonly used signal because the velocity of radio frequency is so fast that the time is too short to be counted. Although the range accuracy of this method is relatively high, the time synchronization which is difficult for a large scale WSN is required. Moreover, the slow speed of sound aggravates the Doppler effect in the UASN. By contrast, the symmetric double sided two-way ranging approach [27, 28] can avoid the time synchronization and the uncertainties, such as the misalignment between the actual signal emission and the time delay of recognition of signal arrival. As described in Fig. 8, the B transmits a signal at T_{B1} . The A receives this signal and sends back an acknowledgment signal at T_{A1} and T_{A2} respectively. The B receives the returned package at

Table 4: Domains of applicability of underwater acoustic propagation models [24] [26]

Model type	Applications							
	Shallow water				Deep water			
	Low frequency		High frequency		Low frequency		High frequency	
	RI	RD	RI	RD	RI	RD	RI	RD
Ray theory	○	○	◐	●	◐	◐	●	●
Normal mode	●	◐	●	◐	●	◐	◐	○
Multipath expansion	○	○	◐	○	◐	○	●	○
Fast field	●	○	●	○	●	○	◐	○
Parabolic equation	◐	●	○	○	◐	●	◐	◐

Low frequency (< 500 Hz)
 High frequency (> 500 Hz)
 RI: Range-independent environment
 RD: Range-dependent environment

● Modeling approach is both applicable (physically) and practical (computationally)
 ◐ Limitations in accuracy or in speed of execution
 ○ Neither applicable nor practical

Table 5: Summary of underwater acoustic noise models [24]

<i>Ambient noise</i>	<i>Beam-noise statistics</i>	
	<i>Analytic</i>	<i>Simulation</i>
AMBENT [1]	BBN shipping noise [11]	BEAMPL [15]
ANDES [2]	BTL [12]	DSBN [16]
CANARY [3]	USI array noise [13]	NABTAM [17]
CNOISE [4]	Sonobuoy noise [14]	
DANES [5]		
DINAMO [6]		
DUNES [7]		
FANM [8]		
Normal mode ambient noise [9]		
RANDI - I / II / III [10]		

T_{B2} . T_{Ai} and T_{Bi} are belong to the local clock of A and B respectively. Then, $T_{A1} = T_{B1} + \Delta + T_{Prop}$ and $T_{B2} = T_{A2} - \Delta + T_{Prop}$, where Δ is the time difference between the local clocks of the A and B , T_{Prop} is the propagation time of one single route. Hence, the following equation can be used to measure the distance:

$$Dist = V \cdot T_{Prop} = V \cdot \frac{(T_{A1} + T_{B2} - T_{B1} - T_{A2})}{2}, \quad (3)$$

This method can not only has the accuracy as good as one-way TOA's, but also does not need the time synchronization. However, the more energy consumption trades off with these advantages.

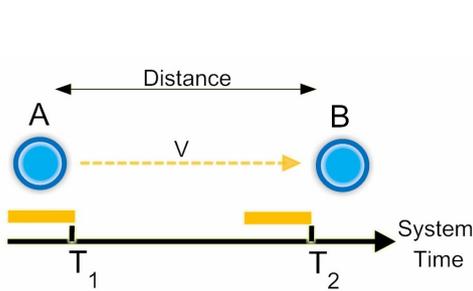


Figure 7: TOA

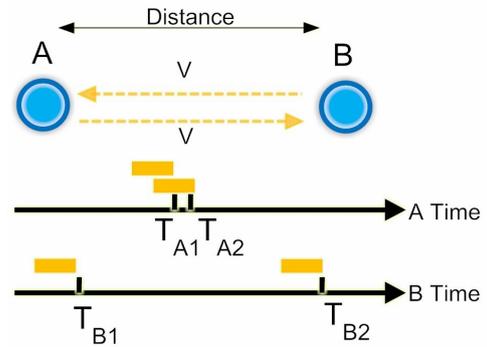


Figure 8: TOA without time synchronization

3.2.2 Time Difference of Arrival

Time Difference of Arrival (TDOA) measures the distance by two different types of signals. As shown in Fig. 9, the transducer A can transmit a RF signal (green line) and an ultrasonic sound (yellow line) simultaneously. The RF signal is usually considered to be received by the transponder B immediately since it propagates as fast as light. However, it takes a while for the ultrasonic sound to arrive at B . Consequently, the transponder B receives the two signals at different times. When both of them transmitted by A are received, the distance can be calculated by

$$Dist = V_2 \cdot T_B = V_2 \cdot (T_{B2} - T_{B1}), \quad (4)$$

where $Dist$ is the estimated distance, V_2 is the sound propagation velocity, and T_{B2} and T_{B1} are the arrival times of the RF and sound by the clock of B respectively. Although TDOA has the good ranging accuracy as TOA without time synchronization, it needs more hardware and energy to generate, detect and process the different signals.

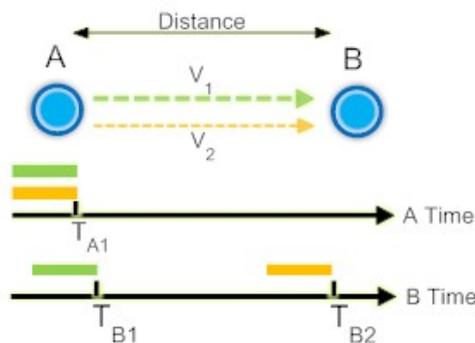


Figure 9: Time Difference of Arrival

3.2.3 Received Signal Strength Indicator

Received Signal Strength Indicator (RSSI) estimates the distance by measuring the signal strength, which has the mathematical relationship with distance since the signal is attenuated during the propagation. Theoretically, the weaker the received signal is, the longer the distance is. The signal strength can be measured during the communication without extra hardware or energy. Therefore, RSSI is an energy-saving and low-cost method. However, it is so sensitive to the disturbances that the distance estimation is very imprecise, especially in the underwater environment.

3.3 Several Established Localization Methods

Before discussing the state-of-the-art underwater localization schemes, some basic methods which are the fundamental of the various localization algorithms need to be introduced. Moreover, several established localization algorithms, which are widely used in the terrestrial and arial localization, are described here.

Trilateration The trilateration determines the location using the geometrical constraints of circles or spheres. The location is the intersection point of the three circles or four spheres in the two-dimension or three-dimension respectively, see Fig. 10 and Fig. 11. However, the estimated distances must have some errors in reality, changing the intersection from a point to an overlapped area or solid. Consequently, some additional processes are required to get the location.

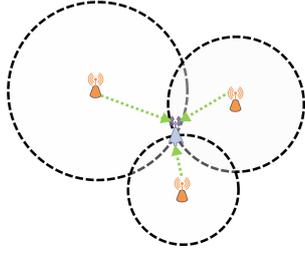


Figure 10: Two-dimensional trilateration

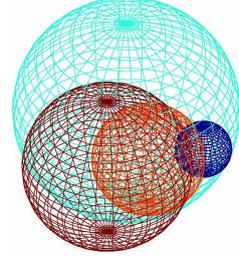


Figure 11: Three-dimensional trilateration

Least Squares Method By contrast, least squares method (LSM) is better than trilateration [29] since it is difficult for the trilateration to perform the accurate localization when suffering from the various noises. As shown in Fig. 12, there is an unknown node which measures the distances to the n beacons. The B_i is the i th beacon with the corresponding coordinate value (x_i, y_i) and estimated distance d_i . Hence, the LSM problem can be formulated as

$$\begin{cases} \sqrt{(x - x_1)^2 + (y - y_1)^2} = d_1 \\ \sqrt{(x - x_2)^2 + (y - y_2)^2} = d_2 \\ \vdots \\ \sqrt{(x - x_n)^2 + (y - y_n)^2} = d_n \end{cases} \quad (5)$$

where (x, y) is the location of the unknown node. The equations can be rewritten as

$$AX = b \quad (6)$$

where $X = [x \ y]^T$ and

$$A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ \vdots & \vdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{bmatrix} \quad b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_1^2 \end{bmatrix} \quad (7)$$

The optimal solution of (6) is the X that reaches the minimum of $\|AX - b\|_2$, which is

$$\|AX - b\|_2^2 = (AX - b)^T (AX - b) = X^T A^T A X - 2X^T A^T b + b^T b. \quad (8)$$

Let the gradient of (8)

$$2A^T A X - 2A^T b = 0 \quad (9)$$

equal zero, then

$$\hat{X} = (A^T A)^{-1} A^T b. \quad (10)$$

\hat{X} is the optimal location of the unknown node. The three-dimensional case can be derived by referring to the above analysis.

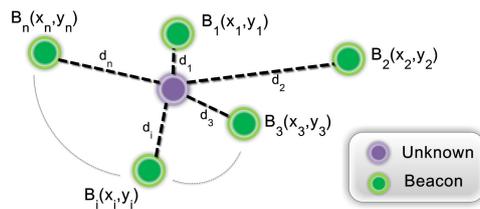


Figure 12: Least squares method

Optimization Method WSN localization can be transformed into the optimization problem. Its key idea is to minimize the differences between the measured distances and the corresponding Euclidean distances. Maximum likelihood estimation is a typical optimization method. A variety of numerical approaches can solve the optimization method and search the global or local optimal result, for example, multi-resolution search algorithm [30], particle swarm optimization technique [31], conjugate-gradient [32] and the Newton-Raphson method [33].

Multidimensional Scaling Map Multidimensional scaling (MDS) algorithm, which is recognized as an algorithm with good performance [34], introduces the statistical techniques to perform the accurate WSN localization [35]. Both a relative map and an absolute map are constructed during the computation. First, the shortest path between each pair of nodes is created. Then, with only three or four beacons, the relative map created by MDS is transformed to the absolute map, which is the final localization result. Its main problem is the high energy consumption and the centralized property. The result is also highly influenced by the irregularly shaped network, where the shortest path distance does not correspond well to the Euclidean distance. A distributed MDS-MAP, namely MDS-MAP(P), is proposed to realize the distributed localization with low computation [36]. It builds many local maps at each node and then merge them together to form a global map. MDS-MAP(P) can tackle the non-convex deployment problem with high accuracy and low computational complexity.

Semi-definite Programming Semi-definite programming (SDP) method represents the WSN localization as a constrained programming problem [37]. It converts the geometric constraints of sensors to a group of linear matrix inequalities. By solving this semi-definite programming problem, the satisfied localization result can be obtained. However, the localization error may be high because of the max-rank property of the SDP solution. In [38], both the regularization term and optimization methods are designed to reduce the rank of the SDP. Unfortunately, there is no efficient way to determine an important parameter used in the regularization term.

Iterative Localization Iterative localization can be employed to overcome drawback of limited network coverage and provide more anchors [39]. It qualifies the sensors that have already been localized as the anchors to assist the unlocalized nodes. Although this mechanism extremely improves the localization rate, the localized sensors certainly have some errors in the position estimation, which inevitably propagate and are further accumulated as the localization procedure. Therefore, the control of the error propagation is critical for the localization schemes introduced the iterative localization.

3.4 Summary

In this section, the communication channel, ranging method and some localization algorithms which are mainly used for the terrestrial localization are introduced. The important features of the ranging techniques are summarized in the Table 6. When designing the UASN localization, these factors should be considered before the ranging technique is determined.

Table 6: Summary of ranging techniques

Name	Hardware (Sort)	Accuracy	Time Synchronization	Energy Consumption
One-Way TOA	One	High	Yes	Medium
Two-Way TOA	One	High	No	High
TDOA	Two	High	No	High
RSSI	One	Low	No	Low

4 Localization Algorithm

Localization algorithm usually uses the geographic information of their neighbor nodes to estimate the location. Because its design closely depends on various factors, including system deployment, available resources, accuracy requirements, etc., each algorithm almost aims for the specific application with its own merits and drawbacks, which implies there is no algorithm which is applicable across the spectrum so far. Therefore, the application properties and requirements should be sufficiently investigated before its design. However, the primary goal of all localization algorithms is to make the localized position accurate by mitigating the effects of noises, and reasonably balance the performance and the various constraints.

Even though the underwater and terrestrial localizations have some in common, they are extremely different due to the challenges, such as serious disturbances, poor link quality, high bit error rate, long latency, limited bandwidth, low data rate, etc. In this section, many established underwater localization algorithms are introduced to provide a great number of references for the UASN design.

The localization schemes are divided into three categories in this report according to the sensor mobility: stationary network, mobile network and mobile swarm.

- **Stationary network.** In the stationary network, all the sensors are static including the unknown nodes. This is an ideal scenario in the underwater environment because the underwater sensors are inevitably being pushed due to the ocean current, shipping activities, etc. However, it is the fundamental for the other two networks.
- **Mobile network.** Generally, mobile network can be further divided into three types [19]: unknown nodes are static, while beacons are moving; unknown nodes are moving, while beacons are static; both unknown nodes and beacons are moving. In this report, the mobile network mostly represents the second one, and the third one is called mobile swarm. As shown in Fig. 13, the mobile network constitutes the tethered beacons, which only can be deployed roughly owing to the ocean environment, and moving sensors (AUVs and nodes). Because the beacons always sway around the fixed positions without updating, the known beacon locations are inaccurate. Meanwhile, the mobile feature of the unknown nodes brings greater challenges to accurately localize them.
- **Mobile swarm.** It is a more complicated scheme for WSN localization, see Fig. 14. Because of the ocean environment (currents, wind, etc.) or the actuators equipped for motion, the beacons and sensors both have the motion capabilities. The beacons can also be self-localized (e.g., via GPS). The movement feature overcomes the disadvantages that the WSN based localization only can be used for the limited area with pre-deployed beacons and the network cannot service the pelagic applications. Because the unknown nodes and AUVs cooperate with each other by communication, the range and locations can be determined during this process without extra consumption.

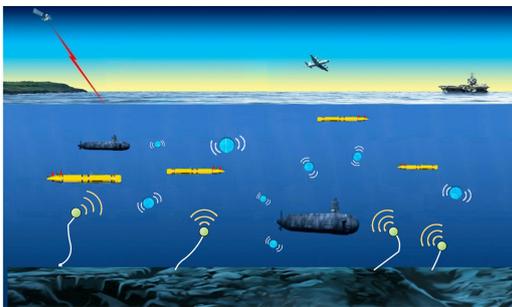


Figure 13: Mobile network

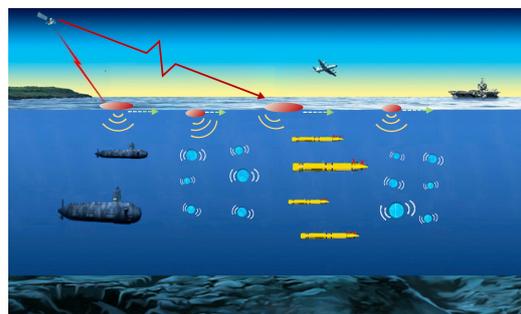


Figure 14: Mobile swarm

4.1 Localization for Stationary Networks

In general, schemes that belong to this category have static beacons whose locations can be determined through GPS or pre-deployment depending on whether they are deployed on the surface buoys or the sea floor. Because the unknown nodes are also static, the localization is completed once they are all located. This kind of network is being widely investigated and some solutions are proposed in recent years.

4.1.1 Underwater Positioning System

Underwater positioning system (UPS) is a silent positioning scheme which comprises two steps [40]. The time differences of the signal arrival are computed by frequent communications between every beacon and sensors at first, and then they are transformed into the corresponding ranges. The second phase estimates the location by trilateration. A two-dimensional UPS is in Fig. 15 to describe the key idea of the range measurement. The silent feature of UPS can significantly improve the network throughput, especially for the large-scale network, and is suitable for the asymmetric UASN where the sensors only can receive the signal from the beacons due to the limited maximum range. Meanwhile, the sensors and AUVs have very strong location privacy without being easily detected because they do not transmit anything. However, the computation of time differences highly suffers from the serious transmission losses in the underwater environment since the UPS fails once a communication is lost. Furthermore, the assumption that the four beacons have to cover the whole area limits the network extension.

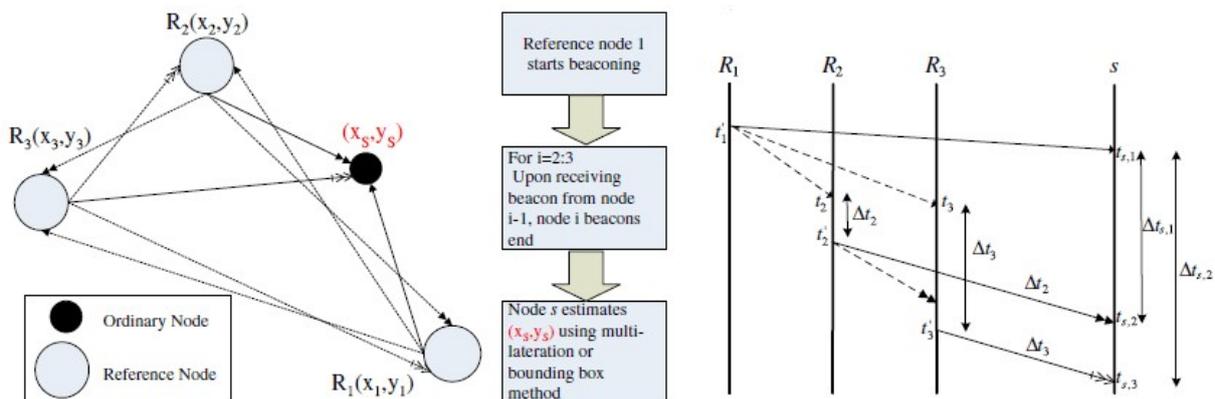


Figure 15: Underwater positioning system [16]

In order to overcome the drawbacks of UPS when using in the harsh and dynamic underwater acoustic channels, Tan *et al.* propose an enhanced UPS (E-UPS) [41], which employs the dynamic leader beacon selection and the time-out mechanism. A wide coverage positioning system (WPS) which introduces the fifth beacon is also presented to increase the feasible space of UPS and ensure the unique localization [42].

4.1.2 Hyperbola-based Approach

Hyperbola-based approach (HA) uses the hyperbolas to calculate the location instead of the circles [43], ensuring the existence of the beacon intersection, see Fig. 16. When two circles intersect with either two or zero cross point(s), two hyperbolas always can intersect with each other with one cross point. This is significant for the underwater localization where the range measurement suffers from the serious disturbances and the imperfect time synchronization. Moreover, HA combines the error probability distribution [44] to further improve the localization accuracy. However, the beacons have to be fixed at the corners of the region.

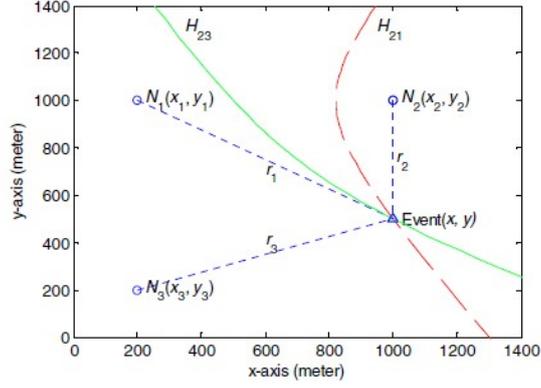


Figure 16: Hyperbola-based approach [43]

4.1.3 Anchor Free Localization

Anchor free localization (AFL) or GPS-less protocol which does not need any beacon only relies on the shared information of the network [45,46]. First, a relative coordinate system is built using the information gained from the first three seed node discoveries. Specifically, a seed node S_1 broadcasts a ranging packet and receives the neighbors' replies, which contain the sensor ID and their distances without locations. The furthest sensor is then selected as the second seed S_2 , and its ID is broadcasted. The seed S_3 is the sensor which has the maximum summation of distance from S_1 and S_2 . With these three seeds, the relative coordinate system can be constructed. As shown in Fig. 17, the sensors in the intersection area can estimate their locations using trilateration, while the outside sensors are further localized with the aid of another new seed node. AFL is highly energy consuming owing to the frequent communications among the nodes. Moreover, the disturbance on the sensor position, which is very common in the UASN, seriously influences the localization accuracy.

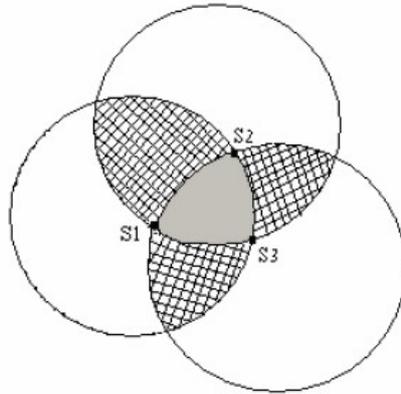


Figure 17: Anchor free localization [46]

4.1.4 Simultaneous Localization and Synchronization

The simultaneous localization and synchronization (L-S) can simultaneously achieve the localization and time synchronization for the large scale three-dimensional underwater sensor network by one computation [47]. The key idea is that the time difference between the package arrivals is also introduced into the multilateration algorithm. L-S also adopts the atomic multilateration and iterative multilateration to increase the network coverage. Moreover, two solutions, new beacon and weighted least squares, are provided to handle the error propagation. Its trade-off of time synchronization is the needed fifth beacon.

The precision of the time synchronization is also seriously affected by the velocity of propagation, which constantly varies in the ocean.

4.1.5 Large-Scale Hierarchical Localization

In [48], a large-scale hierarchical localization (LSHL) is proposed for the static network. Fig. 18 shows its architecture where there are three kinds of nodes: surface buoys, anchor nodes and ordinary nodes. The surface buoys floated on the water surface can get the real-time locations via the equipped GPS. The submerged anchor nodes can not only directly communicate with surface buoys to be localized at the forefront, but also can be as the reference nodes to assist the ordinary nodes' localization. Ordinary nodes, however, only can transmit data with anchor nodes rather than surface buoys due to various constraints, e.g. communication cost. In general, LSHL consists of two sub-processes: anchor node localization and ordinary node localization, especially focusing on the second part.

A distributed localization scheme which integrates a three-dimensional Euclidean distance estimation method with a recursive location estimation method is proposed to perform the ordinary node localization. First, the anchors periodically broadcast their information for the ordinary nodes to estimate the distances through one-way ranging TOA method or multi-hop ranging Euclidean distance estimation. If the ordinary node receives at least four distance estimations to different anchors in one-hop, it can be localized by iteration, calculating and checking its confidence value to determine if it can become the reference node. Otherwise, the Euclidean approach is used to estimate the multi-hop distance for the non-localized ordinary nodes. The three-dimensional Euclidean approach is also described in [48]. The confidence value is used to alleviate the error propagation effect. It is defined as follows

$$\eta = \begin{cases} 1 & \text{anchor} \\ 1 - \frac{\delta}{\sum(u-x_i)^2+(v-y_i)^2+(w-z_i)^2} & \text{ordinary nodes} \end{cases} \quad (11)$$

where $\delta = \sum_i |(u-x_i)^2+(v-y_i)^2+(w-z_i)^2-l_i^2|$ is the location error. If an ordinary node's η is bigger than the confidence threshold, it becomes a reference node. Otherwise, it remains the ordinary node, continuing to be localized. The choice of the threshold relies on the network coverage and the required localization accuracy. The drawbacks of LSHL lie in the high energy consumption and communication overhead [17], time synchronization requirement (due to the one-way TOA ranging method) and the assumption that the localized anchors are accurate. By introducing the fourth type of node - Detachable Elevator Transceivers, Detachable Elevator Transceiver Localization (DETL) scheme [49] as an extension of LSHL can improve the accuracy of the anchor localization and reduce the energy consumption in long range communication.

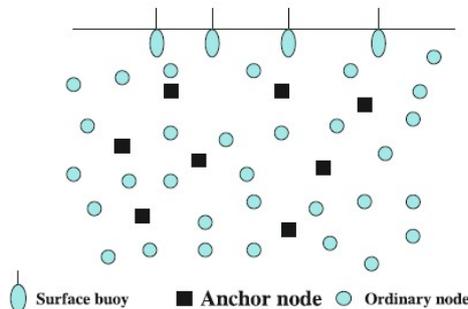


Figure 18: Architecture of LSHL [48]

4.1.6 Underwater Sensor Positioning

Teymorian *et al.* propose an underwater sensor positioning (USP) scheme [50, 51], which transforms the three-dimensional localization into two-dimensional counterpart to enable the traditional 2D localization algorithms using the depth information (can be got by pressure sensor) and the projection technique. USP comprises two steps: the offline pre-distribution and the distributed localization. In the first phase, three randomly selected anchors announce their location information to launch the localization procedure. Secondly, the unknown node performs the distributed localization algorithm. A scenario is described in Fig. 19, where three anchors and an unknown sensor are deployed. The anchors are projected onto the horizontal plane of the node X after the distances between them are measured. With the non-degenerative projection, the location of X can be calculated by the simple bilateration method in the 2D space. Otherwise, another anchor node set is re-selected if the projection is not non-degenerative. The localized sensors are also qualified to be the reference node in USP.

The novel idea of USP is that it can utilize the 2D algorithm to address the 3D localization. Moreover, the no less than four anchors requirement of 3D localization is removed by introducing the depth knowledge and the projection technique. However, the nodes are required to be synchronized, and its successful localization rate is lower than the other techniques [50].

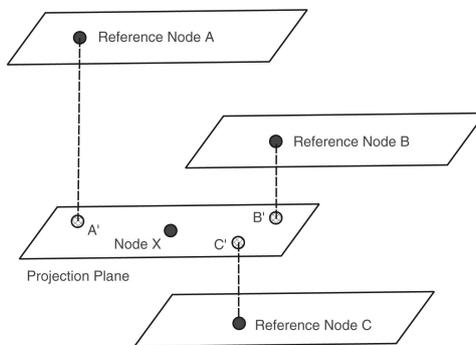


Figure 19: Underwater sensor positioning [50]

4.1.7 Localization Scheme for Large Scale Underwater Networks

In [52], the localization scheme for large scale underwater networks (LSLS), which is composed by sea surface anchor localization, iterative localization and complementary phase, is designed. Before reaching the LSLS, the basic time synchronization-free localization (BSFL) [52] should be introduced first since it is the foundation of LSLS. With the depth information and the projection technique, BSFL computes the range differences and further estimates the coordinates by performing the trilateration. Then, the LSLS uses BSFL to localize the directly localizable area in the sea surface anchor localization step. During the iterative localization, a new localizable area which is built by enrolling the localized nodes as the reference nodes continues to be localized using BSFL. If there are nodes that have not been localized yet, the complementary phase will provide to-be-localized areas for them. Without time synchronization, LSLS just needs three surface buoys. What is more, the Coppens model regarding sound velocity variation with the ocean environment [53] is considered. However, it consumes more energy than UPS due to the iterative and complementary phases.

4.1.8 Three-Dimensional Underwater Localization

Another projection technique based localization protocol is three-dimensional underwater localization (3DUL) [28], see Fig. 20. With the aid of only three surface beacons, it can employ a distributed and iterative algorithm to achieve the robust 3D localization. This two steps scheme works as follows. First,

the surface anchor nodes broadcast their locations determined by GPS. The unknown node that receives these packages then uses the aforementioned two-way ranging TOA technique (see Fig. 8) to measure the distance. In the second step, the anchors are projected onto each unknown node's horizontal plane, forming a virtual geometric structure. If all the sub-triangles of the virtual anchors plane are robust, the unknown node can use the trilateration to estimate the location and then becomes an anchor to iteratively help the other unknown nodes. Note that the triangle is robust if the length of the shortest side a and the smallest angle θ of a triangle satisfy $a \sin^2 \theta > d_{min}$, where d_{min} is a threshold depends on the noise.

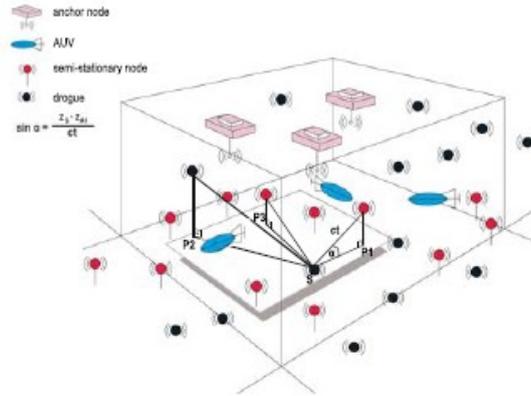


Figure 20: Three-dimensional underwater localization [28]

3DUL does not require the time synchronization, and estimates the sound speed through conductivity (salinity), temperature and depth (pressure) sensors. However, the two-way ranging and the only three surface anchors increase the localization time even though it does not introduce the intelligent anchor selection mechanism. More seriously, some unknown nodes are unable to be localized since there is no three robust anchors for them, influencing the network localizing rate.

4.1.9 Comparison

The properties of the aforementioned localization schemes for stationary UASN are summarized in Table 7. LSLS and 3DUL have taken into account the ocean environment, e.g., sound speed varies with the temperature, salinity and depth. Moreover, 3DUL which is hybrid protocols can also be used for the mobile network even though it is just estimation-based methods without movement prediction. This is the difference between these and the schemes outlined later [17].

Table 7: Summary of localization schemes for stationary network

Scheme	Dimension	Beacon Deployment	Ranging Technique	Time Synch	Iterative Method	Positioning Method	
UPS	3D	3 surface and 1 sea bed	TDOA	No	No	Silent	
E-UPS	2D+pressure	2D sea bed	TDOA	No	No	Silent	
WPS	3D	like UPS and a fifth	TDOA	No	No	Silent	
HA	2D	2D sea bed	TOA	Yes	No	Active	
AFL	2D	one initial seed	unspecified	unspecified	No	Active	
L-S	3D	5 surface	TOA	No	Yes	Silent	
LSHL	3D	surface, underwater	one-way TOA	Yes	Yes	Active	
projection	USP	2D+pressure	3 surface	unspecified	unspecified	Yes	Active
	LSLS	2D+pressure	3 surface	TDOA	No	Yes	Active
	3DUL	2D+pressure	3 surface	two-way TOA	No	Yes	Active

4.2 Localization for Mobile Networks

The static network in the last subsection assumes that all the nodes are stationary or semi-stationary fluctuating around the actual positions. However, the WSN is sometimes deployed in the dynamic environment, where the sensors actively or passively float along the surroundings (e.g. ocean current, wind) beyond the confine of static network. Therefore, the mobile network described in Fig. 13 is urgently required.

The characteristics of mobile network, especially the node mobility, inevitably create many new challenges of localization [22]. The main problem is that the sensors are no longer localized once but repeatedly. The location information should be revised continuously in order to track the mobile sensors and mitigate the localization error. Moreover, the mobility and the produced Doppler effect heavily influence the range measurement. As shown in Fig. 21, the ideal range measurement supposes that the beacons are static and the mobile sensor can immediately estimate the distances to all the beacons without any position shift, which is impossible in reality. The real situation, which is also described in the right figure, is that the beacons are swaying around an area, and more importantly the mobile sensor gathers the distances with its varying location. The effect of this is more serious in the underwater scenario due to the long ranges between the sensors and the slow propagation speed of the acoustic signal. The ranging error significantly increases with the sensor mobility.

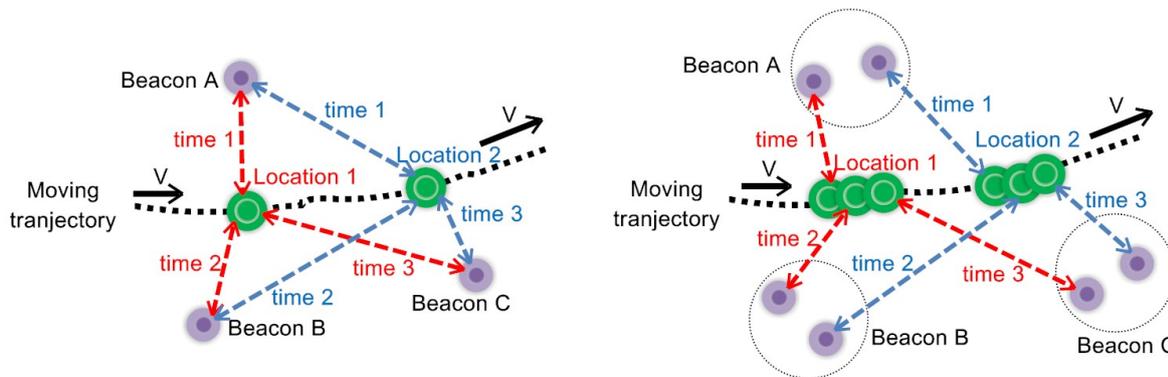


Figure 21: Ideal and real rang measurements of the mobile network

In general, there are three kinds of method to perform the mobile localization. First is the GPS. However, the high costs in hardware and energy are both inappropriate for the WSN. Secondly, the static network can repeatedly execute to serve the real-time mobile localization under the condition that the update frequency of the localization algorithm can meet the accuracy requirements. However, it suffers from the aforementioned practical ranging problem, and does not sufficiently use the motion information to improve the accuracy. It is also energy consuming under the high update frequency. Mobile localization which relies on the prior information of node mobility to ameliorate the localization performance is the third approach [54]. It has intrinsic advantages to the dynamic applications like target tracking [55, 56]. Therefore, this subsection presents several localization algorithms designed for it.

4.2.1 Monte Carlo Localization

In the mobile robot localization area, the prediction-based schemes are preferred due to the inherent merits of addressing the mobile localization and the acknowledged good performance in practice. The localization can benefit from the mobility in terms of the efficiency and accuracy. They get the current location by integrating the prediction from the prior information (e.g., the mobility model) with the measurement update from the environment observation. Various filtering methods have been applied to the mobile robot localization, such as Extended Kalman Filter (EKF) [57], Markov method and Monte Carlo localization (MCL) [58]. The EKF as a kind of Gaussian filter assumes that the probabilities follow

the normal distributions. However, the models in the real world always contain the non-Gaussian and non-linear noises. After representing the localization problem as a Markov process (the current location is entirely determined by the last location), MCL overcomes these difficulties by employing a set of weighted particles to present the uncertainty. It has become one of the most popular localization algorithms since it is easy to use and tends to produce good results. Therefore, some studies aim to address the WSN localization of the mobile networks using the MCL.

Although MCL in the context of WSN localization still consists of the prediction phase and the measurement update phase, it has many differences from the MCL based robot localization. The major one is that the probabilistic knowledge of the robot are relatively more reachable than that of the WSN because the sensor in UASN is difficult or impossible to acquire the speed or the direction. Also the robot localization usually performs the localization under a predefined map while the WSN is in a unknown area without maps. Therefore, in order to achieve MCL in WSN, the two important steps should be determined according to WSN condition. Note that the key idea of MCL is the particle filter that describes the posterior distribution by a set of weighted samples drawn from it [59]:

$$p(x_t|y_t) \approx \{x_t^i, w_t^i\}_{i=1,2,\dots,N} \quad (12)$$

where $p(x_t|y_t)$ is the posterior distribution of the node locations at time t given the measurements y_t , and $\{x_t^i, w_t^i\}$ is the set that contains the sampled particle x_t^i and the normalized weight w_t^i associated with x_t^i . The two iteratively running distribution functions as well as the initial distribution are as follows:

- Initial distribution. The best way to determine the initial distribution $p(x_0)$ are to have the knowledge of the starting locations of the sensors. However, it is often impossible in practice. Then, it can be replaced by a uniform distribution over the whole monitored area.
- Transition equation $p(x_t|x_{t-1}, u_t)$. It describes that the prediction of the current possible locations x_t depends on the last positions x_{t-1} and the control strategy u_t . The MCL draws the particles from the $p(x_t|x_{t-1}, u_t)$ to represent the distribution. For some range-free method [19], the sensors are aware of nothing except the maximum speed v_{max} . Thus, the possible location x_t^i after a unit of time is only distributed in a circular region with origin at x_{t-1}^i and radius v_{max} .
- Marginal equation $p(y_t|x_t)$. It is applied to determine how the predicted positions x_t satisfies the measurement y_t . The measurement is used to eliminate the predicted positions that do not satisfy the requirements like $p(y_t|x_t) > 0$. Because the number of the particles may be less than the predicted after the filtering, the re-sampling is introduced to sample the other particles. The measurement also determines the important weighs of the particles.

Hu *et al.* are the first to extend the MCL to a range-free WSN localization [19]. It employs the Sequential Monte Carlo (SMC) method to estimate the posterior distribution of nonlinear discrete time dynamic models. The area of the possible particles is restricted by the the maximum speed v_{max} , which is the uniquely available information of the sensor. Meanwhile, the two defined types of beacons, arrivers and leavers are useful for filtering the particles located outside the anchor constraints. However, the assumptions that the messages are received instantly and the maximum communication range is constant are unsuitable for UASN [60]. More importantly, the localization performance highly depends on the anchor density. If the density is low, the possible area is too large, degrading the localization accuracy. Mobile and Static sensor network Localization (MSL) in [61] considers the varying transmission range to overcome the disadvantage in [19]. Another range-free method called Monte Carlo localization boxed (MCB) is proposed in [62]. The samples are drawn from a box area, which is the overlapping of the anchors' radio ranges. The major difference between MCB and SMC lies in the usage of the anchor information and the extraction of the new samples. It can draw good samples more easily and faster. The range-free Improved MCL (IMCL) introduces the anchor node constraint, the on-hop sensor constraint and the pioneered moving direction constraint to filter the impossible positions [60]. An adaptive mechanism of number selection depending on the possible sampling region is designed for the

resource-limited sensor nodes. However, the maximum communication range is also assumed to be constant. The Monte Carlo based methods described thus far are range-free. In [63], a range based Monte Carlo localization uses the range measurements, connectivity constraints and mobility information to improve the localization accuracy and reduce the computational costs.

4.2.2 Passive Mobile Robot Localization

In [64], the underwater robot localization and tracking are addressed by two experiments based on the geometric and visual approaches. In the geometric method, the beacons and ranges measured by acoustic communication are used to localize the mobile AUVs. The passive mobile robot localization algorithm (PMRL) [65] first localizes the beacons by the static localization algorithm in [66], and then employs the geometric approach to calculate the positions, see Fig. 22. It only needs the knowledge of the maximum AUV velocity rather than the detailed motion models assumed by Monte Carlo or SLAM methods. This makes it more suitable for implementation since the motion models in real-world situation are usually inaccurate or difficult to be obtained. Moreover, the distance measurements are non-simultaneous, which is extremely significant for the underwater localization where delays between measurements are common and the aforementioned range measurement problem is serious.

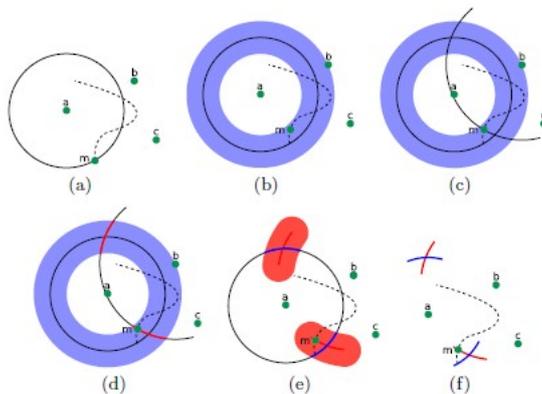


Figure 22: Passive mobile robot localization

4.2.3 Moving-baseline Localization

The moving-baseline localization (MBL) algorithm aims for the localization in the environment where no external coordinate reference or previously deployed infrastructure is available [67]. When the sensors cannot communicate with all the nodes directly, each sensor can infer its own view of the network using a time series of range measurements at each node (see Fig. 23), i.e., the spatial and motional relationships of all other nodes with respect to itself. This approach consists of several steps [67]: hyperbola estimation, path estimation geometry, local cluster localization, global view construction and local cluster update. Because MBL does not require the fixed coordinate system, it is suitable for the underwater environment where an overall coordinate system is difficult to be defined. However, each node is assumed to be moving along a straight-line, which is impossible under the water.

4.2.4 Scalable Localization with Mobility Prediction

Scalable localization scheme with mobility prediction (SLMP) [68], a kind of hierarchical network, is the extension of LSHL with mobility prediction, and the network components and the architecture are similar to LSHL's. The introduced mobility prediction of anchor node and ordinary node can reduce the communication consumption when localizing the positions. Anchor nodes periodically check the validity of the pattern in order to prevent the obsolete mobility pattern using the Euclidean difference between

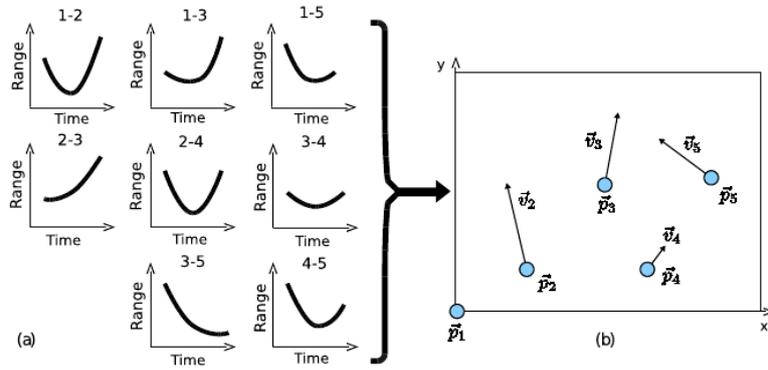


Figure 23: Construction of the relationships in moving-baseline localization [67]

the predicted and the estimated locations. The reference node selection mechanism uses the arrival time-stamp, which is an new criteria for LSHL.

4.2.5 AUV-aided Localization

There are some AUV aided localization methods, such as the range free ones UDB [69] and LDB [70]. As a range- and estimation- based scheme, AUV-aided localization (AAL) consists of the stationary sensors and the mobile AUV [71]. The sensors are localized with the aid of AUV, which can estimate its location by integrating the dead-reckoning with the periodical GPS update. AUV roams in the UASN area, communicating with the sensors by the two-way ranging method. Once receiving three non-collinear AUV locations, the static node equipped with the pressure sensor can be successfully localized. As shown in Fig. 24, the position of the AUV can be updated to improve the accuracy of dead-reckoning when it rises to the ocean surface using the GPS. However, the frequency of this calibration affects the localization accuracy, which implies that the frequent update drains the battery of the AUV. Then, the cooperation of multiple AUVs is meaningful. Another drawback of AAL is that the obtained three positions are close to each others in a short interval, which may produce the flip ambiguity.

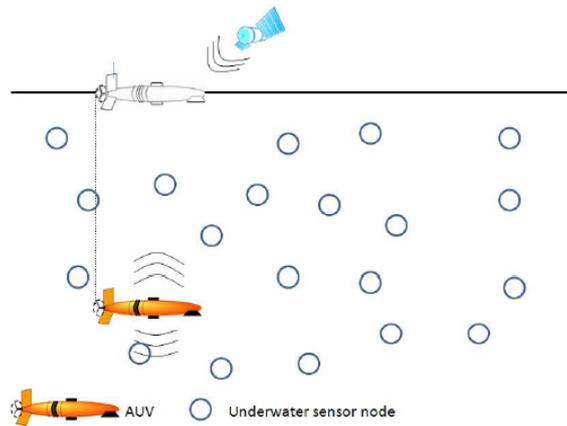


Figure 24: Architecture of AAL [15]

4.2.6 Dive and Rise Localization

Dive and rise localization (DNRL) [72] addresses the localization using the vertically mobile beacons, whose diving and rising are controlled by the weight force and a bladder. They get their updated positions via GPS at the surface, and broadcast them by acoustic transceiver as they are diving. When the sensor

nodes passively receive the DNR beacon messages, the range is measured by time of arrival under the assumption that the nodes are synchronized. Then, the locations of the sensors are estimated using either bounding box or triangulation algorithm. DNRL is a silent localization scheme and considers the horizontal motion with the force of slow currents. On the other hands, a large number of DNR beacons are needed for high localization success, and the time synchronization and Doppler effect affect the performance. In order to enhance the the coverage of DNRL, the multi stage localization (MSL) [73] employs the localized ordinary nodes as the beacon. It also uses the “Meandering Current Mobility with Surface Effect model” to represent the mobility model of the underwater sensors when performing the simulation. However, due to this iterative localization, MSL is high communication overhead and is much energy consuming than DNRL. Moreover, MSL suffers from the error accumulation.

In [74], 3D multi-power area localization scheme (3D-MALS) that combines the area localization scheme (ALS) [75] and DETL is proposed. It extends ALS to 3D by introducing the detachable elevator transceivers in DETL, which can descend and ascend under the water.

4.2.7 Simultaneous Localization and Environmental Mapping

As a method which can concurrently estimate the location and build a map of the environment, Simultaneous Localization and Environmental Mapping (SLAM) has been widely used in robot localization [76,77].

Because the good performance of SLAM in reality, it is also introduced to the WSN. D. Marinakis et al. [78] present an Expectation Maximization (EM) algorithm for simultaneously localizing the sensors and mapping the environment. A prior probability distribution function (PDF) is built using the topographic map and then it is refined by the other environmental measurements, such as salinity, temperature and current velocity. The novelty of this method is to improve the WSN localization using the smoothly varying parameters. In [79], the integration of underwater sensor networks and magnetometer is used for silent localization. The moving trajectory of the vessel and the sensor locations are estimated using the Extended Kalman Filter (EKF) based SLAM.

An underwater localization system for monitoring nuclear waste storage pool is proposed in [80–84]. The initial prototype of the AUV looks like a ball whose diameter is approximately 10cm (see Fig.25). They are equipped with acoustic transmitter and receiver, which can be used to communicate with each other and measure the distances. The architecture of the system is illustrated in Fig. 26. It can be seen that the cluttered underwater environment is the primary challenge faced by this system since the irregularly shaped obstacles produce many difficulties on the localization and environment mapping. In order to address this Non-Line-Of-Sight (NLOS) problem, the convex programming based method [83] and dynamic node placement [82] can be used.



Figure 25: A prototype robot [83]

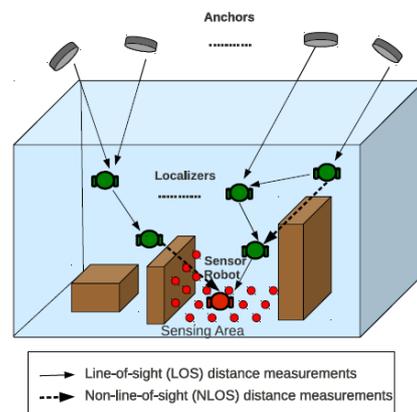


Figure 26: Architecture of the system [81]

4.3 Localization for Mobile Swarm

As shown in Fig. 14, both of the beacons and the unknown nodes in the mobile swarm are mobile. It is different from the aforementioned mobile network in the mobility of the anchors or sensors [85, 86].

Mobile swarm is the general situation of WSN based localization and has several advantages:

- Its network coverage and flexibility are enhanced. The network coverage can be increased by the mobility of the whole network, which can move to the interesting region without the constraint of fixed static beacon. Therefore, it is a promising solution for the pelagic application although it suffers from the execrable ocean environment and is constrained by the limited energy.
- It is efficient. Since the deployment of the fixed anchors or the data collection using the vessels are time- and energy- consuming, and may be infeasible or undesirable in some cases, mobile swarm is more efficient than the stationary and mobile networks.
- It is suitable for cooperation. Although the low ranging precision and the physical constraints of the sensor nodes aggravate the difficulty of localization for mobile sensor nodes, the inherent character of sharing information between many nodes enables the multiple sensors to complete the task by cooperation.

However, mobile swarm is more complicated than the mobile networks, and encounters many tough problems, such as the localizability. They became more difficult in the underwater environment because of the long time delay of signal propagation, the disturbances of the wind and ocean current, etc.

4.3.1 Motion-Aware Self Localization

Motion-aware self-localization (MASL) which is appropriate for the offline applications saves the gathered information for the posterior central processing when the mission ends [87]. It aims to accurately localize the sensors by tackling the inaccurate distance measurements. As illustrated in Fig. 27, a swarm of autonomous nodes which drift freely in the surveillance region collaborate with each other by acoustic communication. A sensor prototype whose diameter is only 25cm is presented in Fig. 28. The factor graph and the sum-product algorithm [88, 89] are used to compute the position distribution of the mobile sensors via message passing. The MASL highly reduces the computation and energy consumption of the AUVs, and makes use of the inter-node distance constraints to improve the accuracy. However, it cannot be used for the real-time application, which is its great weakness. Another drawback is the need of synchronization and the frequent messaging for distance. The synchronization problem can be addressed using the Sufficient Distance Map Estimation(SDME) [90], which is the improvement of MASL. Note that both MASL and SDME have considered the ocean environment.



Figure 27: Motion-aware self-localization [87]



Figure 28: A sensor prototype of MASL [91]

4.3.2 Collaborative Localization

As a prediction-based method, collaborative localization (CL) [92] is designed for a swarm of underwater sensors which float freely with currents. It aims to determine the locations without prior planning or pre-deployed infrastructure (e.g., long range transponders on surface buoys or ships). There are two types of nodes diving vertically in the system: profiler and follower. The former is always much deeper than

the latter when descending. The position of profiler with respect to the followers is estimated using the distances periodically measured using TOA, see Fig. 29. Since the nodes are assumed to move in the same reference frame with the same speed, the position of the profiler can be a prediction of the future locations of the followers. The required time synchronization and the disturbance of the ocean currents are the serious influences of CL. Moreover, CL is not suitable for the applications in a large area due to its mainly vertical data collection.

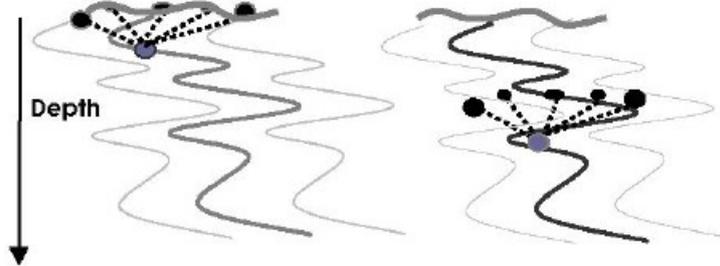


Figure 29: Trajectories of CL [92]

A cooperative localization scheme (CLS) is proposed in [93] for mobile swarm. It aims to estimate the position and velocity of the unknown nodes given the distance measurement to the mobile beacons. Its key point is to use the velocity estimation to assist the network localization because the velocities provide useful information. An extended Kalman filter is introduced to fuse the estimated node position with the node velocity estimation, improving the localization performance. The proposed algorithm is also distributed, which is suitable for the mobile swarm. However, a drawback is the need of the Doppler sensor, which increases the hardware cost and consumes more energy. The approach proposed in [94] can overcome this problem.

4.3.3 Monte Carlo Localization

The third situation in [19] uses the Monte Carlo method described in Subsection 4.2.1 to address the mobile swarm. The principle remains the same. According to the simulation results [19], the localization accuracy is much better than Centroid and Amorphous methods. But the localization error increases as the grow of the node speed.

4.4 Summary

In this section, many underwater localization algorithms are introduced according to the three different categories. As a kind of relatively mature network, the stationary network has been widely investigated, and there are many underwater localization methods specifically designed for it. In contrast, there are lack of localization schemes for the mobile network and mobile swarm, and many challenging problems still demand prompt solutions.

5 Existing Underwater Sensor Network Systems

As the increasing demand of the underwater applications, there are some off-the-shelf underwater testbeds and systems. An online database lists more than 100 existing oceanic systems investigated by the different research institutions and companies [95]. However, each system has its own advantages and disadvantages due to the different purposes, performance requirements and application scenarios.

5.1 Traditional Underwater Positioning Systems

As the traditional underwater positioning systems, Long Baseline (LBL) system, Short Baseline (SBL) system and Ultra Short Baseline (USBL) system have been widely used in various underwater applications, especially for offshore oil and gas exploration. There are also many commercial systems of them, which are summarized in [96] and [97].

As shown in Fig. 30(a), LBL employs the beacons deployed on the sea floor, the acoustic range measurements and the trilateration method. It usually has high localization accuracy. However, the pre-deployment of the beacons is time consuming and costly. Both SBL and USBL are ship-based positioning systems, which use the transceiver attached on a pole under a ship instead of the sensors mounted on the sea bottom, see Fig. 30(b) and Fig. 30(c). SBL requires three or more sonar transducers to perform the localization, while USBL which introduces the signal run time and phase shift to measure the distance and direction only needs a transducer array. As a successful commercial “underwater GPS” system, NASNet which integrates these three kind of systems (see Fig. 31) has served the offshore industry since 2000.

However, the employed devices (beacons, sensors, ships, etc.) of these three methods tend to be energy consuming, expensive and heavy, which means they are all unsuitable for the underwater localization of robot.

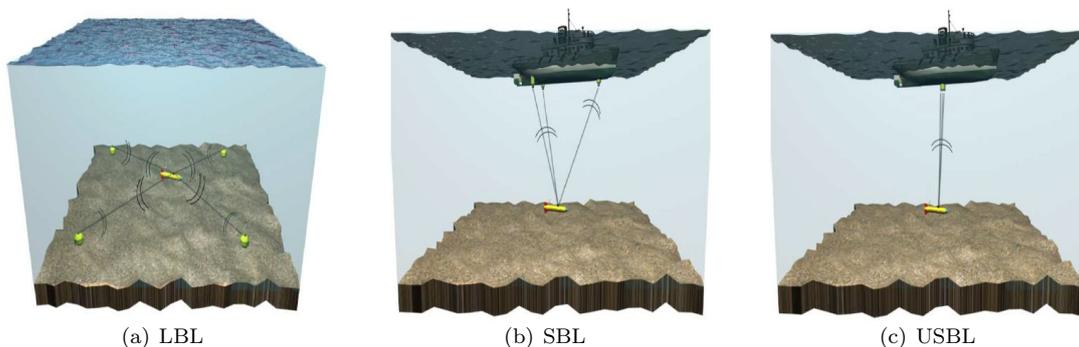


Figure 30: Baseline based underwater acoustic positioning systems

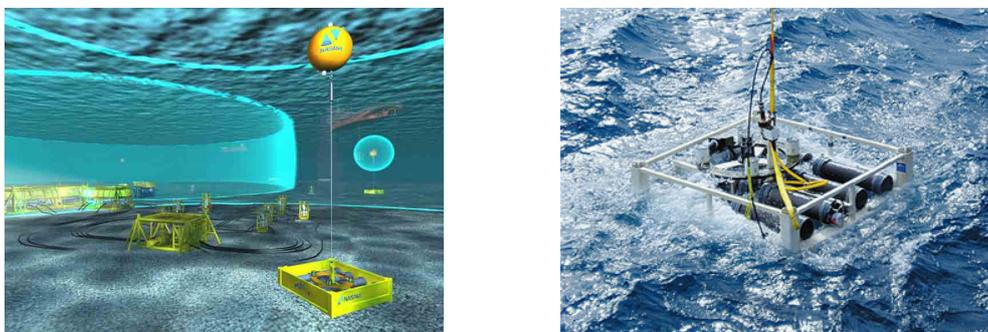


Figure 31: NASNet [98]

5.2 Localization Systems for Underwater Robots

The underwater robots usually have limited space and energy resources. Moreover, its driving force is not very powerful and the onboard sensors should be energy saving and light. Therefore, there are many constraints to be seriously considered when designing a localization system for underwater robot.

5.2.1 Systems Using the Stationary or Semi-stationary Beacons

The system with the stationary or semi-stationary beacons is the most common form of the underwater localization system. The beacons can be deployed on the surface or on the sea floor.

The Actuated Acoustic Sensor Networks for Industrial Processes (AASN4IP) project [84,99] which is developed for monitoring nuclear waste storage pools has been presented in Subsection 4.2.7. As shown in Fig. 32, the small robot equipped with acoustic sensors can be localized with the aid of the beacons fixed to the storage pond, and then can monitor the nuclear waste storage pool in real time. This system is not seriously influenced by the harsh water environment although the NLOS problem is encountered. Some preliminary results have been obtained [80–84]. However, there are still many problems for this underwater robotic network to address, especially the cooperation of robots in the water environment. Surface beacons can also be mounted to the surface buoys. The Autonomous Ocean Sampling Network (AOSN) [100] uses this method, see Fig. 33.

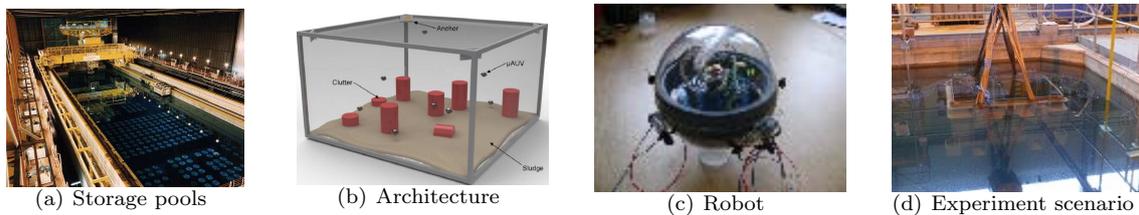


Figure 32: Underwater robotic network for monitoring nuclear waste storage pools [83,84,99]

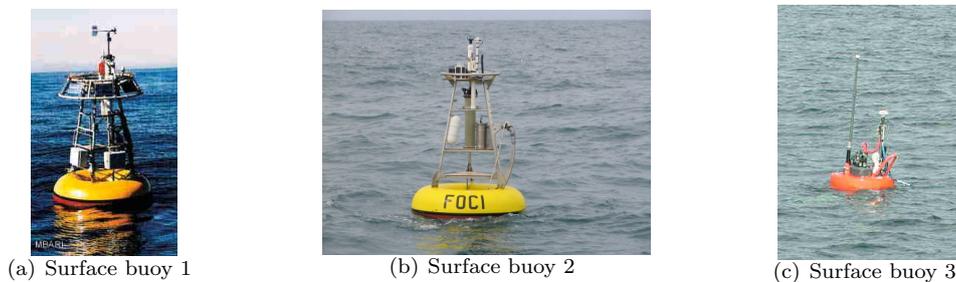


Figure 33: Autonomous Ocean Sampling Network [100]

The beacons deployed on the sea floor is also tested. The researchers from CSIRO ICT Centre, Massachusetts Institute of Technology and University of California conducted some novel experiments in the University of California Berkeley’s Richard B. Gump South Pacific Research Station to test the underwater robot localization and tracking [64]. The estimated locations of the Autonomous Modular Optical Underwater Robot (AMOUR) [101] using the acoustic sensor networks (see Fig. 34(a)) is compared with GPS, and the localization accuracy is better than 2.5m.

As described in Fig. 35(a), the US Navy Seaweb program which uses the surface and underwater beacons together aims to interconnect the fixed and mobile nodes, the satellites, the submarines, vessels, etc., performing the long-term acoustic ranging, localization, and navigation [102–105]. It is comprised of many parts including the design of AUVs (see Fig. 35(b)). Many experiments have been conducted since 1998, and there are over 40 Seaweb deployments, see Fig. 35(c).

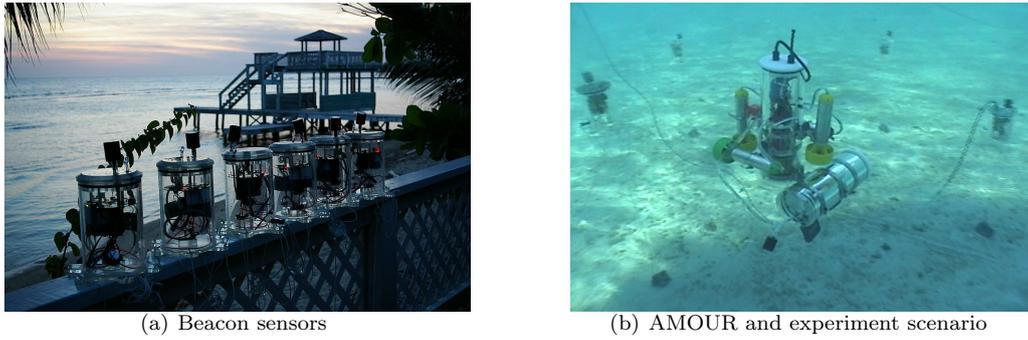


Figure 34: Experiments with underwater robot localization and tracking [64]

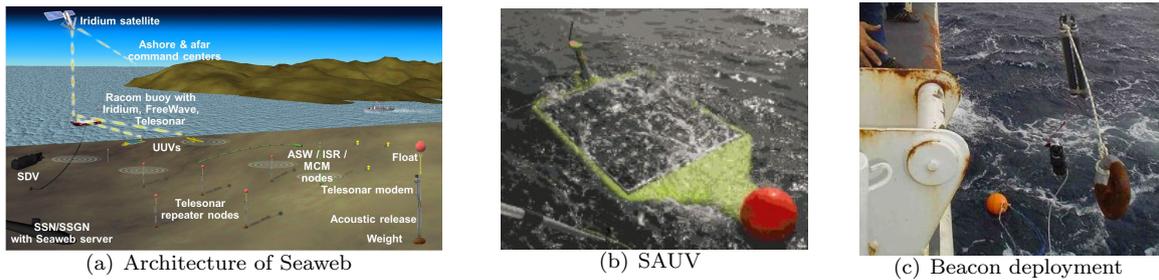


Figure 35: US Navy Seaweb program [102–105]

There are also some simulation and test tools for underwater sensor networks, such as the recent Sapienza University Networking framework for underwater Simulation, Emulation and real-life Testing (SUNSET) [106]. As shown in Fig. 36, it has been tested in reality although some other experiments are still carrying out.

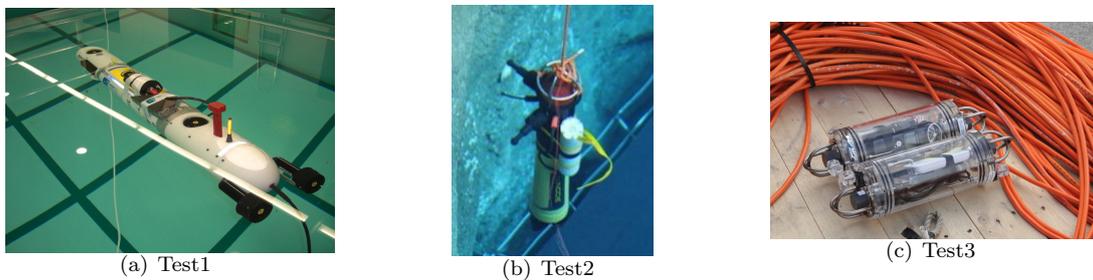


Figure 36: SUNSET [106]

5.2.2 Systems Without Static Beacon

However, almost all of the proposed UASN real systems perform the localization of the underwater robots powered by the propeller with the aid of the stationary or semi-stationary anchored sensors. To the best of our knowledge, MASL introduced in Subsection 4.3.1 is the only system which is tested in the actual sea without fixed anchors [91]. The vehicles can be commanded to maintain the various specific depths for a given amount of time in the trails. The experiment results verify the feasibility of this method.

5.2.3 Localization System for Robotic Fish

The localization of the robotic fish is the one where the underwater robot is not driven by the propeller. Because the onboard resources of the robotic fish are more limited than the general AUV's, the localization

problem of the robotic fish is more challenging, and it remains a great challenge to build an effective localization system for robotic fish. So far there are only two research groups investigating on the localization of robotic fish. One team is with Chonnam National University. The researchers separately use the GPS [107] and UASN [108, 109] methods to localize the robotic fish. With the aid of these localization systems, the robotic fish can autonomously swim, monitoring the water pollution and sending the environmental data.



Figure 37: Robotic fish [107]



Figure 38: GPS method [107]

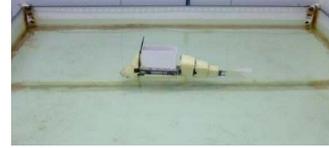


Figure 39: UASN method [108]

The other team is the Smart Microsystems Laboratory in Michigan State University. Its robotic fish equipped with acoustic sensors and RF utilizes the TDOA method to measure the distances [110]. In order to precisely detect the arrival of a monotone acoustic signal, a sliding-window discrete Fourier transform based algorithm is designed [111, 112]. Because the RF communication is used, the TDOA only works when the fish is on the surface. When it is underwater, the location is calculated using dead reckoning [113].

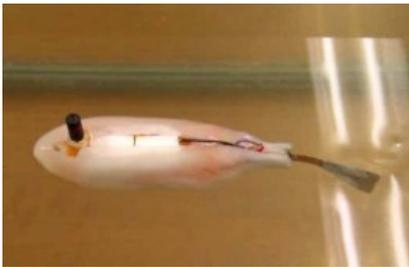


Figure 40: Robotic fish [110]

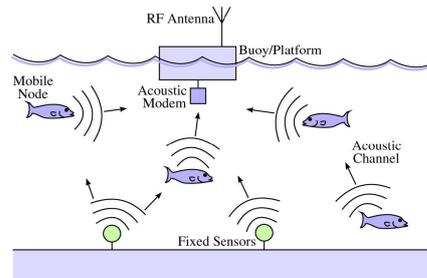


Figure 41: Architecture [112]

5.3 Summary

Although the experiment and test of the underwater sensor network system is more difficult than the terrestrial counterpart, many systems are implemented in practice. This is due to the increasingly demand of the underwater monitoring and exploring systems. Because of the constraints produced by the harsh underwater environment, the limited resources of the AUVs, etc., none of the underwater sensor network system is perfect now. There are still many problems for the implementation of the underwater sensor network systems.

6 Conclusions

In this report, a survey is conducted to summarize the challenges, the state-of-the-art algorithms and systems of underwater localization using WSN. First, several classic architectures and ranging methods are introduced. Then, many underwater localization algorithms and existing systems are presented.

Although the WSN based underwater localization has been investigated for years, there are still many challenging problems to be addressed, especially for the localization of the mobile networks and the mobile swarm. The underwater localization of robotic fish is also more difficult than that of the common AUV powered by the propeller.

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