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Low-rank approximation for underwater drone localization

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Abstract

We herein propose a low-approximated least-squares method for underwater drone localization that does not require depth information. On the basis of error analysis, we propose a rule to deploy a set of surface drones that minimizes the impact of measurement errors such as GPS or distance measurement errors. The Evaluation results indicate that the proposed method outperforms the least-squares method when depth information is not provided.

Keywords: Underwater; Localization; SVD

1. Introduction

In recent years, using multiple mobile sensors or robots has gained increasing attention due to demand from various applications, such as search, rescue, disaster relief, target tracking and monitoring [1–4]. Wireless sensor networks have proven to be effective and efficient for many tasks in different environments, utilizing small, low-power, wireless sensor nodes to collect and transmit real-time data on physical phenomena such as temperature, humidity, pressure, light, sound, and motion. Mobile sensors and robots are also being used in underwater environments for various applications such as ocean exploration, marine life monitoring, and underwater infrastructure inspection. These underwater mobile sensors and robots can collect data and perform tasks that would otherwise be difficult or impossible for humans to do. By enabling the mobility of a sensor or robot in underwater environments, systems can cover a vast area and rapidly adapt, even when sudden events occur. In such situations, the localization of sensors and robots plays an important role. Locations can be used to collect data, track nodes, locate targets, and optimize routing protocols and medium access.

Unlike in terrestrial environments, radio waves are rapidly attenuated in underwater environments; therefore, direct localization using the Global Positioning System (GPS) cannot be performed [5]. Instead, floating anchor nodes (defined as surface drones, SDs) that receive GPS signals are deployed to provide reference positions to the underwater drones (UDs). Sonar waves were then used to determine the distance or angle between the SDs and the UDs. However, the speed of sonar waves varies according to the temperature and density of the water. Furthermore, the direction of these waves is not always fixed in a straight line owing to changes in the water density. Therefore, the propagation time cannot be translated into exact range measurements; there exists a mismatch between the measured ranges.

Various solutions have been proposed for the localization of underwater robots and sensors. Autonomous underwater vehicle (AUV)-based localization for sparsely distributed sensors was proposed in [6]. Grid-based localization and transmit beamforming using pre-computed channel-stage information on every grid point were proposed in [7]. In line with recent developments in artificial intelligence, deep-learning-based localization was proposed in [8,9]. Among these methods, range-based schemes have been widely used. For instance, most recent algorithms often take the form of a range-based method by adding additional assistance such as a Doppler shift [10] or hybrid forms that mix range and angle [11,12]. The least-squares algorithm is usually used to estimate the location of UDs, as in [13,14].

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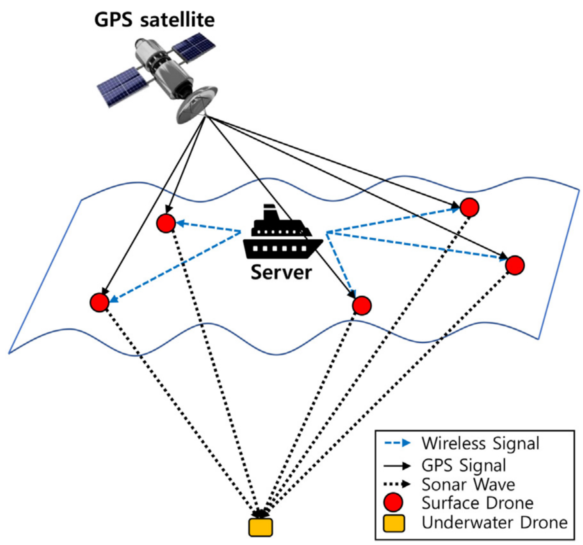

Fig. 1. Overview of underwater localization and system.

However, if only SDs are used as anchor nodes, identifying underwater locations can become challenging. Since all SDs are placed on the horizontal plane, system may encounter significant measurement errors. To avoid this problem, it is usually assumed that depth information is provided, as in [15–17]. Depth information was used to project the location of the UD on the plane where the underwater sensors reside. However, enabling the ability to measure depth for UDs could be a burden, since adding additional devices to measure depth would consume significant power, and battery replacement is difficult underwater.

To address this issue, this paper proposes a new localization method, namely the low-rank approximated least-squares localization algorithm. This algorithm does not require depth information, thereby eliminating the need for depth measurement and associated burdens. However, our low-rank approximated least-squares localization algorithm does not require depth information, which relieves the burden of depth measurement. Furthermore, using an error analysis, we show that the relative placement of SDs for UDs can affect localization; and propose deployment conditions for SDs to reduce localization errors.

The remainder of this paper is organized as follows. In Section 2, we provide an overview of the proposed system model. In Section 3, the localization algorithm and an error analysis are presented. Section 4 describes the details of the simulation and simulation results. Finally, our contributions are summarized in Section 5.

2. System model

Fig. 1 illustrates the operational model considered in this study. The system consists of a server, multiple floating SDs, and a group of UDs. The server controls and navigates both SDs and UDs and can be located on a ship, airplane, satellite, or terrestrial basement. SDs float on the surface of water, and because they have the ability to receive GPS signals, they can localize themselves accordingly. They were connected to the central server via radio communication. The server chooses a set of SDs that transmit the position information or beacon signals. The UDs then receive this position information from the SDs and estimate the distance to each SD based on the transmission delay, received signal strength, and arrival-time difference. Subsequently, the UDs perform a localization calculation and transmit their position information to any nearby SDs, which then relays the location of each UD to its server.

The location of a single UD is of interest herein. The position of the UD of interest is defined as $\mathbf{p} = [x, y, z]^{\mathrm{T}} \in \mathbb{R}^3$. M SDs, numbered $\mathrm{SD}_1, \mathrm{SD}_2, \ldots, \mathrm{SD}_M$, are located on the surface of the water and sensor node UD is submerged with underwater depth z. We assume that the SDs can receive GPS signals from the satellite and compute their position. We express the location error of each SD_i as $\mathbf{n}_i$; and the estimated location of SD_i is described by the sum of true locations $\mathbf{s}_i$ and $\mathbf{n}_i$ as follows:

$$\hat{\mathbf{s}}_i = \mathbf{s}_i + \mathbf{n}_i, \qquad \text{for} \quad i = 1, 2, \ldots, M. \tag{1}$$

The position coordinates of SD_i obtained by GPS are given by $\hat{\mathbf{s}}_i = \left[\hat{s}_{x_i}, \hat{s}_{y_i}, \hat{s}_{z_i}\right]^{\mathrm{T}} \in \mathbb{R}^3$. The jitter of the range of the SD_i is expressed as J_i, and the range measurement $\hat{d}_i$ of SD_i including jitter is described as follows

$$\hat{d}_i = d_i + J_i, \qquad \text{for} \quad i = 1, 2, \ldots, M. \tag{2}$$

When the number of available information sources is M, M Euclidean vector-norm equations can be obtained by

$$\left\|\hat{\mathbf{s}}_i - \mathbf{p}\right\|^2 = \hat{d}_i^2, \qquad \text{for} \quad i = 1, 2, \ldots, M. \tag{3}$$

Without loss of generality, $\hat{\mathbf{s}}_1$ is moved to the origin, and all others are redefined as $\hat{\mathbf{s}}_i = \hat{\mathbf{s}}_i - \hat{\mathbf{s}}_1$ and $\mathbf{p} = \mathbf{p} - \hat{\mathbf{s}}_1$. Upon additional modification, (3) becomes

$$\|\mathbf{p}\|^2 = \hat{d}_1^2 \quad \text{and} \quad \hat{\mathbf{S}}\mathbf{p} = \mathbf{b}, \tag{4}$$

where $\hat{\mathbf{S}} = [\hat{\mathbf{s}}_2, \hat{\mathbf{s}}_3, \ldots, \hat{\mathbf{s}}_M]^{\mathsf{T}}$ and $b_i = \frac{1}{2}(\|\hat{\mathbf{s}}_i\|^2 + \hat{d}_1^2 - \hat{d}_i^2)$ for $i = 2, 3, \ldots, M$. Localization is to estimate $\mathbf{p}$ given $\hat{\mathbf{s}}_i$ and $\hat{d}_i$ for $i = 1, \ldots, M$.

3. Proposed localization method

Fig. 2 shows a brief overview of the proposed method. m SDs are randomly selected during the first localization, and the selected SDs transmit their position information and beacon signals to the UD. Then, the UD estimates the distance to each SD by using beacon signals, and the estimated location of the UD is obtained using the low-rank approximated least-squares method. From this estimated location of the UD, a set of SDs is newly chosen using the proposed selection rule. This selected set of SDs is then used to update the location of the UD, and can further update its own membership at later instances.

3.1. Localization with low-rank approximated least square

The localization computation is expressed by solving (4). However, because the SDs are located near the surface plane, the z-coordinates of the SDs are approximately zero. Thus,

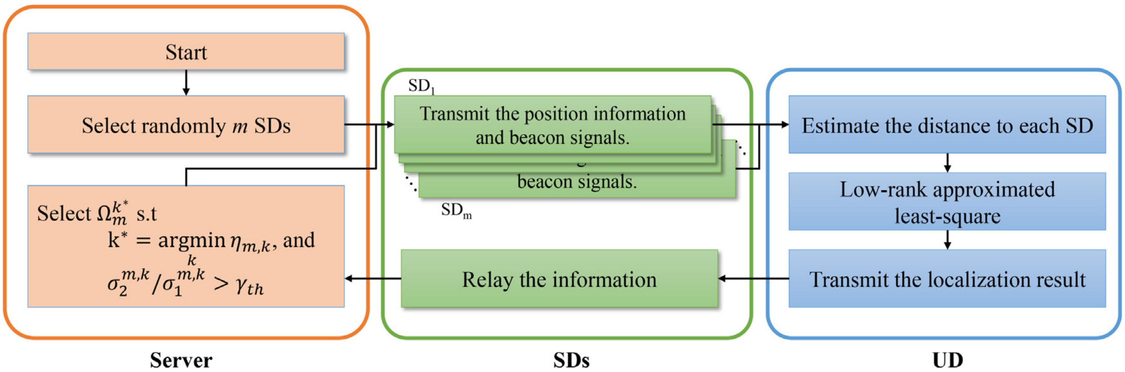

Fig. 2. Illustration of the proposed method.

$\hat{\mathbf{S}}^\intercal\hat{\mathbf{S}}$ is an ill-conditioned matrix and is likely not invertible. When applying the least square solution $\hat{\mathbf{p}} = \left(\hat{\mathbf{S}}^\intercal\hat{\mathbf{S}}\right)^{-1}\hat{\mathbf{S}}^\intercal\mathbf{b}$, a small error in $\hat{\mathbf{S}}$ and $\mathbf{b}$ results in a large error in the estimation of $\mathbf{x}$. Therefore, in conventional works [15–19], the depth of the UD is usually assumed to be given and is used to project the coordinates of SDs to the plane where the UD resides. To solve this problem without depth information, we convert the 3D problem into a 2D problem by using the low-rank approximated least-squares method in singular value decomposition (SVD). The SVD of $\hat{\mathbf{S}}$ can be expressed as follows

$$\hat{\mathbf{S}} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\intercal, \tag{5}$$

where $\mathbf{U} \in \mathbb{R}^{(M-1)\times 3}$; $\mathbf{\Sigma} \in \mathbb{R}^{3\times 3}$, $\mathbf{V} \in \mathbb{R}^{3\times 3}$; $\mathbf{U}^\intercal\mathbf{U} = \mathbf{I}$; $\mathbf{V}^\intercal\mathbf{V} = \mathbf{I}$; $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3]$; and $\Sigma = \mathrm{diag}\,(\sigma_1, \sigma_2, \sigma_3)$ where $\sigma_1 \geq \sigma_2 \gg \sigma_3 \approx 0$, because all SDs are co-plane. Because $\mathbf{v}_1$, $\mathbf{v}_2$, and $\mathbf{v}_3$ are orthonormal, $\mathbf{p}$ can be expressed as

$$\mathbf{p} = \mathbf{V}_{1,2}\mathbf{q} + k\mathbf{v}_3, \tag{6}$$

where $\mathbf{V}_{1,2} = [\mathbf{v}_1, \mathbf{v}_2]$, $\mathbf{q} \in \mathbb{R}^{2\times 1}$, and $k \in \mathbb{R}$. By using (4) and (6), we get

$$\begin{aligned}\hat{d}_1^2 &= \left\|\mathbf{V}_{1,2}\mathbf{q} + k\mathbf{v}_3\right\|^2 = (\mathbf{V}_{1,2}\mathbf{q} + k\mathbf{v}_3)^\intercal(\mathbf{V}_{1,2}\mathbf{q} + k\mathbf{v}_3)\\ &= \|\mathbf{q}\|^2 + k^2.\end{aligned} \tag{7}$$

Therefore,

$$k = \pm\sqrt{\hat{d}_1^2 - \|\mathbf{q}\|^2}. \tag{8}$$

By applying (6) to (4), we obtain

$$\begin{aligned}\hat{\mathbf{S}}\mathbf{p} &= \hat{\mathbf{S}}\mathbf{V}_{1,2}\mathbf{q} + \mathbf{k}\hat{\mathbf{S}}\mathbf{v}_3 = \hat{\mathbf{S}}\mathbf{V}_{1,2}\mathbf{q} + \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\intercal\mathbf{v}_3\\ &= \hat{\mathbf{S}}\mathbf{V}_{1,2}\mathbf{q} + \mathbf{U}\mathbf{\Sigma}[\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3]^\intercal\mathbf{v}_3 = \hat{\mathbf{S}}\mathbf{V}_{1,2}\mathbf{q} + \mathbf{U}[0, 0, \boldsymbol{\sigma}_3]\\ &\approx \hat{\mathbf{S}}\mathbf{V}_{1,2}\mathbf{q} + 0 = \tilde{\mathbf{S}}\mathbf{q} = \mathbf{b},\end{aligned} \tag{9}$$

where $\tilde{\mathbf{S}} = \hat{\mathbf{S}}\mathbf{V}_{1,2}$. The problem of finding $\mathbf{x} \in \mathbb{R}^{3\times 1}$ becomes finding $\mathbf{q} \in \mathbb{R}^{2\times 1}$. The solution for $\mathbf{q}$ is obtained from the least-squares method as follows:

$$\hat{\mathbf{q}} = \left(\tilde{\mathbf{S}}^\intercal\tilde{\mathbf{S}}\right)^{-1}\tilde{\mathbf{S}}^\intercal\mathbf{b}. \tag{10}$$

Finally, $\mathbf{p}$ is estimated as

$$\hat{\mathbf{p}} = \mathbf{V}_{1,2}\hat{\mathbf{q}} + k\mathbf{v}_3, \tag{11}$$

where $\hat{\mathbf{q}} = \left(\tilde{\mathbf{S}}^\intercal\tilde{\mathbf{S}}\right)^{-1}\tilde{\mathbf{S}}^\intercal\mathbf{b}$. By using (8), the sign of k must be determined. The sign of k is determined by choosing the sign that results in $\hat{\mathbf{x}}$ whose third element is lower than zero, because the UD is underwater.

3.2. Error analysis

The estimated locations of the SDs and distance measurements are inaccurate, which may affect the localization of the UD. The error is calculated by applying (1) and (2) to (4), and the result is expressed as

$$\mathbf{e} = \mathbf{S}\mathbf{p} - \mathbf{b} = \underbrace{\begin{pmatrix} H_2 - H_1\\ H_3 - H_1\\ \vdots\\ H_m - H_1\end{pmatrix}}_{\mathbf{H}} + \underbrace{\begin{pmatrix} G_2 - G_1\\ G_3 - G_1\\ \vdots\\ G_m - G_1\end{pmatrix}}_{\mathbf{G}}, \tag{12}$$

where

$$G_i = -(\hat{\mathbf{s}}_i - \mathbf{p})^\intercal\mathbf{n}_i - \frac{1}{2}\|\mathbf{n}_i\|^2 \quad \text{and} \tag{13}$$

$$H_i = J_i\hat{d}_i + \frac{1}{2}J_i^2. \tag{14}$$

To further elucidate this analysis, the error covariance matrix of $\mathbf{G}$ and $\mathbf{H}$ must be constructed; however, the covariance matrix of error includes many unnecessary components. For the covariance matrix of $\mathbf{G}$, the core parts are expressed as

$$(\hat{\mathbf{s}}_i - \mathbf{p})^\intercal(\hat{\mathbf{s}}_j - \mathbf{p})\mathbf{n}_i^\intercal\mathbf{n}_j, \quad \text{for} \quad i, j = 1, 2, \ldots, M. \tag{15}$$

The vector $(\hat{\mathbf{s}}_i - \mathbf{p})$ for any i can be considered as the vector from the SD$_i$ to UD, for $i = 1, \ldots, M$. Then, (15) is the multiplication of two vectors from each SD to UD. The larger the correlation $(\hat{\mathbf{s}}_i - \mathbf{p})^\intercal(\hat{\mathbf{s}}_j - \mathbf{p})$ for the system for any i and j where $i \neq j$, the more sensitive does the system become. Because $(\hat{\mathbf{s}}_i - \mathbf{p})^\intercal(\hat{\mathbf{s}}_j - \mathbf{p})$ is the inner product of the two vectors, it is recommended to select SDs in the direction orthogonal to the UD to reduce errors. For jitter, H_i is dependent on the range $\hat{d}_i$ in (14), and selecting SDs located in a relatively short range from the UD is beneficial to reduce localization errors.

On the basis of error analysis, we propose a selection rule to reduce errors when m SDs out of M SDs are used for localization. The SD group set contains K SD groups, which are defined as $\boldsymbol{\Omega}(m, M) = \{\Omega_m^1, \Omega_m^2, \ldots, \Omega_m^K\}$, where K is the number of possible $\binom{M}{m}$ combinations of SDs. Ω_m^k denotes the kth SD group, which is defined as $\Omega_m^k = \{\mathrm{SD}_{m,k}^1, \mathrm{SD}_{m,k}^2, \ldots, \mathrm{SD}_{m,k}^m\}$. The metric $\eta_{m,k}$ for selection is defined as follows:

$$\eta_{m,k} = \sum_{\mathrm{SD}_{m,k}^i, \mathrm{SD}_{m,k}^j} (\hat{\mathbf{s}}_{\mathrm{SD}_{m,k}^i} - \mathbf{p})^{\mathsf{T}} (\hat{\mathbf{s}}_{\mathrm{SD}_{m,k}^j} - \mathbf{p}), \tag{16}$$

for $i \neq j$ and $i, j = 1, 2, \ldots, m$. As the vector correlation $(\hat{\mathbf{s}}_{\mathrm{SD}_{m,k}^i} - \mathbf{p})^{\mathsf{T}} (\hat{\mathbf{s}}_{\mathrm{SD}_{m,k}^j} - \mathbf{p})$ increases, the system becomes increasingly localization error-sensitive. Therefore, we propose a selection rule that chooses the group with the smallest $\eta_{m,k}$.

The complexity of M choose m can be high, with a time complexity of $\mathcal{O}(\min(M^m, M^{M-m}))$, particularly for large values of M and m. However, in underwater channels, using a large number of SDs, either M or m, can cause performance degradation due to localization delay. Having many SDs sequentially send position information to the UD increases the time required for a single localization process, leading to UD drift and an increase in localization errors. To address this, it is recommended to use a limited number of SDs. Therefore, the proposed selection rule does not impose a significant computational burden. Additionally, the selection process is performed on a server with sufficient computational capacity, ensuring that the complexity of the selection rule is not an issue.

In addition to the relative locations of the SDs and UD, the location between the SDs also affects the localization performance. When the SDs are in a straight line, $\tilde{\mathbf{S}}^{\mathsf{T}}\tilde{\mathbf{S}}$ becomes an ill-conditioned matrix, and the estimation performance degrades. To prevent degradation, an SD group is selected based on a criterion where the ratio of the second singular value to the first singular value is larger than a given threshold as follows:

$$\sigma_2^{m,k} / \sigma_1^{m,k} > \gamma_{th}, \tag{17}$$

where $\sigma_1^{m,k}$ and $\sigma_2^{m,k}$ are the first and second singular values of the location matrix $\hat{\mathbf{S}}$ made by an SD set Ω_m^k, respectively.

4. Numerical analysis

For the simulation, we used MATLAB and simulated on a computer running on a 64-bit system with 32G memory and i7-10700 CPU. A scenario was considered wherein SDs and a UD are uniformly dropped in a 500 m × 500 m × 250 m 3D space. SDs are on the surface of the water. For a given parameter, the GPS measurement errors of the SDs and jitter were assumed as uncorrelated Gaussian noise. For the performance metric, we used the root-mean-square error (RMSE). With the given number of SDs, the SDs were selected according to the minimization η. In the simulation, we assumed a total of nine SDs. Then, the proposed low-rank approximated least-squares method is performed with the selected SDs.

We compare the RMSE performance of the low-rank approximated least-squares method with the least-squares and the non-linear least-squares method. As shown in Fig. 3, the proposed method outperforms the least-squares method. Furthermore, when comparing the non-linear least-squares method with the proposed method, the proposed method shows better performance than the non-linear least-squares method with 10 iterations, but worse performance than the non-linear least-squares method with 1000 iterations. Notably, the proposed method shows better performance than the non-linear least-squares method when fewer than 7 SDs are used with 100 iterations. These results show that when fewer SDs are used for localization, the non-linear least-squares method requires a considerable number of iterations (between 100 to 1000) to achieve comparable or better performance than the proposed method. As a result, the non-linear least-squares method imposes a significant computational burden on the UD, making the proposed method more desirable from a computational point of view.

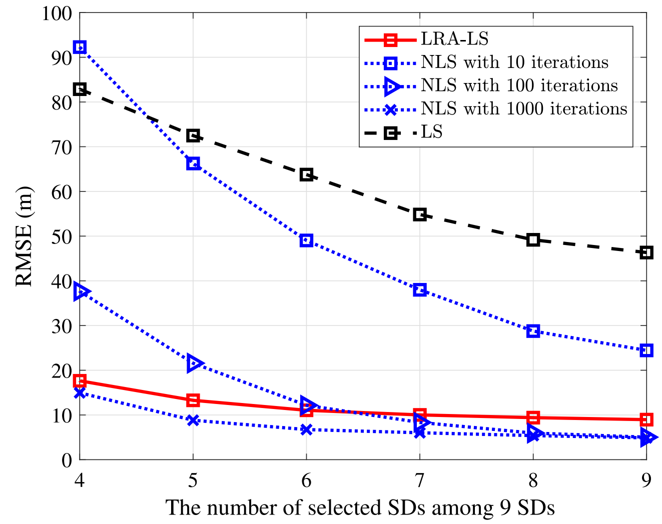

Fig. 3. The performance of low-rank approximated least square method compared to least square method and non-linear least-squares method.

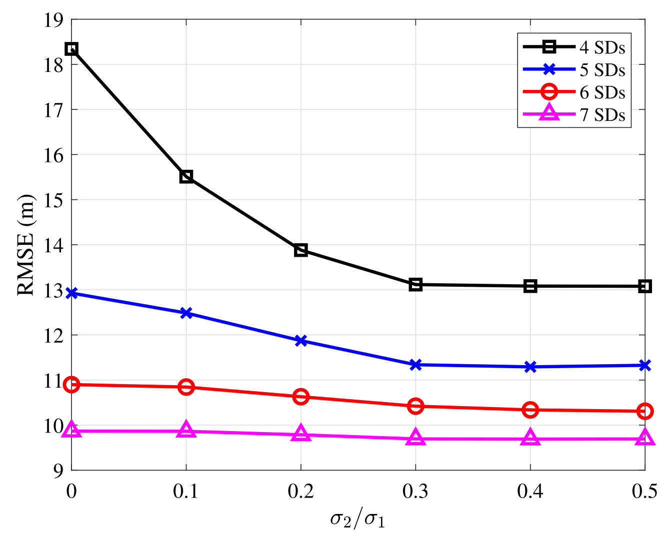

Fig. 4. The performance when selecting a set of SDs based on ratio of the first and second singular value.

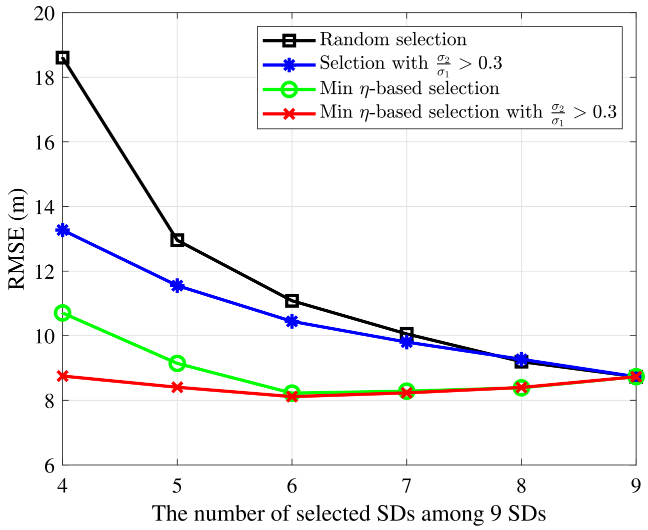

Fig. 5. The performance of low-rank approximated least square method when the selection rule is applied.

Fig. 4 shows the RMSE of the proposed method when selecting a set of SDs from the nine SDs based on the ratio of the first and second singular values of the location matrix. The RMSE converges when we choose a set of SDs with $\frac{\sigma_2}{\sigma_1} > 0.3$. Fig. 5 shows the results of the RMSE when selecting an SD set from nine SDs with the minimum η value. The ratio of singular value-based selection to minimum η-based selection shows better performance than a random selection of SDs. Furthermore, integrating the two selection methods can significantly improve the performance over random selection. As shown in Fig. 5, when using the integrated selection method, even if the number of selected SDs is as small as four to six, it shows similar to smaller RMSE compared to when all nine SDs are used. Even though the number of SDs is small, the RMSE performance is similar to or better than that obtained using all SDs. This result shows that our method appropriately eliminates the SDs that cause errors.

5. Conclusion

In this study, a low-rank approximated least-squares algorithm for estimation was devised to simplify the implementation of UDs by removing the need for depth measurement. From the error analysis revealed, it was found that the selection of SDs is key to increasing the localization accuracy. Based on the analysis, a selection rule for a given set of SDs was introduced, which can be applied in scenarios that require a limited number of SDs. Through simulations, we showed that the proposed method provides reliable localization results. For future studies, we will analyze cases where the position of the UD changes over time, which can cause changes in the underwater channel environment. We also consider a channel estimation issue that takes these changes into account and addresses unsynchronized timing problems.

CRediT authorship contribution statement

Goo-Jung Park: Conceptualization, Software, Draft writing. **Jung-Hoon Noh:** Methodology, Writing. **Seong-Jun Oh:** Supervision, Reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] N. Saeed, A. Celik, T.Y. Al-Naffouri, M.-S. Alouini, Underwater optical wireless communications, networking, and localization: a survey, Ad Hoc Netw. 94 (2019) 101935, http://dx.doi.org/10.1016/j.adhoc.2019.101935.

[2] R. Duan, J. Du, C. Jiang, Y. Ren, Value-based hierarchical information collection for AUV-enabled internet of underwater things, IEEE Internet Things J. 7 (10) (2020) 9870–9883, http://dx.doi.org/10.1109/JIOT.2020.2994909, https://ieeexplore.ieee.org/document/9094182.

[3] H. Kim, J. Ben-Othman, K. Hwang, B. Choi, Intelligent aerial-ground surveillance and epidemic prevention with discriminative public and private services, IEEE Netw. 36 (3) (2022) 40–46, http://dx.doi.org/10.1109/MNET.002.2100510, https://ieeexplore.ieee.org/document/9829309.

[4] H. Kim, J. Ben-Othman, L. Mokdad, J. Son, C. Li, Research challenges and security threats to AI-driven 5G virtual emotion applications using autonomous vehicles, drones, and smart devices, IEEE Netw. 34 (2020) 288–294, http://dx.doi.org/10.1109/MNET.011.2000245, https://ieeexplore.ieee.org/document/9220178.

[5] H. Thomas, Gib buoys: an interface between space and depths of the oceans, in auton. underw. veh, in: 1998. AUV'98. Proc. 1998 Work, 1998, pp. 181–184, doi:10.1109/AUV.1998.744453.

[6] T. Ojha, S. Misra, M.S. Obaidat, SEAL: Self-adaptive AUV-based localization for sparsely deployed underwater sensor networks, Comput. Commun. 154 (2020) 204–215, http://dx.doi.org/10.1016/j.comcom.2020.02.050, https://www.sciencedirect.com/science/article/abs/pii/S0140366419307285?via%3Dihub.

[7] L. Liao, Y.V. Zakharov, P.D. Mitchell, Underwater localization based on grid computation and its application to transmit beamforming in multiuser UWA communications, IEEE Access 6 (2018) 4297–4307, http://dx.doi.org/10.1109/ACCESS.2018.2793962, https://ieeexplore.ieee.org/document/8263106.

[8] L. Houegnigan, P. Safari, C. Nadeu, M. Andre, M. van der Schaar, Machine and deep learning approaches to localization and range estimation of underwater acoustic sources, in: 2017 IEEE/OES Acoustics in Underwater Geosciences Symposium (RIO Acoustics), 2017, pp. 1–6, http://dx.doi.org/10.1109/RIOAcoustics.2017.8349716, https://ieeexplore.ieee.org/document/8349716.

[9] J. Yangzhou, Z. Ma, A deep neural network approach to acoustic source localization in a shallow water tank experiment, J. Acoust. Soc. Am. 146 (2019) 4802–4811, http://dx.doi.org/10.1121/1.5138596.

[10] A. Datta, M. Dasgupta, On accurate localization of sensor nodes in underwater sensor networks: A Doppler shift and modified genetic algorithm based localization technique, Evol. Intell. 13 (1) (2020) 1–13, http://dx.doi.org/10.1007/s12065-019-00343-1.

[11] H. Huang, Y.R. Zheng, Node localization with AoA assistance in multi-hop underwater sensor networks, Ad Hoc Netw. 78 (2018) 32–41, http://dx.doi.org/10.1016/j.adhoc.2018.05.005.

[12] I. Ullah, J. Chen, X. Su, C. Esposito, C. Choi, Localization and detection of targets in underwater wireless sensor using distance and angle based algorithms, IEEE Access 7 (2019) 45693–45704, http://dx.doi.org/10.1109/ACCESS.2019.2909133, https://ieeexplore.ieee.org/document/8681065.

[13] F. Liu, H. Chen, L. Zhang, L. Xie, Time-difference-of-arrival-based localization methods of underwater mobile nodes using multiple surface beacons, IEEE Access 9 (2021) 31712–31725, http://dx.doi.org/10.1109/ACCESS.2021.3060565, https://ieeexplore.ieee.org/document/9358133.

[14] P. Carroll, S. Zhou, H. Zhou, X. Xu, J.-H. Cui, P. Willett, Underwater localization and tracking of physical systems, JECE 2012 (2012) 2:1–2:11, http://dx.doi.org/10.1155/2012/683919.

[15] M. Isik, O. Akan, A three dimensional localization algorithm for underwater acoustic sensor networks, IEEE Trans. Wirel. Commun. 8 (9) (2009) 4457–4463, http://dx.doi.org/10.1109/TWC.2009.081628, https://ieeexplore.ieee.org/document/5285165.

[16] I. Ullah, J. Chen, X.Su, C. Esposito, C. Choi, Localization and detection of targets in underwater wireless sensor using distance and angle based algorithms, IEEE Access 7 (2019) 45693–45704, http://dx.doi.org/10.1109/ACCESS.2019.2909133, https://ieeexplore.ieee.org/document/8681065.

[17] Y. Li, M. Liu, S. Zhang, R. Zheng, J. Lan, Node dynamic localization and prediction algorithm for internet of underwater things, IEEE Internet Things J. 9 (7) (2020) 5380–5390, http://dx.doi.org/10.1109/JIOT.2021.3108424, https://ieeexplore.ieee.org/document/9524741.

[18] J. Luo, L. Fan, S. Wu, X. Yan, Research on localization algorithms based on acoustic communication for underwater sensor networks, Sensors 18 (1) (2018) 1–25, doi:10.3390/s18010067.

[19] W. Cheng, A. Teymorian, L. Ma, X. Cheng, X. Lu, Z. Lu, Underwater localization in sparse 3d acoustic sensor networks, in: Proc. IEEE the 27th Conf. Comput. Commun. (INFOCOM), 2008, pp. 236–240, http://dx.doi.org/10.1109/INFOCOM.2008.56, https://ieeexplore.ieee.org/document/4509651.