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Differential Received Signal Strength-Based Localization for an Iso-gradient Sound Speed Profile with Unknown Transmitted Power

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Abstract- **localization plays a significant role in many underwater applications. Underwater communications encounter critical challenges different from terrestrial wireless sensor networks. In this study, we focus on the challenges of the variable sound speed underwater and synchronization. Among localization approaches, the received signal strength (RSS) is cost-effective and, unlike time-based approaches is synchronization-free. In some applications, the source transmitted power is unknown or hard to obtain. While this parameter is required to be known in RSS-based approaches, it is not a requirement in differential RSS (DRSS) based approaches. Regarding these issues, in this paper, we propose a DRSS-based localization algorithm considering an iso-gradient sound speed profile in an underwater medium when the source transmitted power is unknown. To improve the received signals' SNR, we use a network of sensor arrays where beamforming is conducted within each array. Then, DRSS values are calculated and the iterative DRSS-based localization algorithm is presented. We show the effectiveness of the proposed algorithm compared with the Array-RSS and the Array-TDOA algorithms via computer simulations. Results indicate that the Array-DRSS performs accurately when the source transmitted power is unknown. Moreover, it outperforms the Array-TDOA algorithm when low bandwidth is available.**

Index Terms- Asynchrony, Differential Received Signal Strength (DRSS), Localization, Sound speed profile, Unknown transmitted power.

I. INTRODUCTION

Estimating the location of an unknown source has attracted significant attention due to its extensive usage in lots of underwater applications. Generally, localization can be accomplished via time-based, energy-based, or angle-based approaches. Each approach has its specifications which makes it suitable to be applied in a specific application. Time-based approaches include the time of arrival (TOA) and the

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time difference of arrival (TDOA) methods. In the former case, all sensors should be synchronized not only with each other but also with a source node, while in the latter, only synchronization between source and sensor nodes is required. It should be noted that one of the serious challenges of underwater communications is the lack of synchronization among sensor nods. This problem is more critical in underwater acoustic sensor networks (UASNs) than in terrestrial wireless sensor networks (WSNs) due to the long and variable propagation delay in underwater channels. It results from the low propagation speed of acoustic waves in the underwater medium [1]. Generally, underwater communications encounter other challenges, such as low bandwidth, large delay spread, time-variability of the medium, variable sound speed, and multipath propagation [1]. However, here we focus on the asynchrony challenge and variable sound speed in an underwater medium. It should be noted that the performance of time-based approaches is weak in asynchronous networks. However, they are accurate in synchronous networks especially when high bandwidth is available. Thus, for underwater communications' inherently limited channel bandwidth, time-based localization approaches have lower performance in UASNs than terrestrial WSNs. The other localization approach is the energy-based one, including received signal strength (RSS), and differential received signal strength (DRSS). The most important characteristic of these two approaches is their robustness against the challenge of asynchrony. Thus, they are considered suitable approaches for localization in asynchronous UASNs. On the other hand, the performance of energy-based approaches depends on the fading phenomenon. The main difference between RSS and DRSS approaches is that, contrary to DRSS, the source transmitted power must be known at receiving sensors in RSS-based approaches. However, this parameter is unavailable in some applications, such as those with an uncooperative transmitter. Furthermore, in surveillance applications, localization should be performed without informing the source node. Although the source transmitted power parameter can be estimated in some ways, the results are primarily inaccurate due to the noisy underwater measurements. Therefore, DRSS-based approaches are a good alternative for these purposes. In this study, we focus on the DRSS to address the unknown transmitted power problem.

It is worth mentioning that machine learning-based techniques and meta-heuristic algorithms can overcome some of the shortcomings of traditional methods such as high localization error and long computation time. However, applying these techniques in underwater applications is not as popular as in terrestrial WSN due to some technical issues. In this regard, limited investigations are available. As an example, [2] addressed machine learning-based UASN Localization where linear frequency modulation is applied to detect the target’s position and velocity. Furthermore, some investigations employed various meta-heuristic techniques to solve the localization problem, such as Genetic algorithm [3], particle swarm optimization [4], Whale optimization [5], Elephant herding optimization [6], Ant colony [7], and Cuckoo search [8]. The aim of these approaches is mainly the reduction of localization error and improving accuracy.

Regarding the considerable progress in underwater networks, localization is assumed a fundamental task in a great number of underwater applications and requires deep investigation. It is worth pointing out that acoustic waves are the best choice for underwater communications. The principal reason is that radio frequency (RF) waves incur strong attenuation in an underwater medium, and optical wave propagates over a short distance. It should be noted that one of the main differences between acoustic communications in underwater environments and free space is sound speed. The underwater, contrary to the free space, is an inhomogeneous medium due to the water salinity, temperature, and pressure on the sound speed. These factors cause the acoustic wave travels over a curved path when propagating underwater, however, the wave speed is constant in a free space and propagates along a straight line. In general, as the salinity, pressure, and temperature of the water are depth-dependent, it causes the sound speed to change nonlinearly and non-monotonically with depth. The sound speed variation versus depth is demonstrated via a curve named sound speed profile (SSP). An actual SSP can be assumed to compose of several layers with iso-gradient sound speed [9]. However, in this study, we consider a deep underwater medium and model the sound speed variation with a single iso-gradient layer. Extensive DRSS-based localization methods and algorithms are developed in free space (as a homogeneous medium). Examples are [10]-[22] which address the localization problem with unknown transmitted power. However, these methods cannot be applied underwater because they are developed under the assumption of straight-line wave propagation. In this case, the LOS distance between a transmitter and a receiver relates to the RSS. However, in an underwater medium where waves propagate along a curved path, the distance between a transmitter and a receiver relates to the RSS via very nonlinear relations. This makes solving a localization problem complicated. Even in the localization approaches proposed for underwater applications, researchers ignored assuming the inhomogeneity of the underwater medium [23]-[26]. For that, these algorithms' accuracy significantly degrades when applied in actual underwater conditions. Some studies took the challenge of the underwater medium inhomogeneity into account and examined the localization problem in a UASN. Examples are the OSMF-RSS [27], the Array-RSS [28], the RD-TLA [29], and the developed algorithms in [30]-[31]. In these algorithms, the source transmitted signal is assumed to be known, and localization is performed based on measuring the RSS parameter.

To the best of our knowledge, the problem of DRSS-based localization under the assumption of variable sound speed in an underwater environment has not been addressed in previous studies. In this work, we address the localization problem in an iso-gradient sound speed profile when a priori knowledge of source transmitted power is unavailable. For that, we take advantage of the DRSS approach in a network of asynchronous arrays and propose the Array-DRSS localization algorithm while considering the challenge of the underwater medium inhomogeneity. Thus, the contributions of this study are:

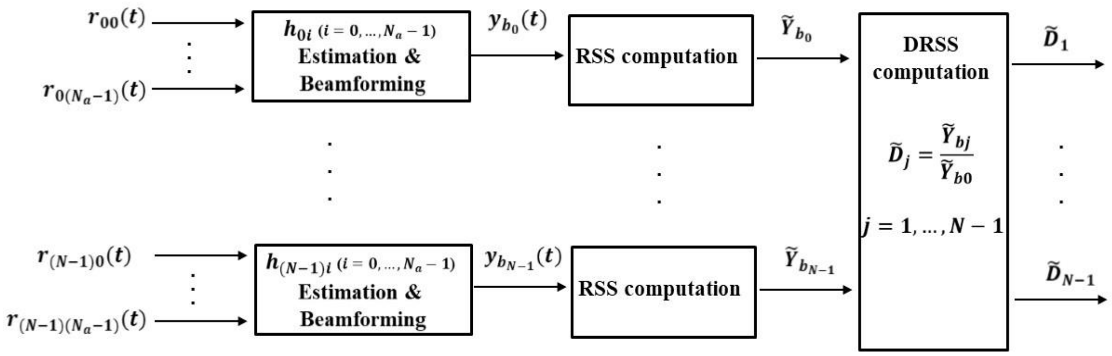

Fig. 1. The procedure of measuring the DRSS parameter in a sensor array.

- developing a DRSS-based localization algorithm under the assumption of an iso-gradient sound speed profile for underwater environment when source transmitted power is known,
- applying a network of asynchronous sensor arrays to boost the signal-to-noise ratio (SNR) of the received signal.

The rest of this paper is organized as follows. Section II explains the DRSS model in a sensor array under the iso-gradient sound speed variation assumption. In section III, we develop the Array-DRSS localization algorithm in an asynchronous UASN. Then, the results of the computer simulations are presented in section IV. Finally, the conclusion is given in section V.

II. MODEL DESCRIPTION

In this paper, the network is assumed to be composed of N uniform arrays where each array consists of N_a sensors with known positions. The spacing between the array's element, d, satisfies $d \leq \frac{\lambda}{2}$ where $\lambda = \frac{c}{f_C}$ is the signal wavelength and f_C shows the wave frequency. In each array, one sensor node is chosen as a reference node. The position of the i-th sensor in an array is defined as $\mathbf{x}_i = (x_i, y_i, z_i)$ for $i = 0, 1, \ldots, N_a - 1$. The source node position, which we aim to estimate, is shown as $\mathbf{x}_t = (x_t, y_t, z_t)$. In the network, it is assumed that sensors within each array are synchronous with each other while being asynchronous with the source node. In our proposed approach, as depicted in Fig. 1, the source transmitted signal is first received via N sensor arrays. The first step estimates the beamforming weights of sensors within each array to have a high SNR signal. Then, beamforming is performed, and a high SNR signal is obtained in the reference sensor of each array. In the next step, the RSS of high SNR signals is computed and the DRSS parameter is calculated. In the following, the proposed approach is explained in detail.

In this study, we assume the underwater environment is deep with no reflections from the sea surface or sea bottom. The variation of different environmental parameters such as water salinity, temperature, and pressure in different underwater depths causes an acoustic wave propagates along a curved path. Here, the variation of the environmental parameters is assumed constant. Thus, the underwater environment can be considered a single layer with an iso-gradient sound speed profile. In other words, the sound speed is modeled via $c(z) = \alpha z + b$ [32] where α shows the sound speed gradient and b is the sound speed at the water surface. It should be mentioned that precise modeling of sound speed in an underwater environment is complicated. To be more accurate, the underwater medium can be modeled as multiple iso-gradient layers and are not in the scope of this paper. Noted that due to the curved path wave propagation in an inhomogeneous underwater medium, the previously developed DRSS-based localization algorithms do not work accurately underwater.

Consider that a sound source transmits signal $S(t)$ with the power p_S and the effective bandwidth W. The received signal via sensors of an array can be expressed in a vector form as

$$\mathbf{r}(t) = \mathbf{a}s(t) + \mathbf{n}(t), \tag{1}$$

where $\mathbf{a} = [a_0, \dots, a_{N_a-1}]^T$ defines the steering vector of the array, and for an inhomogeneous underwater medium, its i-th element is defined as

$$a_i(r_t - r_i, \theta_{ti}, \theta_i) = A_i \exp(-j\omega\tau_i). \tag{2}$$

Here, τ_i shows the TOA of the received signal at the i-th sensor of the array and is as [32]

$$\tau_i = \frac{-1}{\alpha}\left(\ln\frac{1+\sin\theta_{ti}}{\cos\theta_{ti}} - \ln\frac{1+\sin\theta_i}{\cos\theta_i}\right), \tag{3}$$

where θ_{ti} and θ_i are, respectively, the wave angle at the i-th sensor and source. The parameter A_i in (2) indicates the attenuation of the transmitted signal while propagating the channel to reach the i-th sensor of the array and is calculated in [27] as

$$A_i{}^2 = \frac{1}{L_i(r_t - r_i, \theta_{ti})}, \quad -\frac{\pi}{2} < \theta_{ti} < \frac{\pi}{2}, \tag{4}$$

and L_i is called the signal spreading loss and is calculated as $L_i(r_t - r_i, \theta_{ti}) = \frac{(r_t - r_i)^2}{\cos\theta_{ti}{}^2}$. The term $(r_t - r_i) = \sqrt{(x_t - x_i)^2 + (y_t - y_i)^2}$ shows the horizontal distance between the i-th sensor and the source node.

The noise in (1) is zero mean Gaussian white and is as $\mathbf{n}(t) = [n_0(t), \dots, n_{N_a-1}(t)]^T$. Regarding the noises of an array's sensors are uncorrelated and of the same power, the noise covariance matrix is as $\sigma^2\mathbf{I}$ where $\sigma^2 = WN_0$ and $\frac{N_0}{2}$ is the noise power spectral density. Thus, the signal-to-noise ratio of the array's i-th sensor is defined as $SNR_i = \frac{A_i{}^2 p_S}{\sigma^2}$.

According to Fig. 1, the received signal in sensors is first passed through a beamformer to produce a high SNR signal. For that, it is required to estimate the beamforming weights. According to [28], the weight coefficient of the array's i-th sensor is computed from TDOA measurement as Here, the measured

$$\hat{h}_i = \exp\left(-j\omega\left(\hat{T}_{i0}\right)\right). \tag{5}$$

measured TDOA is defined as $\hat{T}_{i0} = T_{i0} + \varepsilon_i$ where the TDOA parameter can be obtained from (3) as $T_{i0} = \tau_i - \tau_0$. The TDOA estimation noise is Gaussian distributed as $\varepsilon_i \sim \mathrm{N}\ (0, \sigma_{f_i}^2)$ with

$$\sigma_{f_i}{}^2 = \sigma_{f_0}{}^2 = \frac{6}{8\pi^2 W^2 SNR_0}. \tag{6}$$

the variance Therefore, the array's beamformer output, which is the sum of weighted received signals at the array's reference node, can be written as

$$y_b(t) = N_a A_0 s(t - \tau_0) + \sum_{i=0}^{N_a-1} n_{bi}(t), \tag{7}$$

with the zero mean Gaussian noise distribution $n_b \sim \mathrm{N}\ (0, \sigma_b^2)$. Under the assumption of similar noise power for sensor nodes within an array, we have

$$\sigma_b^2 = N_a(A_0^2 p_{S'} \sigma_{f_0}^2 + \sigma^2). \tag{8}$$

Here, $p_{S'}$ is the power of $\acute{s}(t)$, the derivative of the signal $s(t)$, and $\sigma_{f_0}^2$ is defined in (6). Thus, the SNR of the array's beamformer output is as

$$SNRI = \frac{N_a^2 A_0^2 p_s}{N_a A_0^2 p_{S'} \sigma_{f_0}^2 + N_a \sigma^2}. \tag{9}$$

It should be noted that if the source's signal bandwidth is high enough that the estimation noises of weight coefficients can be neglected (in comparison with the receiver noise), (9) can be expressed as $SNRI \cong N_a SNR_0$. Note that sensors within an array must be synchronized with each other. Thus, TDOA can be performed. However, different arrays can be asynchronous.

Regarding (9), the output of each array can be a high SNR signal where, as displayed in Fig. 1, its RSS value should be computed. The RSS computation block in Fig. 1 consists of a matched filter through which the beamformed signal is first passed; then, the output is oversampled several times the Nyquist rate. Based on [27], the sample with the maximum value is the best candidate for the RSS value. Thus, to decrease the samples' noise variance, corresponding samples over an observation time interval are averaged; then, the maximum value is chosen. It is proven in [27] that the peak of the averaged observed samples in a time interval can be considered as the RSS value of a received signal with high probability. We make use of this result and obtain the RSS of the beamformed signal as

$$\tilde{Y}_b = \frac{N_a p_s}{\sqrt{L_0}} + \delta\,. \tag{10}$$

The upper bound of the noise variance of the RSS sample can be written as $var[\tilde{Y}_b] \leq \frac{N_a p_s p_{\acute{s}} \sigma_{f_0}^2}{M L_0} + \frac{N_a p_{\acute{s}}^2}{M L_0 SNR_0}$.

In the next step, after computing RSS values in all arrays' reference nodes, DRSS values must be calculated, as shown in Fig. 1. For that, one array should be considered as a reference. The array with

$j = 0$ is assumed as the reference, and the RSS values calculated from other arrays are divided by the RSS of the reference array. In this way, the measured DRSS between the j-th and the reference array, regarding (10), can be formulated as where, regarding (4), L_{00} and L_{j0} are the loss of the beamformed

$$\widetilde{D}_j = \frac{\tilde{Y}_{b_j}}{\tilde{Y}_{b_0}} = \frac{\frac{1}{\sqrt{L_{j0}}} + \frac{\delta_j}{N_a p_S}}{\frac{1}{\sqrt{L_{00}}} + \frac{\delta_0}{N_a p_S}}, \qquad j \neq 0, \tag{11}$$

signals computed at the reference sensor nodes of the reference and the j-th array, respectively. Note that the size of the DRSS sample set becomes $N - 1$. By applying the Taylor series expansion, (11) can be approximated as

$$\widetilde{D}_j = \frac{\sqrt{L_{00}}}{\sqrt{L_{j0}}} + \sqrt{L_{00}}\left(\frac{\delta_j}{N_a p_S}\right) - \frac{L_{00}}{\sqrt{L_{j0}}}\left(\frac{\delta_0}{N_a p_S}\right) - L_{00}(\delta_0 \delta_j) + \frac{\sqrt{L_{00}^3}}{\sqrt{L_{j0}}}{\delta_0}^2 + \cdots, \;\; j \neq 0. \tag{12}$$

The mean of the DRSS parameter obtained in (12) is

$$E\left[\widetilde{D}_j\right] = \frac{\sqrt{L_{00}}}{\sqrt{L_{j0}}} + \frac{\sqrt{L_{00}^3}}{\sqrt{L_{j0}}}\left(\frac{\sigma_{\delta_0}^2}{N_a^2 p_S^2}\right)\cdots, \qquad j \neq 0, \tag{13}$$

and its variance is

$$var\left[\widetilde{D}_j\right] = L_{00}\left(\frac{\sigma_{\delta_i}^2}{N_a^2 p_S^2}\right) + \frac{L_{00}^2}{L_{j0}}\left(\frac{\sigma_{\delta_0}^2}{N_a^2 p_S^2}\right) + \cdots, \qquad j \neq 0 \tag{14}$$

Thus, (11) can be reformulated as

$$\widetilde{D}_j = \frac{\tilde{Y}_{b_j}}{\tilde{Y}_{b_0}} = \frac{\sqrt{L_{00}}}{\sqrt{L_{j0}}} + w_j, \qquad j \neq 0, \tag{15}$$

where w_j is the DRSS measurement noise between the j-th and the reference array with mean $\frac{\sqrt{L_{00}^3}}{\sqrt{L_{j0}}}\left(\frac{\sigma_{\delta_0}^2}{N_a^2 p_S^2}\right)$ and variance

$$\sigma_{w_j}^2 = L_{00}\left(\frac{\sigma_{\delta_j}^2}{N_a^2 p_S^2}\right) + \frac{L_{00}^2}{L_{j0}}\left(\frac{\sigma_{\delta_0}^2}{N_a^2 p_S^2}\right), \qquad j \neq 0. \tag{16}$$

Equation (15) indicates that the measured DRSS is related to the source location via $\frac{\sqrt{L_{00}}}{\sqrt{L_{j0}}}$. It should be noted that N_a and SNR values affect the DRSS measurement noise. Thus, in sufficiently high SNRs and when arrays with an increased number of elements are used, it can be assumed that $L_{00}\left(\frac{\sigma_{\delta_0}^2}{N_a^2 p_S^2}\right) \ll 1$. In other words, the mean of the DRSS measurement noise in (15) approaches zero.

III. ARRAY-DRSS BASED LOCALIZATION ALGORITHM

This section develops an iterative localization algorithm based on the DRSS. It is assumed the network that is composed of N arrays consisting of N_a sensor nodes. The DRSS measured at $N-1$ reference sensors of arrays can be formulated as

$$\widehat{\mathbf{D}} = \mathbf{D} + \mathbf{w}, \tag{17}$$

where $\mathbf{D} = [D_1,\ D_2, \dots, D_{N-1}]^{\mathrm{T}}$ and D_j is defined regarding (15) as $\frac{\sqrt{L_{00}}}{\sqrt{L_{j0}}}$. Moreover, $\widehat{\mathbf{D}} = [\widehat{D}_1,\ \widehat{D}_2, \dots, \widehat{D}_{N-1}]^{\mathrm{T}}$ is obtained through measurements, and $\mathbf{w} = [w_1,\ w_2, \dots, w_{N-1}]^{\mathrm{T}}$ is the Array-DRSS measurement noise with the covariance matrix as

$$\mathbf{R}_w(\mathbf{q}) = \frac{L_{00}}{N_a^2 p_s^2}\begin{bmatrix} \sigma_{bf_1}^2 + \frac{L_{00}\sigma_{bf_0}^2}{L_{10}} & \cdots & \frac{L_{00}\sigma_{bf_0}^2}{\sqrt{L_{10}L_{(N-1)0}}} \\ \frac{L_{00}\sigma_{bf_0}^2}{\sqrt{L_{20}L_{10}}} & \cdots & \frac{L_{00}\sigma_{bf_0}^2}{\sqrt{L_{20}L_{(N-1)0}}} \\ & \vdots & \\ \frac{L_{00}\sigma_{bf_0}^2}{\sqrt{L_{(N-1)0}L_{10}}} & \cdots & \sigma_{bf_{N-1}}^2 + \frac{L_{00}\sigma_{bf_0}^2}{L_{(N-1)0}} \end{bmatrix}. \tag{18}$$

When the source signal bandwidth is high enough, and the estimation noises of weight coefficients is ignored, (18) can be rewritten as

$$\mathbf{R}_w(\mathbf{q}) = \frac{1}{N_a p_s SNR_{00}}\begin{bmatrix} 1 + \frac{L_{00}}{L_{10}} & \cdots & \frac{L_{00}}{\sqrt{L_{10}L_{(N-1)0}}} \\ \frac{L_{00}}{\sqrt{L_{20}L_{10}}} & \cdots & \frac{L_{00}}{\sqrt{L_{20}L_{(N-1)0}}} \\ & \vdots & \\ \frac{L_{00}}{\sqrt{L_{(N-1)0}L_{10}}} & \cdots & 1 + \frac{L_{00}}{L_{(N-1)0}} \end{bmatrix}. \tag{19}$$

Although the noise covariance matrix is unknown, it can be obtained from measurements. Therefore, the source location can be estimated via

$$\hat{\mathbf{x}}_t = \underset{\mathbf{x}_t}{\operatorname{argmin}} \ \{(\mathbf{D}(\mathbf{x}_t) - \widehat{\mathbf{D}})^T \mathbf{R}_w{}^{-1}(\mathbf{D}(\mathbf{x}_t) - \widehat{\mathbf{D}})\}. \tag{20}$$

Regarding the nonlinear solution of (20), Gauss-Newton is applied where in the $l+1$ iteration, we have

$$\mathbf{x}_t^{l+1} = \mathbf{x}_t^l - \left(\left(\nabla\mathbf{D}(\mathbf{x}_t^l)\right)^T \mathbf{R}_w{}^{-1}\left(\nabla\mathbf{D}(\mathbf{x}_t^l)\right)\right)^{-1}\left(\nabla\mathbf{D}(\mathbf{x}_t^l)\right)^T \mathbf{R}_w^{-1}\left(\mathbf{D}(\mathbf{x}_t^l) - \widehat{\mathbf{D}}\right). \tag{21}$$

The term $\nabla\mathbf{D}(\mathbf{x}_t^l)$ is calculated as

$$\nabla\mathbf{D}(\mathbf{x}_t^l) = \left[\frac{\partial D_1(\mathbf{x}_t)}{\partial \mathbf{x}_t}, \dots, \frac{\partial D_{N-1}(\mathbf{x}_t)}{\partial \mathbf{x}_t}\right]^T_{\mathbf{x}_t = \mathbf{x}_t^l}, \tag{22}$$

where for $j = 1, \dots, N-1$, we have

$$\frac{\partial D_j(\mathbf{x}_t)}{\partial \mathbf{x}_t} = \left[\frac{\partial D_j(\mathbf{x}_t)}{\partial x_t}, \frac{\partial D_j(\mathbf{x}_t)}{\partial y_t}, \frac{\partial D_j(\mathbf{x}_t)}{\partial z_t}\right]^T. \tag{23}$$

The partial derivatives in (23) for the inhomogeneous underwater medium are computed as

$$\frac{\partial D_j(\mathbf{x}_t)}{\partial x_t} = \frac{\partial D_j(\mathbf{x}_t)}{\partial r_t}\frac{\partial r_t}{\partial x_t}, \tag{24a}$$

$$\frac{\partial D_j(\mathbf{x}_t)}{\partial y_t} = \frac{\partial D_j(\mathbf{x}_t)}{\partial r_t}\frac{\partial r_t}{\partial y_t}. \tag{24b}$$

IV. COMPUTER SIMULATIONS

Computer simulations are carried out to evaluate the effectiveness of our proposed Array-DRSS algorithm in estimating the location of a sound source that is asynchronous with our deployed sensor network. The results are compared with the Array-RSS [28] and the Array-TDOA algorithms in different scenarios. As the accuracy of TOA based localization algorithm degrades considerably in asynchronous networks, obtained results are not compared with this approach. Simulations are carried out assuming that the underwater environment is inhomogeneous and acoustic signals travel over curved paths. The parameters of the assumed sound speed model are chosen as $\alpha = 0.1\ s^{-1}$ and $\beta = 1480\ \frac{m}{s}$.

The proposed algorithm is assumed to conduct in a sensor network composing $N = 5$ asynchronous square arrays to localize a sound source located at an unknown position. The sensor arrays are considered at positions $[100\ 100\ 0;\ 0\ 0\ 0;\ 100\ 0\ 0; 0\ 100\ 0; 0\ 0\ 100]$ which show a cube's vertices that its sides' length is 100 m. Each array consists of $N_a = 9$ synchronous sensor nodes. The sound source position is assumed to be $[50\ 50\ 50]$; however, this position is unknown for sensor arrays, and the aim is to estimate it via the proposed Array-DRSS algorithm. When an acoustic sound is emitted from a sound source and is received by sensors of the deployed network, the proposed algorithm procedure begins. In the first step, responsible for obtaining a high SNR signal, the reference sensor node in each array conducts beamforming within its array. Note that sensors located within an array must be synchronized. In this way, the reference nodes can compute the TDOA value, which is required to calculate the beamforming weights. After beamforming, reference nodes calculate the RSS of the obtained high SNR signals. For computing DRSS values, one of the arrays is chosen as the reference array, and the RSS values of all the other arrays are divided by the reference RSS value. Then, the sound source location is estimated through the proposed iterative algorithm. The results are evaluated via the root mean square error. Remembering synchrony among arrays is not required in computing DRSS values for source localization is essential. However, in time-based localization algorithms, the asynchrony among arrays severely degrades the localization performance. In simulations, $M = 1000$ is chosen.

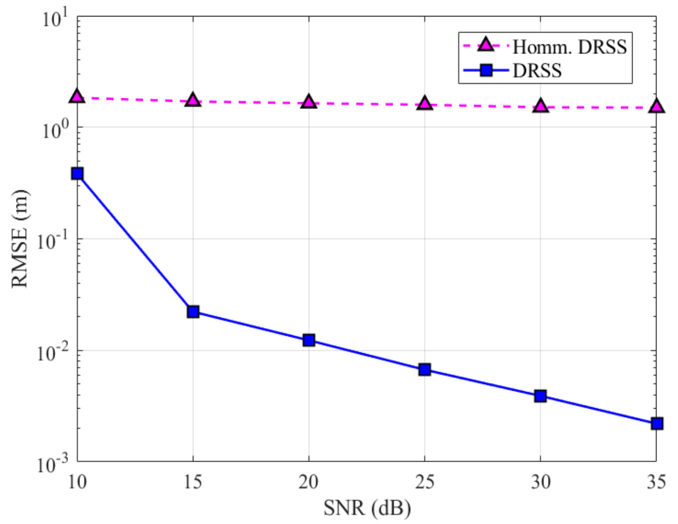

Fig. 2. RMSE of location estimation vs. SNR when $N_a = 1$.

The effect of the underwater medium inhomogeneity on the DRSS-based localization algorithm performance is depicted in Fig. 2. In a simulation, we neglect the inhomogeneity of the underwater medium and assume the acoustic waves propagate along a straight line underwater. The DRSS algorithm is executed, and its results are demonstrated by a curve named “Homm. DRSS”. This curve shows that the accuracy of location estimation severely degrades and is not improved by increased SNR. In another simulation, we take the inhomogeneity of the underwater medium into account and assume a change in an acoustic wave speed during propagation. This time, a significant improvement in the accuracy of the DRSS algorithm is observed when SNR increases. Fig. 2 demonstrates that the localization techniques proposed in WSNs do not work accurately in underwater applications. The reason is that underwater communications encounter challenges not considered in developing WSN localization techniques.

In Fig. 3, different localization algorithms' performance in terms of SNR is compared when they are used in an array structure with $N_a = 9$. Moreover, the performance of the proposed Array-DRSS is compared with its CRLB. It is demonstrated that the Array-DRSS converges to the CRLB in high SNRs. It can also be observed that the increase in the SNR causes the performance improvement of the Array-DRSS, the Array-RSS, and the Array-TDOA algorithms. It should be noted that the Array- DRSS is executed in a case where the source transmitted power is unknown for sensor arrays. However, the source transmitted power must be known in both the Array-RSS and the Array-TODA algorithms. Moreover, the Array-DRSS and the Array-RSS algorithms are performed in an asynchronous scenario. It means the source is assumed to be asynchronous with the sensor array network, and the arrays are also asynchronous. However, in the Array-TDOA approach, the sensor arrays must first become synchronized, which is a challenging task in an underwater medium. In the absence of synchronization, the accuracy of this algorithm in location estimation severely degrades.

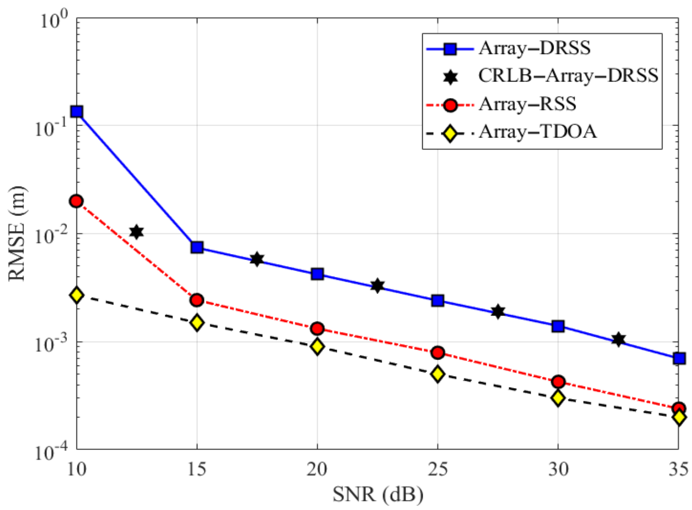

Fig. 3. RMSE of location estimation vs. SNR when $N = 5$.

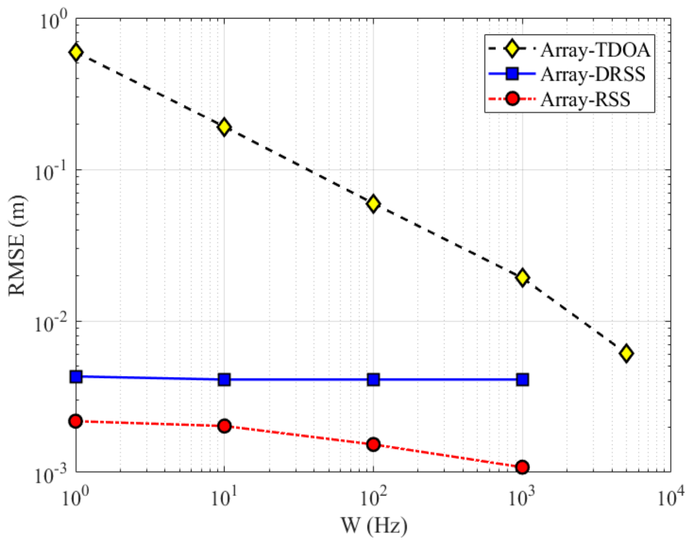

Fig. 4. RMSE of location estimation vs. bandwidth when $N = 5$.

Another point about the Array-TDOA algorithm is that its performance is highly dependent on the signal bandwidth. In Fig. 3, it is assumed that $W = 500$ KHz. However, in an underwater medium, the available bandwidth is limited, and this algorithm shows weak accuracy. The effect of signal bandwidth on different algorithms is discussed in more detail in the following.

In Fig. 4, the performance of different localization algorithms is compared in terms of the received signal bandwidth for SNR $= 20$ dB, and $N_a = 9$. As observed, the performance of the Array-TDOA, contrary to energy-based approaches, highly depends on the source signal bandwidth. It works accurately in high bandwidths. However, the available bandwidth underwater is limited. For that, the Array-DRSS and the Array-RSS algorithms perform more accurately in underwater applications.

The effect of an increase in the number of arrays' elements on the Array-DRSS algorithm's accuracy is displayed in Fig. 5. When N_a increases, the SNR of the beamformed signal improves and causes more accurate location estimation via the Array-DRSS algorithm.

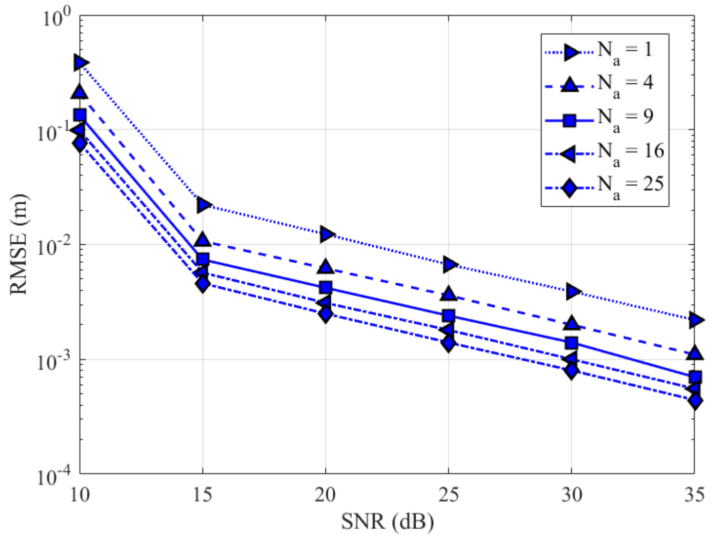

Fig. 5. RMSE of location estimation vs. SNR in the Array-DRSS in terms of different N_a.

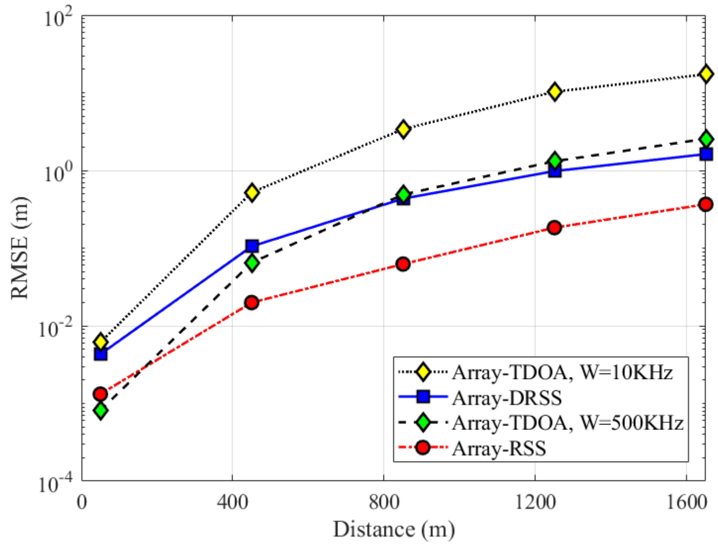

Fig. 6. RMSE of location estimation vs. the source distance from the center of the network when $N = 5$ and SNR = 20 dB.

It can be concluded that although the performance of the DRSS-based algorithm is not considerably improved by increasing W, using arrays with a high number of elements can boost its accuracy. As an example, the error in Fig. 5 degrades from 0.385 to 0.077 when the number of array elements increases to 25 in SNR = 10 dB.

In Fig. 6, the source node is assumed to get far from the network center, and different algorithms are evaluated in SNR = 20 dB and $N_a = 9$. The performance of all approaches degrades by increasing the distance of the sound source from the network. The performance of the Array-TDOA is illustrated for two different bandwidths. As shown in Fig. 6, in low bandwidths, for example, $W = 10$ KHz, the Array-TDOA has a weak performance, while its performance improves by an increase in W.

V. CONCLUSIONS

In this paper, we addressed the problem of location estimation in an asynchronous UASN under the assumption of iso-gradient sound speed profile when the source transmitted power is unknown. The unknown transmitted power is a critical problem in some applications. Regarding this issue, we proposed the Array-DRSS localization algorithm and evaluated its performance via computer simulations.

Simulation results indicated that DRSS-based localization algorithms developed in WSN do not work accurately in underwater applications as the challenge of variable speed of acoustic waves is not considered. Moreover, comparing the results of the Array-RSS and Array-DRSS algorithms revealed some performance degradation of the Array-DRSS algorithm. Noted that this degradation is the cost of overcoming the unknown transmit power. Moreover, the Array-RSS algorithm was assumed to perform in a fully synchronized network. A comparison of the results with the Array-TDOA algorithm indicated the outperformance of our proposed approach in low bandwidths. In other words, the effectiveness of the Array-TDOA algorithm, contrary to the Array-DRSS, highly depends on the signal bandwidth. The results furthermore revealed the performance improvement of the proposed approach by an increase in the number of array’s elements.

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