An Actively Positioning System with an Accurate Localization Technique for Sunken Container via a Three-layer Network Structure

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ABSTRACT

Searching for the sunken container is a significant task when an accident happens. However, it is challenging to figure out the accurate position of the container in such a highly dynamic and complex ocean environment. The container must have passively waited for detection on the seabed via scanning technology, which is inefficient. To get rid of the situation, the paper proposes a three-layer network structure where the container equipped with the sensors can indirectly but actively indicate its location in the underwater layer and share it with users. Moreover, considering the acoustic signal stratification effect, a localization technique that combines the bisection method and a linear estimator is presented in the underwater layer. A theoretical analysis of the proposed technique is also conducted. Simulations demonstrate that the proposed method has a relatively satisfactory localization accuracy compared with other state-of-the-art approaches.

1. Introduction

Maritime shipping is the backbone of world trade, wherein the global container fleet is an essential part of the shipping industry (Tsiotas and Ducruet 2021). In what concerns the fleet, how to ensure the safety and completeness of the cargo is the crucial mission. Unfortunately, the property loss frequently happens when it suffers the extreme weather or the situation where containers are fastened inappropriately (Sunaryo and Hamka 2017). The loss might be huge, especially in the accident. In this case, finding the overboard containers as much as possible is considered a way to reduce the loss (Kim and Kwak 2016).

However, it is infeasible to figure out the lost containers in such a highly dynamic and complex ocean environment. Even though the containers may drift for a while on the sea surface, most cases are sunken to the seabed (Lydon 2021). Seafarers or the related staff cannot find the containers directly through vision, but some technology-aided, for instance, the scanning technology by radar or sonar (Yu et al. 2021). Nevertheless, the problem is that the sunken container has to wait for detection passively. What is worse, the area for scanning is generally undetermined because of the drifting behavior and the dynamics in the ocean environment. In this case, the scanning mission by radar or sonar may sometimes last for several days or months.

To this end, the paper proposes a novel positioning system where the sunken container can actively but indirectly indicate its location by the potential observations. Specifically, a three-layer network structure is proposed, including the underwater, surface, and space layers. The space layer is responsible for transmitting data to users, whereas the surface layer is for sharing information with satellites and assisting in locating the nodes underwater. Compared with the other two layers, the underwater layer communicates and is set up with the underwater wireless sensor networks via acoustic signal (J Luo et al. 2021). Moreover, the autonomous underwater vehicle (AUV) is considered a relay node that periodically moves from underwater to the surface to locate the rest of the nodes. Once the sunken container transmits the signal, the underwater layer would carry out some algorithms to locate the container and share the information with the relay node. Afterward, the information is shared and transmitted from the surface layer to users through the space layer. By doing this way, the container can indirectly but actively indicate its location.

After employing the three-layer network structure, the problem of finding the sunken container is then converted into localization in the underwater layer via the underwater sensors network. To locate the container accurately, the paper further investigates the localization method considering the stratification effect, a well-acknowledged but generally ignored factor in underwater localization. An accurate localization technique combing the bisection method and a linear estimator is further presented. In addition, the theoretical limit of the proposed positioning system is also analyzed.

The main contributions of the paper are:

1) a three-layer network structure is proposed, with which the sunken container can indirectly but actively

indicate its location;

2) by employing the structure, the mission for the searching container is converted into localization in the underwater layer;

3) an accurate localization technique and the theoretical limit of the proposed system are investigated.

The remainder of this paper is organized as follows. In Section 2, an overview of the related works for localization underwater is given. Section 3 presents a three-layer network structure and formulates the localization model. This model is further transformed into another expression in Section 4 to develop the proposed localization technique, and the corresponding theoretical limit is derived. Simulation results for several scenarios are presented in Section 5 to evaluate the performance of the proposed scheme. Finally, a summary of the paper is given in Section 6.

2. Related works for localization underwater

Unlike the terrestrial wireless sensor networks, the underwater wireless sensor networks suffer severe attenuation if directly using radio signals for communication. In this case, the acoustic signal is generally utilized for communication underwater (J Luo et al. 2021). Nevertheless, it is still challenging for localization underwater due to the low propagation speed and high time delay (Toky, Singh, and Das 2020). Consequently, extensive research has been dedicated to the literature on localization in underwater sensor networks (Junhai Luo et al. 2021; Saeed et al. 2019; Toky, Singh, and Das 2020).

To name a few, the authors in (Li et al. 2022) have investigated the underwater localization problem using mobility-constrained nodes, where two steps were presented to the system. In the former step, a delay compensation approach was designed to acquire the motion model whereas a particle system-based localization algorithm was proposed to figure out solution in the later step. The authors in (Kumari, Mishra, and Anand 2021) further considered the localization scenario with failure in anchors, wherein a metaheuristic scheme was proposed. In the scheme, the authors applied two techniques, including fuzzy logic and NSGA II to find the target location. On the contrary, the authors in (Misra, Ojha, and P 2020) holding the assumption of well-function anchors proposed a secure range-based localization scheme to handle the attack in the network.

In addition to the attack and failure of anchors in the network, localization in uncertain parameters or biases has been studied in the literature. For instance, the authors in (Mei et al. 2020) have presented an absorption mitigation technique in underwater target localization, wherein the absorption parameter is assumed to be unknown. In the reference of (Chang et al. 2019), the authors studied localization method without transmitting power. The localization problem is reformulated to a weighted least square expression, which is solved by a convex algorithm. Moreover, the localization technique proposed to tackle the non-line-of-sight bias has been illustrated in (Cao et al. 2021). A cepstrum-autocorrelation-based multipath estimation algorithm was developed to figure out a reliable solution.

However, aforementioned research simply assumes that the acoustic signal propagates along the straight line, which does not hold in practice. It has been well acknowledged since at least (Dong et al. 2022; Han et al. 2018) that the acoustic signal may suffer the stratification effect and propagate along with an isogradient model (Su, Li, and Ali 2022). Even though the previous research can have a relatively good localization accuracy, the same performance cannot be guaranteed in the presence of the stratification effect (Yan et al. 2021). Unfortunately, only a few studies have been investigated in that conditions. For instance, the author in (Dong et al. 2022) utilized the ray theory method to compensate for the stratification effect and developed an improved particle swarm optimization to search for the solution. Also, the authors in (Zhao et al. 2020) have developed a localization scheme in the underwater layer considering secure private information. Nevertheless, the accuracy still cannot meet the requirement for some specific schemes, for example, locating a sunken container in a highly dynamic environment.

To this end, the paper proposes an accurate localization technique in the underwater wireless sensor networks of the underwater layer. The original problem is converted into a generalized trust regional subproblem by simple manipulation and restricted conditions. A multiplier is then introduced in the procedure, where a bisection method integrated with a linear estimator is presented to figure out the solution.

3. Problem Formulation

3.1. Network Structure

The proposed positioning system is a three-layer structure that includes the underwater, surface, and space layers. It is worth noting that the radio signal may suffer severe attenuation underwater, which dramatically limits the capability of underwater communication (Khan, Das, and Pati 2020). Therefore, sensor nodes utilize acoustic signals for communication and networking in the underwater layer. In addition, to obtain the location information of the underwater sensor nodes, the proposed system considers AUV a relay node to interact with surface nodes via a periodic motion from surface to underwater. In the surface layer, vessels in navigation, buoys, and other deployed sensor nodes communicate and network through a radio signal. Some surface nodes also facilitate the acoustic system to communicate with the AUV and underwater nodes. The satellites collect the information from the surface layer in the space layer and transmit it to the base station and users. The corresponding structure diagram is depicted in Fig. 1. Specifically, when the container falls into the water and sinks to the seabed, the embedded nodes in the container would transmit the acoustic signal periodically. The underwater layer integrated with the surface layer uses the localization technique to determine container location and share its location with users via the network structure. Consequently, using the proposed structure, we would achieve the goal that the sunken container can be actively located instead of passively detected.

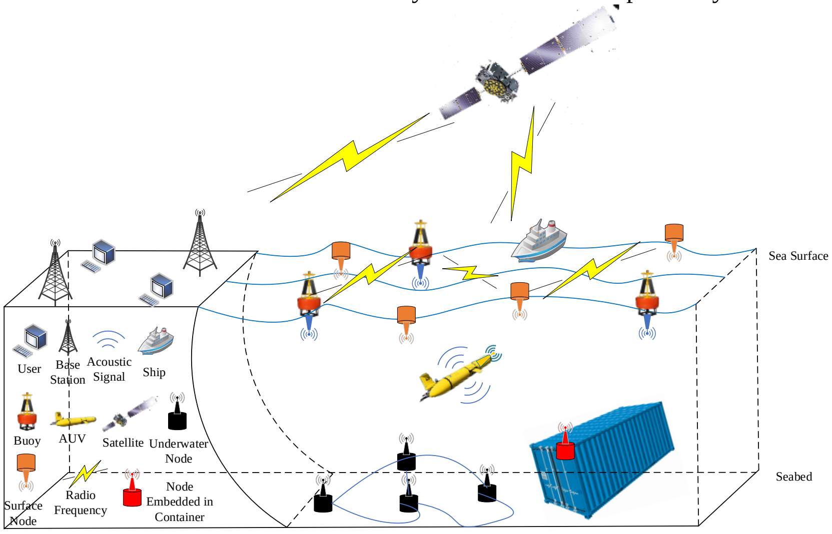

Fig. 1 A three-layer structure positioning system diagram

3.2. Acoustic Propagation Model Underwater

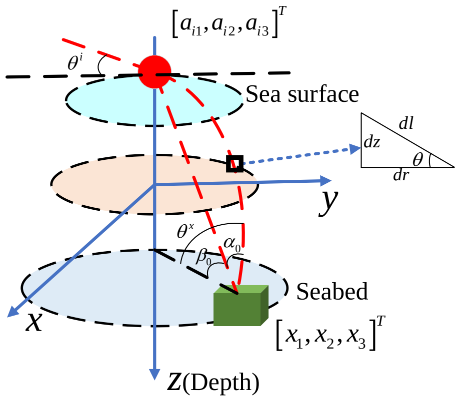

Fig. 2. Acoustic propagation model with stratification effect

Compared to the other two layers, the underwater layer seems more challenging since acoustic communication suffers the low propagation speed and limited bandwidth (Khan, Das, and Pati 2020). In this case, to some extent, whether the system can successfully locate the container depends on the underwater layer. Subsequently, we take more focus on the underwater layer, especially the localization by the acoustic signal.

To obtain accurate location information, inspired by (Ghafoor and Noh 2019), the proposed system adopts the ray-tracing model to formulate the localization problem, as shown in Fig. 2. Assume the sensor nodes can sense the depth information accurately with the depth unit equipped. The sunken container on the seabed can transmit the acoustic signal wherein the transmitting angle is θ^x. The received angle of the i^{th} sensor node is assumed to be θ^i. Let $\boldsymbol{a}_i = [a_{i1}, a_{i2}, a_{i3}]^T$ and $\boldsymbol{x} = [x_1, x_2, x_3]^T$ be the i^{th} sensor node and the container location, respectively, where T means the transpose operation. Then, following the Snell's law (J. Zhang et al. 2020), the acoustic signal obeys

$$\frac{\cos\theta}{C(z)} = \frac{\cos\theta^x}{C(x_3)} = \frac{\cos\theta^i}{(a_{i3})} = k, \text{and } \theta^i, \theta^x \in [-\pi/2, \pi/2], \tag{1}$$

where k is the constant, $C(\cdot)$ is the function of sound speed following the isogradient model (Su, Li, and Ali

2022) such that $C(z) = az + b$ wherein a represents the steepness of SSP, z indicates the depth, and b is the sound speed on the water surface.

Also, we can obtain from Fig. 2 that

$$\partial r = \frac{\partial z}{\tan\theta}, \partial l = \frac{\partial z}{\sin\theta}, \partial t = \frac{\partial l}{C(z)}, \tag{2}$$

where $r = \sqrt{(x_1 - a_{i1})^2 + (x_2 - a_{i2})^2}$, l is the arc length of a ray, and t indicates the travel time as given by

$$t = -\frac{1}{a}\left(\ln\frac{1+\sin\theta^i}{\cos\theta^i} - \ln\frac{1+\sin\theta^x}{\cos\theta^x}\right). \tag{3}$$

and $\theta^x = \beta_0 + \alpha_0$ and $\theta^i = \beta_0 - \alpha_0$ with $\beta_0 = \arctan[(a_{i3} - x_3)/r]$ and $\alpha_0 = \arctan\{ar/[2b + a(a_{i3} + x_3)]\}$.

With appropriate operation exploited from (1) and (2), the distance between the sunken container and the i^{th} sensor node can be rewritten as

$$R_i(\boldsymbol{x}) = -(ax_3 + b)\frac{\theta^x - \theta^i}{a\cos\theta^x}. \tag{4}$$

4. Proposed Localization Technique in Underwater Layer

4.1 Localization Framework

Unfortunately, it is infeasible to acquire the exact distance measurement in (4) due to the environmental noise underwater. In this case, we assume the distance measurements follow a specific distribution, such that

$$\rho_i = R_i(\boldsymbol{x}) + \gamma_i, \tag{5}$$

where ρ_i is the i^{th} observed measurement with the noise γ_i, which is supposed to be the Gaussian noise following zero mean and variance σ_i^2, i.e., $\gamma_i \sim \mathbb{N}(0, \sigma_i^2)$.

Only if at least four distance measurements are obtained in the 3D scenario, the container location can be determined via the localization technique (Saeed et al. 2020), for instance, maximum likelihood estimation (MLE) (Marxim Rahula Bharathi and Mohanty 2018).

Let $\boldsymbol{\rho}$ be the observation vector such that $\boldsymbol{\rho} = [\rho_i]^T, i = 1, \cdots, N$, then the probability density function (PDF) is

$$p(\boldsymbol{\rho}|\boldsymbol{x}) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma_i^2}} \left\{\frac{(\rho_i - \|\boldsymbol{x} - \boldsymbol{a}_i\|)^2}{2\sigma_i^2}\right\}, \tag{6}$$

where $\|\cdot\|$ is the ℓ_2 norm.

The container location can be obtained by maximizing the PDF in (6). Unfortunately, the computational complexity of MLE is relatively significant. In this case, the paper presents an alternative scheme described in the next part to figure out a solution.

4.2 Proposed Technique

In this part, as an alternative scheme for MLE, the localization problem is reformulated to a generalized trust regional subproblem (GTRS) by employing a certain restriction. A bisection method integrated with an unbiased linear estimator is presented to solve the problem.

With a simple transformation exploited, the MLE can be rewritten as a weighted least square expression (Jin, Xu, and Zhang 2018), as given by

$$\underset{\boldsymbol{x}}{\operatorname{argmin}} \sum_{i=1}^{N} \omega_i (\rho_i - \|\boldsymbol{x} - \boldsymbol{a}_i\|)^2. \tag{7}$$

where $\omega_i = 1 - \rho_i / \sum_{i=1}^{N} \rho_i$.

After squaring each term and expanding them, we have

$$\underset{\boldsymbol{x}}{\operatorname{argmin}} \sum_{i=1}^{N} \omega_i (\rho_i^2 - \chi + 2\boldsymbol{a}_i^T \boldsymbol{x} - \|\boldsymbol{a}_i\|^2)^2. \tag{8}$$

where $\chi = \|\boldsymbol{x}\|^2$.

An appropriate manipulation is conducted, then (8) can be rewritten as the GTRS problem, as given by

$$\underset{\boldsymbol{x}}{\operatorname{argmin}} \|\boldsymbol{\omega}(\boldsymbol{\Gamma\phi} - \boldsymbol{\Psi})\|^2, \tag{9a}$$

$$\text{s.t. } \boldsymbol{\phi}^T \boldsymbol{D} \boldsymbol{\phi} + 2\boldsymbol{f}^T \boldsymbol{\phi} = 0, \tag{9b}$$

where $\boldsymbol{\omega} = \operatorname{diag}([\omega_1^2, \cdots, \omega_N^2])$, $\boldsymbol{\phi} = [x_1, x_2, x_3, \chi]^T$, $\boldsymbol{f} = [\boldsymbol{0}_{1\times3}, -1/2]^T$, $\boldsymbol{D} = [\boldsymbol{I}_3, \boldsymbol{0}_{3\times1}; \boldsymbol{0}_{1\times3}, 0]^T$,

$$\boldsymbol{\Gamma} = \begin{bmatrix} -2\boldsymbol{a}_1^T & 1 \\ \vdots & \vdots \\ -2\boldsymbol{a}_N^T & 1 \end{bmatrix}, \text{and } \boldsymbol{\Psi} = \begin{bmatrix} \rho_1^2 - \|\boldsymbol{a}_1\|^2 \\ \vdots \\ \rho_N^2 - \|\boldsymbol{a}_N\|^2 \end{bmatrix}$$

with $\boldsymbol{I}$ indicating identity matrix and $\mathbf{0}$ representing zero matrix.

The problem in (9) is solvable if and only if some conditions are satisfied according to (Sun, Ho, and Wan 2019) such that

$$(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Gamma}+\lambda\boldsymbol{D})\boldsymbol{\phi}=\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Psi}-\lambda\boldsymbol{f}, \tag{10a}$$

$$\boldsymbol{\phi}^T\boldsymbol{D}\boldsymbol{\phi}+2\boldsymbol{f}^T\boldsymbol{\phi}=0, \tag{10b}$$

$$\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Gamma}+\lambda\boldsymbol{D}\succ 0, \tag{10c}$$

where $\lambda\in\mathbb{R}$ is the multiplier.

The entire process for solving (9) by a bisection method can be concluded as

1. Calculate λ according to $\varphi(\lambda)=\mathcal{H}^T\boldsymbol{D}\mathcal{H}+2\boldsymbol{f}^T\mathcal{H}=0$ with $\mathcal{H}=(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Gamma}+\lambda\boldsymbol{D})^{-1}(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Psi}-\lambda\boldsymbol{f})$.
2. Find optimal multiplier λ^* through $\max(-\mathrm{diag}(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Gamma})/-\mathrm{diag}(\boldsymbol{D}),\lambda)$.
3. Figure out $\widehat{\boldsymbol{\phi}}$ by $(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Gamma}+\lambda^*\boldsymbol{D})^{-1}(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Psi}-\lambda^*\boldsymbol{f})$.

After figuring out $\widehat{\boldsymbol{\phi}}$, the location of the sunken container can be determined, i.e., $\widehat{\boldsymbol{x}}=\widehat{\boldsymbol{\phi}}_{1:3}$. To further refine and maintain the stability of the solution, the paper proposes an unbiased linear estimator where the initiate is $\widehat{\boldsymbol{x}}$.

The cost function is constructed as

$$J=\left(\boldsymbol{g}-\widehat{\boldsymbol{\phi}}_{1:4}\right)^T\boldsymbol{\Gamma}^T\boldsymbol{\Gamma}\left(\boldsymbol{g}-\widehat{\boldsymbol{\phi}}_{1:4}\right), \tag{11}$$

where $\boldsymbol{g}=[\boldsymbol{x}^T,\boldsymbol{x}^T\boldsymbol{x}]^T$.

By exploiting the first-order Taylor series expansion of $\boldsymbol{g}-\widehat{\boldsymbol{\phi}}_{1:3}$ for $\boldsymbol{x}$ around $\widehat{\boldsymbol{x}}$, then we can obtain

$$\boldsymbol{g}-\widehat{\boldsymbol{\phi}}_{1:4}=\boldsymbol{\mathfrak{I}}+\boldsymbol{\mathcal{L}}(\boldsymbol{x}-\widehat{\boldsymbol{x}}), \tag{12}$$

where $\boldsymbol{\mathfrak{I}}=\boldsymbol{g}-\widehat{\boldsymbol{\phi}}_{1:3}=\begin{bmatrix}\mathbf{0}_{3\times1}\\ \|\widehat{\boldsymbol{x}}\|^2-\widehat{\boldsymbol{\phi}}_4\end{bmatrix}$ and $\boldsymbol{\mathcal{L}}=\frac{\partial\boldsymbol{g}}{\partial x^T}=\begin{bmatrix}2\widehat{\boldsymbol{x}}^T\\ \boldsymbol{I}_3\end{bmatrix}$.

Substituting (11) with (12), the unbiased linear estimator can be acquired as

$$J=\left(\boldsymbol{\mathfrak{I}}+\boldsymbol{\mathcal{L}}(\boldsymbol{x}-\widehat{\boldsymbol{x}})\right)^T\boldsymbol{\Gamma}^T\boldsymbol{\Gamma}\left(\boldsymbol{\mathfrak{I}}+\boldsymbol{\mathcal{L}}(\boldsymbol{x}-\widehat{\boldsymbol{x}})\right), \tag{13}$$

Eventually, the optimized solution can be expressed as (14) by taking the derivative of (13) and forcing it to 0.

$$\widetilde{\boldsymbol{x}}=\widehat{\boldsymbol{x}}-(\boldsymbol{\mathcal{L}}^T\boldsymbol{\Gamma}^T\boldsymbol{\Gamma}\boldsymbol{\mathcal{L}})^{-1}\boldsymbol{\mathcal{L}}^T\boldsymbol{\Gamma}^T\boldsymbol{\Gamma}\boldsymbol{\mathcal{L}}. \tag{14}$$

The corresponding pseudo-code of the proposed technique can be simply concluded below

The proposed localization technique:
1. Initiation: sensors' position, measurements according to (5)
2. Reformulate the problem to GTRS according to (9)
3. $\lambda\leftarrow\varphi(\lambda)=\mathcal{H}^T\boldsymbol{D}\mathcal{H}+2\boldsymbol{f}^T\mathcal{H}=0$.
4. $\lambda^*\leftarrow\max(-\mathrm{diag}(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Gamma})/-\mathrm{diag}(\boldsymbol{D}),\lambda)$
5. $\widehat{\boldsymbol{\phi}}\leftarrow(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Gamma}+\lambda^*\boldsymbol{D})^{-1}(\boldsymbol{\Gamma}^T\boldsymbol{\omega}\boldsymbol{\Psi}-\lambda^*\boldsymbol{f})$
6. $\widehat{\boldsymbol{x}}\leftarrow\widehat{\boldsymbol{\phi}_{1:3}}$
7. Construct the unbiased linear estimator according to (11) to (13)
8. Figure out the optimized solution according to (14)

4.3 Theoretical Limits for the Proposed Localization Technique

As the fundamental theoretical limit to an estimator in the system, Cramer Rao low bound (CRLB) is considered an effective calibration of one proposed estimation method (Sengijpta 1995). Basically, CRLB can be expressed as the trace of the inverse of the Fish Information Matrix (FIM), i.e.,

$$CRLB=\mathrm{trace}(FIM^{-1})=\left[\left(\frac{\partial R_i(\boldsymbol{x})}{\partial\boldsymbol{x}}\right)^T\sigma^{-2}\left(\frac{\partial R_i(\boldsymbol{x})}{\partial\boldsymbol{x}}\right)\right]^{-1}, \tag{15}$$

The derivative of $R_i(\boldsymbol{x})$ with subject to $\boldsymbol{x}$ can be conducted as

$$\frac{\partial R_i(\boldsymbol{x})}{\partial x_1}=-\frac{ax_3+b}{a\cos\theta^x}\left\{(1+(\theta^x-\theta^i)\tan\theta^x)\frac{\partial\theta^x}{\partial r_i}-\frac{\partial\theta^i}{\partial r_i}\right\}\frac{\partial r_i}{\partial x_1}, \tag{16a}$$

$$\frac{\partial R_i(\boldsymbol{x})}{\partial x_2}=-\frac{ax_3+b}{a\cos\theta^x}\left\{(1+(\theta^x-\theta^i)\tan\theta^x)\frac{\partial\theta^x}{\partial r_i}-\frac{\partial\theta^i}{\partial r_i}\right\}\frac{\partial r_i}{\partial x_2}, \tag{16b}$$

$$\frac{\partial R_i(\boldsymbol{x})}{\partial x_3}=-\frac{ax_3+b}{a\cos\theta^x}\left\{(1+(\theta^x-\theta^i)\tan\theta^x)\frac{\partial\theta^x}{\partial x_3}-\frac{\partial\theta^i}{\partial x_3}\right\}-\frac{\theta^x-\theta^i}{\partial\cos\theta^x}, \tag{16c}$$

where $r_i=\sqrt{(x_1-a_{i1})^2+(x_2-a_{i2})^2}$;

$$\frac{\partial\theta^x}{\partial r_i}=\frac{-F_1F_2}{1-F_2}\text{ and }\frac{\partial\theta^i}{\partial r_i}=\frac{F_1}{1-F_2}, \tag{17a}$$

$$\frac{\partial \theta^x}{\partial x_3} = \frac{F_4 - F_2 F_3}{1 - F_2} \text{ and } \frac{\partial \theta^i}{\partial x_3} = \frac{F_3 - F_4}{1 - F_2}, \tag{17b}$$

with

$$F_1 = \frac{x_3 - a_{i3}}{r_i^2} \frac{(\sin\theta^x - \sin\theta^i)^2}{1 - \cos(\theta^x - \theta^i)} \text{ and } F_4 = \frac{a}{a a_{i3} + b} \frac{\cos\theta^i}{\sin\theta^x}, \tag{18a}$$

$$F_2 = -\frac{a x_3 + b}{a a_{i3} + b} \frac{\sin\theta^i}{\sin\theta^x} \text{ and } F_3 = \frac{1}{r_i^2} \frac{(\sin\theta^x - \sin\theta^i)^2}{1 - \cos(\theta^x - \theta^i)}. \tag{18b}$$

By using (16), (17), and (18), the FIM can be rewritten as

$$FIM = \begin{bmatrix} \frac{\partial R_i(\boldsymbol{x})}{\partial^2 x_1} & \frac{\partial R_i(\boldsymbol{x})}{\partial x_1 \partial x_2} & \frac{\partial R_i(\boldsymbol{x})}{\partial x_1 \partial x_3} \\ \frac{\partial R_i(\boldsymbol{x})}{\partial x_2 \partial x_1} & \frac{\partial R_i(\boldsymbol{x})}{\partial^2 x_2} & \frac{\partial R_i(\boldsymbol{x})}{\partial x_2 \partial x_3} \\ \frac{\partial R_i(\boldsymbol{x})}{\partial x_3 \partial x_1} & \frac{\partial R_i(\boldsymbol{x})}{\partial x_3 \partial x_2} & \frac{\partial R_i(\boldsymbol{x})}{\partial^2 x_3} \end{bmatrix}. \tag{19}$$

5. Simulation and discussion

To evaluate the proposed positioning system for sunken container, the paper performs simulations in Matlab R2021b. The sensor nodes are randomly deployed in 200 m × 200 m × 200 m area from the sea surface to underwater. The nodes equipped with GPS can sense their location and network in the surface layer by a certain protocol. Moreover, some nodes underwater can also be aware of their location via periodical communication with the AUV (relay node). In addition, considering the negative effect of the current, we utilize the random walk model (Wang et al. 2021) to mimic the dynamics of sensor nodes and the container. In other words, at each Monte Carlo trial, the positions of nodes and container are changeable. The rest parameters are set as: $a = 0.1$, $b = 1473$ m/s. Besides, some localization methods are introduced, including privacy-preserving localization (PPSL) (Zhao et al. 2020), matrix factorization-based majorization minimization (MFMM) (Mei, Wu, and Xian 2020), weighted least square (WLS) (B. Zhang et al. 2019), and CRLB in (15) as the comparison. The root mean square error is used as the calibration, which can be expressed as

$$RMSE = \sqrt{\frac{1}{M} \sum_{j=1}^{M} (\tilde{\boldsymbol{x}} - \boldsymbol{x})^2}, \tag{20}$$

where M is the total number of Monte Carlo trials that we set 1000 in simulations, and j means the current trial.

5.1 Scenario with different sensor nodes

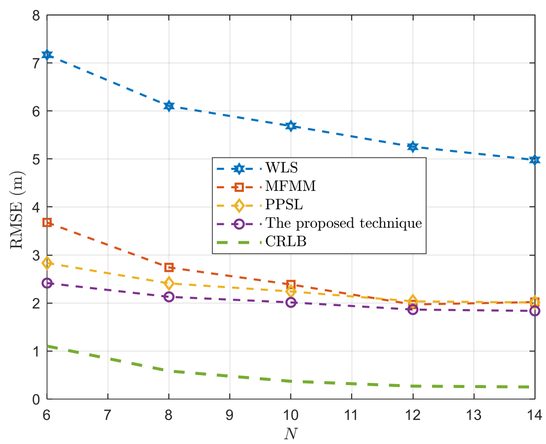

Fig. 3. RMSE versus different sensor nodes

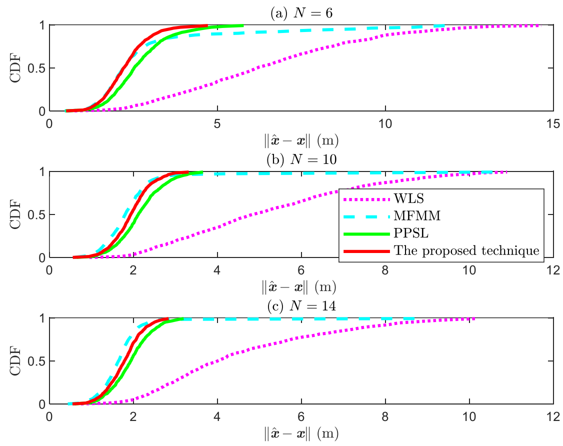

Fig. 4. CDF of the methods in different sensor nodes

To figure out the relationship between the number of sensor nodes and localization performance, the paper executes simulations setup with $\sigma_i^2 = 5$ m. The corresponding RMSE of different sensor nodes is shown in Fig. 3. It is worth noting that the available measurement information increases when N grows. In this context, the localization accuracy is improved for all methods. When N is small, the proposed technique's performance seems to be better than the others. Though the performance is similar among the proposed technique and some methods, including PPSL and MFMM, the average error for the technique is less than the others. The outperformance can be demonstrated further in Fig. 4, in which the cumulative distribution function (CDF) of the methods in different sensors is depicted. When it comes to $N = 6$, the proposed technique can reach $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 3.18$ m at almost 90 percent, whereas the other methods achieve the same probability with $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 5.58$ m for MFMM, $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 3.85$ m for PPSL, and $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 10.46$ m for WLS. Moreover, we can find that even though the performance of MFMM is better than the proposed technique when N increases, the CDF of the proposed technique is superior. For instance, the proposed technique can achieve $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 2.83$ m at 99 percent for $N = 14$, whereas MFMM reaches the same probability at $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 8.66$ m. Overall, the proposed technique is better than the others and approaches to CRLB.

5.2 Scenario with different noises

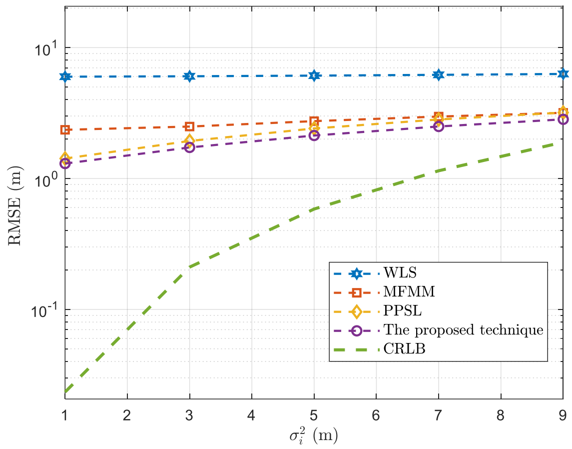

Fig. 5. RMSE versus different noises

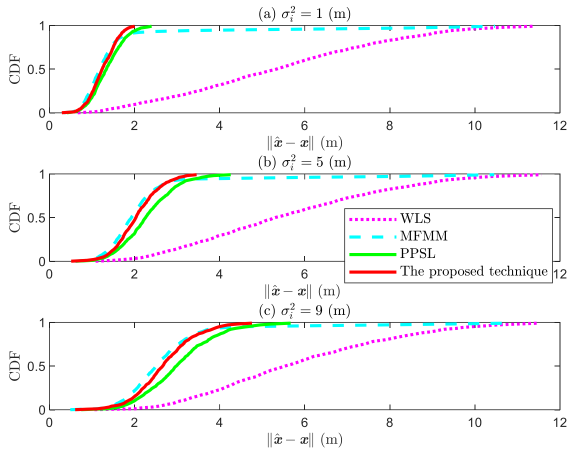

Fig. 6. CDF of the methods in different noises

To evaluate the effectiveness of the proposed technique in different noises, the paper executes simulations setup with $N = 8$. The RMSE versus different noises is depicted in Fig. 5. As expected, the error becomes large over the rise in the noise. Although the performance seems robust in terms of WLS, the localization error is the largest among the methods. Also, it can be seen from Fig. 5 that the margin between CRLB and the others is significant when the noise is slight. However, the margin comes small when the noise grows. The proposed technique seems to be better than the other to some extent, which can be illustrated further in Fig. 6. In the scenario with $\sigma_i^2 = 1$ m, the proposed technique reaches $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 1.98$ m at almost 99 percent, whereas $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 10.38$ m for MFMM, $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 2.39$ m for PPSL, and $\|\tilde{\boldsymbol{x}} - \boldsymbol{x}\| \leq 11.31$ m for WLS. The same outperformance can be seen in the scenario with $\sigma_i^2 = 5$ m and $\sigma_i^2 = 9$ m, as shown in Fig. 6 (b) and Fig. 6 (c).

5.3 Calculation time for different methods

Table 1 Calculation time for different methods

Method	Time for different scenarios (s)					
	Different Sensor Nodes			Different Noises		
	$N = 6$	$N = 10$	$N = 14$	$\sigma_i^2 = 1$ m	$\sigma_i^2 = 5$ m	$\sigma_i^2 = 9$ m
WLS	8.97e-5	1.12e-4	1.35e-4	1.11e-4	9.81e-4	9.55e-5
MFMM	9.91e-4	1.0e-3	1.1e-3	1.10e-3	1.00e-3	9.57e-4
PPSL	2.77e-5	3.16e-5	3.63e-5	3.33e-5	2.88e-5	2.04e-5
The proposed technique	**1.40e-3**	**1.60e-3**	**1.70e-3**	**1.30e-3**	**1.40e-3**	**1.40e-3**

In addition to the localization accuracy, efficiency is another vital factor for the positioning system. Thus, in this part, we count the corresponding calculation time for the methods in different scenarios, as shown in Table 1. Apparently, PPSL has a relatively good calculation efficiency. On the contrary, the proposed technique is not the satisfied one where the average time is 1.45e-3 s. Honestly, this is a common problem in figuring out the trade-off between computational efficiency and localization accuracy. The proposed technique enhances the system's performance at the cost of extra computational time. Luckily, the time seems tolerant because it is less than 0.1 s at each round. Overall, the proposed technique is also a good choice for the positioning system for locating the sunken container.

6. Conclusion

This paper proposes a three-layer network structure wherein the localization of sunken containers is carried out in the underwater layer. With the sensor node embedded in the container, the status of being passively detected becomes actively indicated via the positioning system. Moreover, considering the acoustic signal stratification effect in the underwater layer, the paper proposes a localization technique that transforms the problem to GTRS expression. A bisection method integrated with a linear estimator is represented to figure out the solution. Experiments show that the proposed technique can have a relatively satisfactory performance compared with other state-of-the-art methods at the cost of computational time. After obtaining the solution, the corresponding location information would be transmitted to users from the three-layer network structure. In that way, the container can indirectly but actively indicate its location instead of being passively detected. In future work, we would like to investigate the method that can simultaneously balance the localization accuracy and the efficiency.

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