FIELD REPORT

Alternating landmark navigation of multiple AUVs for wide seafloor survey: Field experiment and performance verification

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Abstract
This paper reports the results of the sea experiments and the performance verification of a navigation method for wide area surveys of the seafloor using multiple autonomous underwater vehicles (AUVs). In the method, AUVs alternately land on the seafloor to act as landmarks for each other, and all AUVs can observe a wide area with accurate positioning relative to the landmark AUV. For self-localization, AUVs are typically supported by long base line (LBL) or super short base line (SSBL) of the support system. Thanks to the proposed method, AUVs can perform near-seafloor surveys requiring real-time and accurate positioning, such as seafloor imaging and sampling, without these support systems. The method was implemented on two AUVs: “Tri-Dog 1” and “Tri-TON.” The performance of the method was verified using these AUVs through sea experiments and postprocessing simulation using experimental data. In addition, it was also verified that the performance of the method is comparable to high-grade conventional navigation methods, such as LBL or SSBL, through simulations of long distance navigation.

KEYWORDS
Autonomous Underwater Vehicles (AUVs), multiple AUVs, position estimation, seafloor survey

1 | INTRODUCTION

This paper reports the results of sea experiments of the navigation method of multiple autonomous underwater vehicles (AUVs). In the method, each AUV alternately becomes a landmark AUV, which remains stationary on the seafloor, enabling all other AUVs to navigate over a wide area with high positioning accuracy based on the landmark AUV. For self-localization, AUVs are typically supported by long base line (LBL) or super short base line (SSBL) of the support system. The proposed method realizes stable navigation using only AUVs. Our aim is to realize surveys near the seafloor using only AUVs without any surface aid. The method is suitable for wide area surveys requiring accurate positioning, such as seafloor imaging and sampling.

Oceans occupy about 70% of the Earth’s surface. Because of water pressure and light attenuation, the seafloor is not easy to access and is still mysterious to humans. Many scientifically meaningful objects such as seafloor minerals, special ecosystems and habitats, and terrain features exist on the seafloor. Moreover, searching for lost cultural objects and surveying the damage caused by natural disasters or accidents are important.

AUVs have received considerable attention as a new technology for seafloor observation. Recently, several surveys of the seafloor have been conducted using hovering-type AUVs, including resource exploration, terrain mapping by sound, searching for lost objects, and making a photomosaic of seafloor life. Hovering-type AUVs can approach the seafloor and observe it while maintaining their altitude from the seafloor. This study focuses on surveying the seafloor using hovering-type AUVs.

Several navigational guides have been proposed for single AUVs using passive acoustic landmarks, GPS buoys, and terrain features. Although these guides enable a small-drift observation of well-located targets near positioning references, it is difficult to achieve a wide area survey with high positioning accuracy because of limited positioning range or limited environmental features. To overcome these problems, we proposed the alternating landmark navigation method using the multiple AUVs described above.
The concept of the alternating landmark navigation approach was first proposed by Kurazume and Hirose,\textsuperscript{13} where it was referred to as a cooperative positioning system (CPS). To the best of our knowledge, this is the first application of the CPS to the field of AUV navigation.

The navigation of multiple vehicles in land and aerial environments has been extensively investigated, and many navigational methods have been proposed and demonstrated using actual vehicles.\textsuperscript{14–17} In marine environments, however, there is less research than in land or aerial environments. In one report, the research group of Woods Hole Oceanographic Institute (WHOI) in the USA has conducted an investigation of the Arctic Ocean using two AUVs called "JAGUAR" and "PUMA".\textsuperscript{18} In another approach, two moving AUVs realize cooperative positioning from range-only measurements.\textsuperscript{19} A research group from Massachusetts Institute of Technology (MIT) proposed a navigation method that uses multiple autonomous surface vehicles (ASVs),\textsuperscript{20} and have studied cooperation between ASVs and AUVs. The methods regarding supporting ASVs for navigation of AUVs have been proposed.\textsuperscript{21–23}

This paper is organized as follows. The method is explained in Section 2. Section 3 describes the system to realize the method. Section 4 presents and discusses the experimental results. This section also evaluates the performance of the method by postprocessing simulation using experimental data. The performance of the proposed method is compared with conventional navigation methods through simulation in Section 5. Section 6 discusses the method based on sea experiments and simulation. Conclusions and ideas for future work are presented in Section 7. The work of our previous study\textsuperscript{24} is extended in this paper. This paper is different from the previous study in the followings:

- The performance of the method is statistically evaluated through a series of postprocessing simulations using experimental data.
- The performance of the method is analyzed against multiple dives, and the robustness of the method is also evaluated.
- For showing one example of the applications of the method, a photomosaic of the seafloor obtained by two AUVs is shown.
- The performance of the method is compared with conventional methods through simulations of long distance navigation.
- Requirements to improve the estimation accuracy of the method are examined.
2 | METHOD

2.1 | Alternating landmark navigation

Alternating Landmark Navigation (ALN) is a navigation method where two AUVs alternate between the moving and landmark roles (defined as the "main AUVs") and the other AUVs constantly estimate their own positions based on the landmark AUV (defined as the "sub AUVs"). All the AUVs can expand their observational coverage with high positioning accuracy based on the landmark AUV. To generalize the ALN, four AUV case is considered. Figure 1 illustrates the concept of the ALN for four AUVs: A, B, C, and D. Let us assume that A and B are the main AUVs and C and D are the sub AUVs. Initially, A is in the moving role, and B is in the landmark role. Then, the procedure is as follows:
1. The moving AUVs A, C, and D perform observation tasks relative to AUV B, which remains stationary on the seafloor. The moving AUVs estimate their states based on B through a probabilistic approach (a particle filter is adopted, which will be described in Section 2.3).

2. After completing the tasks around B, A lands on the seafloor. Once it has landed, A performs accurate positioning with B to reduce uncertainties in state estimation through the observation phase in the particle filter and then transmits the information regarding the estimated states to B. During this time, C and D maintain their own positions or navigate based on their navigation sensors.

3. After communication between A and B has been completed, A becomes the new landmark, and B, C, and D start moving based on A.

This paper deals with the navigation of main AUVs.

### 2.2 Characteristics of the ALN

The ALN has the following advantages:

- Support from the surface is not necessary.
- Observation coverage is not limited by the positioning range because AUVs exchange the landmark role before leaving the range.
AUVs can continue to navigate as long as they have energy.

Many AUVs are able to perform seafloor observation with accurate position estimation with only one landmark AUV.

On the other hand, there are also some problems:

- Position error will occur in the landmark AUV as the AUVs exchange the landmark role. This is caused by measurement errors from the velocity sensor, the angular velocity sensor and the acoustic positioning sensor. In particular, accuracy of the acoustic positioning sensor is easily influenced by environments. Thus the next landmark AUV cannot completely correct position error with respect to the previous landmark AUV when they exchange the landmark. As the AUVs perform landmark exchange, position errors can increase.

- At least one AUV must be a landmark and remain stationary on the seafloor.

The ALN is expected to be one of the leading new seafloor survey technologies. It will become possible to obtain environmental information, such as seafloor photomosaics, chemical concentration maps, and geographical feature maps, from a wide area of the seafloor using only AUVs.

### 2.3 State estimation

State estimation is the most basic technique involved in realizing the method and is performed by moving AUVs. Here, the state estimation technique for main AUVs is shown.

#### 2.3.1 State

An AUV’s state consists of its three-dimensional position \((x, y, z)\), attitude (roll \(\theta\), pitch \(\phi\), and yaw \(\psi\)), and altitude \(a\). The depth \(z\) and altitude \(a\) can be precisely measured by a pressure sensor and an acoustic range sensor.
sensor, respectively. The roll and pitch angles $\theta$ and $\phi$ are measured by an attitude sensor without drift. Thus, the parameters requiring estimation are the horizontal position $(x, y)$ and the heading angle (yaw $\psi$).

In the main group, the moving AUV estimates the parameters of the landmark AUV as well as its own. The states in the main group at time $t$ are represented as $S_t = [x^M_t y^M_t \psi^M_t x^L_t y^L_t \psi^L_t]^T$ where the suffixes $M$ and $L$ denote “moving” and “landmark,” respectively.

### 2.3.2 Procedure

A stochastic approach (such as a particle filter and an extended Kalman filter: EKF) is introduced. Here, the particle filter, in which the probability density of the states is expressed by a set of particles, is adopted. As the number of particles increases, more complicated distributions can easily be expressed. In the ALN, as the landmark AUV also has state uncertainties, states include two AUVs’ positions and headings

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**FIGURE 9** Positioning and communication device ALOC$^{30}$

**FIGURE 10** AUV “Tri-Dog 1”

**TABLE 1** Specifications of AUV “Tri-Dog 1”

| Length | 2.0 m |
|--------|-------|
| Width  | 0.6 m |
| Height | 1.4 m (with the landing gear) |
| Max. depth | 110 m |
| Duration | 4 h |
| Thrusters | 100 W × 6 |
| Sensors | Doppler velocity log (DVL) |
| | Single-axis fiber optic gyro (FOG) |
| | Attitude sensor |
| | Pressure sensor |
| | Acoustic range sensor × 6 |
| | Forward-looking camera |
| | Downward-looking camera |
| | ALOC |
| | Acoustic modem |

**FIGURE 11** AUV “Tri-TON”

**TABLE 2** Specifications of AUV “Tri-TON”

| Length | 1.4 m |
|--------|-------|
| Width  | 0.76 m |
| Height | 1.8 m (with the landing gear) |
| Max. depth | 800 m |
| Duration | 8 h |
| Sensors | DVL |
| | FOG |
| | Attitude sensor |
| | Pressure sensor |
| | Forward-looking camera |
| | Downward-looking camera |
| | ALOC |
| | Acoustic modem |
in the main group. As the states consist of more parameters than in a single AUV case, they can change with complex correlation between each parameter. As the particle filter expresses the states by a set of particles, complex state distributions can be expressed accurately. Several particle filter-based navigation algorithms for vehicular navigation have been proposed, some of which have been implemented in AUVs.\textsuperscript{9,11,12,27–29}

The particle filter updates the states through two phases: the prediction phase and the observation phase. In the prediction phase, the moving AUV estimates the states from its navigation sensors. The ground velocity sensor and heading rate gyro provide the ground velocity $\hat{\mathbf{v}}_t$ and the angular velocity $\hat{\omega}_t$, respectively. The hat symbol indicates sensor measurements. In the observation phase, the states are updated from relative acoustical positioning measurements between the moving and landmark AUVs. The positioning measurements are the relative distance $\hat{r}_t$ and the relative directions $\hat{\theta}^\text{ML}_t, \hat{\theta}^\text{LM}_t$. Note that $\hat{\theta}^\text{ML}_t$ is the direction from the moving AUV to the landmark AUV, whereas $\hat{\theta}^\text{LM}_t$ is the reverse direction. The moving AUV transmits an interrogating signal to the landmark AUV. Then, the landmark AUV receives this signal and calculates the direction to the moving AUV ($\hat{\theta}^\text{LM}_t$). After that, the landmark AUV transmits the reply signal with the direction information ($\hat{\theta}^\text{ML}_t$). Then, the moving AUV receives this reply signal and calculates the range $\hat{r}_t$ and the direction to the landmark AUV ($\hat{\theta}^\text{ML}_t$). Finally, the moving AUV estimates the states based on range and two direction measurements.\textsuperscript{30} Figure 2 shows the concept of state estimation. Figure 3 shows the timeline of the state
estimation process, where \(\hat{S}_t\) and \(\tilde{S}_t\) indicate the states estimated by the prediction and the observation phases, respectively. Figure 3 assumes that the moving AUV transmits an interrogating signal at time \(t\), and receives a response from the landmark AUV at time \(t + \Delta T\). This delay is taken into account while the particles are updated. Although standard state estimation alternately performs the prediction and observation phases, the proposed method mainly performs the prediction phase and performs the observation phase only when the positioning measurements are performed. This enables the observation phase to use sensors that have the following characteristics:

- The interval of measurements has delay.
- The interval of measurements for the observation phase is longer than that for the prediction phase.

2.3.3 Formulation

The state of the main AUVs \(S_t\) at any given time \(t\) can be represented as follows:

\[
S_t \equiv \{s^i_t | i = 1, \ldots, n\} \tag{1}
\]

\[
s^i_t = [x^M_{i,t} y^M_{i,t} \psi^M_{i,t} x^L_{i,t} y^L_{i,t} \psi^L_{i,t}]^T \tag{2}
\]

where \(s^i_t\) is the \(i\)th particle and \(n\) is the number of particles.

Prediction phase

The state from \(t\) to \(t + \Delta t\) is estimated from the ground velocity \(\dot{v}_t\) and the angular velocity \(\dot{\omega}_t\), as discussed above, in the prediction phase.
AUV is updated as

\[
\begin{bmatrix}
\mathbf{x}_t^{M}\ni\mathbf{V}_t^{M}\ni\mathbf{V}_t^{L}
\end{bmatrix} = \begin{bmatrix}
\mathbf{x}_t^M
\mathbf{v}_t^M
\mathbf{v}_t^L
\end{bmatrix} + \mathbf{R}(\psi_t^M)\mathbf{V}_t^M
\]

where \( \mathbf{R} \) is the rotation matrix expressed as

\[
\mathbf{R}(\theta) = \begin{bmatrix}
\cos \theta & -\sin \theta \\
\sin \theta & \cos \theta
\end{bmatrix}.
\]

Since the landmark AUV is stationary on the seafloor, its ground velocity and angular velocity are assumed as 0. The concept of the prediction phase is shown in Figure 4.

**Observation phase**

Observation is implemented in the second phase. If the measurements of relative direction and distance between the two AUVs are successful, they are used by the moving AUV to update the particles. The likelihood of each particle is given by

\[
w_i = L(s'_i) = L_M(s'_i) \cdot L_M(s'_i)
\]

where \( L_M \) and \( L_M \) are the likelihoods estimated from measurements collected by the moving and landmark AUVs, respectively. \( w_i \) denotes the weight of the ith particle. When no positioning measurements are obtained, the weight is assigned as 1, and the likelihood value remains unchanged. The observation data are the relative distance \( t_i \) and the direction \( \theta_i \) measured by the moving AUV. The offsets for direction and distance, calculated from both states at time \( t \) (transmitting signal) and at time \( t + \Delta T \) (receiving signal), are given by

\[
\Delta t_i = \left| \frac{x_{t+\Delta t}^L - x_{t+\Delta t}^M}{2} \right|
\]

\[
\Delta \theta_{ML} = \left| \arg \left( \frac{x_{t+\Delta t}^L - x_{t+\Delta t}^M}{2\sigma_d^2} \right) - \left( \frac{k_{\theta}^2}{2} \right) \right|
\]

where the terms are defined as in Figure 5. The likelihood \( L_M(s'_i) \) is then calculated as follows:

\[
L_M(s'_i) = \begin{cases}
\exp \left( \frac{k_2^2}{2\sigma^2} \right) & \text{if } (\Delta t_i < k_1) \land (\Delta \theta_{ML} < k_3^M) \\
1 & \text{else}
\end{cases}
\]

where \( \sigma_d \) and \( k_3^M \) are the standard deviations of the distance and direction measured by the moving AUV. Gaussian errors are assumed in the measurements. The parameters \( k_1 \) and \( k_3^M \) prevent extreme fallout of the likelihood when outliers enter the measurements. The terms \( k_2^2/2 \) and \( (k_3^M)^2/2 \) in the exponential functions smooth the output at the boundaries.5

Similarly, \( L_M(s'_i) \) is calculated from the relative direction \( \theta_{ML} \) measured by the landmark AUV,

\[
\Delta \theta_{ML} = \left| \arg \left( x_{t+\Delta t}^M - x_{t+\Delta t}^L \right) - \left( \theta_{ML}^L - \theta_{ML}^L \right) \right|
\]
FIGURE 16  Estimated trajectories in real time and SSBL measurements

FIGURE 17  Ground velocities of the AUVs (Dive 4). Vx and Vy indicate surge and sway velocities, respectively. Elapsed time means the time from the discovery of TT by TD

FIGURE 18  Altitudes of the AUVs (Dive 4)
FIGURE 19  Heading angles and angular velocities (Dive 4). The upper panel shows the heading angles obtained from magnetic sensors. The center and lower panels show the heading angles and angular velocities obtained from TD’s and TT’s FOGs, respectively.

where the terms are also defined as in Figure 6.

\[
L_{LM}(x^i_t) = \begin{cases} 
\exp \left( \frac{(k^i)^2}{2} + \frac{-k^i \Delta \theta_{LM}^i}{\sigma_{LM}^i} \right) & \text{if } (\Delta \theta_{LM}^i < k^i \sigma_{LM}^i) \\
1 & \text{else} 
\end{cases}
\]  

(15)

where \( \sigma_{LM}^i \) is the standard deviation of the direction measurement by the landmark AUV. According to the likelihood obtained by Eq. (10), each particle is resampled and made to form \( S_{t+\Delta T} \).

2.3.4  Particle reconstruction

Although the particle filter ensures robustness to sensor noises or lack of measurements, it offers no protection against positioning errors, which may cause incorrect convergence of the particles. This problem is significant for the ALN because it degrades the accuracy of the state of the landmark AUV during the landmark role exchange. Such local-
In the absence of valid positioning measurements, both likelihoods [Eqs. (18) and (19)] are set to 1. The average likelihood also decreases when outliers enter the measurements. To distinguish localization failure from outliers, the likelihood transit is monitored. Continual decreased likelihood is attributed to localization failure when \( L(S_t) < a \cdot L_{\text{max}}, \) \( L(S_{t-\Delta T}) < a \cdot L_{\text{max}}, \) \( L(S_{t-2\Delta T}) < a \cdot L_{\text{max}}, \) … where \( \Delta T \) is the time interval between positioning measurements, and \( a \) is an arbitrary multiplication threshold that decides whether particle reconstruction will be implemented. \( a \) is an arbitrary trial number that determines the time of likelihood monitoring.

Particles are selected and replaced by new particles in order of ascending likelihood. The number of new particles is determined by

\[
\begin{align*}
\text{new} &= \begin{cases} 
0 & \text{if } \max \left( L(S_t) \right) > \log \left( \log \left( L_{\text{max}} \right) \right), \\
100 \% & \text{otherwise},
\end{cases}
\end{align*}
\]

(20)
FIGURE 21 Pictures obtained by TT’s downward-looking camera when it was at the landing positions (upper: first landing position, center: second landing position, lower: third landing position). The left and right panels show the pictures taken immediately after TT landed and immediately before it started moving, respectively. Each line shows corresponding features detected by SIFT. Obtaining time is also shown.

TABLE 4 Displacements of corresponding features

|                                | Average (pixel) | Standard deviation (pixel) |
|--------------------------------|-----------------|---------------------------|
| First landing (TT)             |                 |                           |
| Horizontal                     | $-0.17$         | $0.49$                    |
| Vertical                       | $-0.58$         | $0.26$                    |
| Second landing (TT)            |                 |                           |
| Horizontal                     | $-0.11$         | $0.90$                    |
| Vertical                       | $-1.24$         | $1.33$                    |
| Third landing (TT)             |                 |                           |
| Horizontal                     | $0.23$          | $0.83$                    |
| Vertical                       | $-0.55$         | $0.33$                    |
| First landing (TD)             |                 |                           |
| Horizontal                     | $-0.13$         | $0.61$                    |
| Vertical                       | $-0.61$         | $0.45$                    |
| Second landing (TD)            |                 |                           |
| Horizontal                     | $0.64$          | $0.55$                    |
| Vertical                       | $-0.20$         | $0.74$                    |


TABLE 5 Parameter setting of particle reconstruction

| Parameter                                 | Value              |
|-------------------------------------------|--------------------|
| The multiplication threshold of particle reconstruction $\alpha$ | 0.6                |
| The trial number of monitoring $\alpha$    | 3                  |
| The ratio of particle replacement $r$      | 50%                |
| Offset threshold $\Delta R$                | 1.0 m              |
| Offset threshold $\Delta \psi$             | 1.5°               |

\[
\psi_t^{L_i} = \begin{cases} 
\psi_t^L + \theta_t^{L_i} - \theta_t^{M_i} - \pi & \text{if } (\psi_t^L + \theta_t^{L_i} - \theta_t^{M_i} > \pi) \\
\psi_t^L + \theta_t^{L_i} - \theta_t^{M_i} + \pi & \text{else} \\
\psi_t^L + \theta_t^{L_i} - \theta_t^{M_i} - \pi & \text{if } (\psi_t^L + \theta_t^{L_i} - \theta_t^{M_i} < -\pi) \\
\psi_t^L + \theta_t^{L_i} - \theta_t^{M_i} + \pi & \text{else} 
\end{cases}
\]

(25)

2.4  State communication

2.4.1  Outline

As estimated states are complete summaries of the past, the main AUVs need to share the states when they exchange the landmark role. However, as the states are expressed by particles, complete state sharing is precluded by the typically low data rates of acoustical communications in underwater environments. To overcome this problem, the previously moving AUV A compresses its estimated states before transmitting this information to the next moving AUV B,25 as detailed in the following procedure:

1. A lands on the seafloor and measures the mutual acoustical positioning between itself and B to converge the state uncertainties.
2. To reduce the communication data size, A compresses its estimated states by “particle clustering” using a clustering method and a model selection method.
3. A transmits the compressed information regarding its estimated states to B.

FIGURE 22  Pictures obtained by TD's forward-looking camera when it was at the landing positions (upper: first landing position, lower: second landing position). The left panels show the pictures taken immediately after TD landed. The upper right picture was taken immediately before TD started moving. A moving plastic bag was observed in this time. The lower right picture was taken just before the battery of TD’s camera ran down. Each line shows corresponding features detected by SIFT. Obtaining time is also shown.

FIGURE 23  Estimated trajectories of the AUVs in the case of the ALN.
2.4.2 Procedure

The particle clustering approach is illustrated in Figure 8. The original particles are first divided into groups by k-means clustering [Fig. 8(A)]\textsuperscript{32,33}, which partitions a set of particles into clusters. Next, the statistics of the clusters, namely, the \(k\) average vectors \(\mu_i^t\) and \(k\) variance matrices \(\Sigma_i^t\), are obtained. The original particles are then approximated by mixed Gaussian distributions based on these statistical values [Fig. 8(B)]. The degree of similarity between the original particles and the approximated model is calculated by a typical model evaluation method known as Akaike information criterion (AIC).\textsuperscript{34} The optimal approximated model is determined according to the degree of similarity [Fig. 8(C)].

To determine the optimal approximate model, processes A–C in Figure 8 are repeated \(t_{\text{max}}\) times for each cluster size (controlled by the trial number \(t\)) [Fig. 8(D)]. After \(t_{\text{max}}\) trials, the cluster size is incremented (controlled by the size of clusters \(k\), where \(1 \leq k \leq k_{\text{max}}\)) [Fig. 8(D)]. In the case of \(k = 1\), the original particles are approximated by a Gaussian distribution containing the averages and variances of all particles. The above process eventually returns the optimal approximated model. The averages, variances, and cluster ratios of this optimal approximated model are transmitted to the next moving AUV [Fig. 8(E)].

2.4.3 Formulation

K-means clustering

The particles of the AUVs are subdivided by k-means clustering, which partitions a set of particles into \(k\) clusters. Each particle is assigned to the cluster with the nearest mean.

![FIGURE 24 Estimated trajectories of the AUVs and SSBL measurements. Left are the results of the DR, and right are those of the ALN](image-url)
Normalization of the particles

To calculate Euclidean distance between the particle and the cluster center, the particles are normalized. The $i$th normalized particle $\text{ائن}_i(t)$ is expressed by Eq. (26), where the bar denotes the average of the particles and $\sigma$ indicates their standard deviation.

\[
\begin{bmatrix}
\text{ائن}_M x_{i} \\
\text{ائن}_M y_{i} \\
\text{ائن}_M \psi_{i} \\
\text{ائن}_L x_{i} \\
\text{ائن}_L y_{i} \\
\text{ائن}_L \psi_{i}
\end{bmatrix} = \begin{bmatrix}
\frac{1}{\sigma_t^{\text{ائن}x}} & 0 & 0 & 0 & 0 & 0 \\
0 & \frac{1}{\sigma_t^{\text{ائن}y}} & 0 & 0 & 0 & 0 \\
0 & 0 & \frac{1}{\sigma_t^{\text{ائن}\psi}} & 0 & 0 & 0 \\
0 & 0 & 0 & \frac{1}{\sigma_t^{\text{ائن}x}} & 0 & 0 \\
0 & 0 & 0 & 0 & \frac{1}{\sigma_t^{\text{ائن}y}} & 0 \\
0 & 0 & 0 & 0 & 0 & \frac{1}{\sigma_t^{\text{ائن}\psi}}
\end{bmatrix}
\begin{bmatrix}
\text{ائن}_M x_{i} - \bar{x}_M \\
\text{ائن}_M y_{i} - \bar{y}_M \\
\text{ائن}_M \psi_{i} - \bar{\psi}_M \\
\text{ائن}_L x_{i} - \bar{x}_L \\
\text{ائن}_L y_{i} - \bar{y}_L \\
\text{ائن}_L \psi_{i} - \bar{\psi}_L
\end{bmatrix}
\]

Initialization for clustering

Initially, the centers of the $k$ clusters are undefined. Initial cluster centers are defined by the k-means++ method, which prevents local optimal clustering when initial centers are randomly selected. Initialization by the k-means++ method proceeds as follows:
1. The first center $\mu_1^t$ is randomly selected from the particles.

2. $D(n_i^t)$, the distance between $n_i^t$ and the nearest center (i.e., already selected center), is calculated for each normalized particle $n_i^t$ ($i = 1, \ldots, n$).

3. The new center $\mu_j^t$ is stochastically selected according to a weighted probability distribution, from which particle $n_i^t$ is chosen with probability proportional to $D(n_i^t)^2 / \sum_{i=1}^{n} D(n_i^t)^2$.

4. Steps 2 and 3 are iterated until $k$ centers have been selected.

**Clustering**

Based on the initial centers $\mu_j^0 (j = 1, \ldots, k)$, the cluster number $n_i^t$ to which the $i$th particle belongs is determined by

$$n_i^t = \arg \min_{1 \leq j \leq k} |n_i^t - \mu_j^0|.$$  \hspace{1cm} (27)

Once each particle has been assigned to one cluster, the new cluster centers are updated by averaging the new clusters. Equation 27 is then recalculated using the updated cluster centers. The cluster centers and the clustering process are repeatedly updated until the clustering results have converged. After clustering, the normalized particles are then converted back into their original values.

**Approximation**

Once the particles are clustered, the $k$ averages $\mu_j^t (j = 1, \ldots, k)$ and variances $\Sigma_j^t (j = 1, \ldots, k)$ of the clusters are obtained. To approximate a set of original particles, a mixed Gaussian distributions is compiled from the cluster statistics.

$$p(X) \approx \sum_{j=1}^{k} \epsilon_j N(\mu_j^t, \Sigma_j^t)$$  \hspace{1cm} (28)

where $\epsilon_j$ is the ratio of the number of particles in the $j$th cluster to the total number of particles. $N(\mu_j^t, \Sigma_j^t)$ is the $j$th Gaussian distribution derived from the statistics of the $j$th cluster $\langle \mu_j^t, \Sigma_j^t \rangle$. 

**FIGURE 26** Estimation errors of the DR
FIGURE 27 Positioning measurements for each moving role. Trajectories and landing positions are the same as above figures. Black dotted and green solid lines show positioning measurements of TD and TT, respectively. These are obtained by $\hat{\theta}_t^{\text{ML}}$ and $\hat{r}_t$. Black squares and red circles show the positions where positioning was succeeded by both AUVs (mutual) and only a moving AUV (one side), respectively. One-side positioning means that the moving AUV succeeded in measuring direction ($\hat{\theta}_t^{\text{ML}}$) and range measurement ($\hat{r}_t$) and failed in receiving direction information ($\hat{\theta}_t^{\text{LM}}$) from the landmark AUV via acoustic communication. Mutual positioning means that the moving AUV succeeded in receiving direction information ($\hat{\theta}_t^{\text{LM}}$) via acoustic communication in addition to one-side positioning.

FIGURE 28 Standard deviations of the estimated state (ALN)
Selection of an optimal model

The extent to which the approximated model fits the original particles is evaluated by the AIC. The AIC measures the relative quality of a statistical model and is expressed as follows:

\[ \text{AIC} = -2L(\theta) + 2F(k). \]  

\[ L(\theta) = \sum_{i=1}^{n} \ln \left( \sum_{j=1}^{k} \left( \frac{1}{\sqrt{2\pi} \sigma_j} \right) \exp \left( \frac{-1}{2} (s_{it} - \mu_j)^T (\Sigma_j)^{-1} (s_{it} - \mu_j) \right) \right). \]  

\[ \theta = \{ \varphi_j, \mu_j, \Sigma_j \} \quad (j = 1, \ldots, k). \]  

\[ F(k) = (k - 1) + 6k \times 2. \]  

\[ N(s_{it} | \mu_j, \Sigma_j) = \frac{1}{(\sqrt{2\pi})^m \sqrt{\det(\Sigma_j)}} \exp \left( -\frac{1}{2} (s_{it} - \mu_j)^T (\Sigma_j)^{-1} (s_{it} - \mu_j) \right). \]  

\[ \Sigma_j = \begin{bmatrix} (\sigma_j^{Mx})^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & (\sigma_j^{My})^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & (\sigma_j^{Mx})^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & (\sigma_j^{My})^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & (\sigma_j^{Lx})^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & (\sigma_j^{Ly})^2 \end{bmatrix}. \]  

FIGURE 29 Standard deviations of the estimated state (DR)


\( F(k) \) is the degree of freedom of the parameters in the approximated model, and \( k \) is the number of clusters. In Equation (32), \( k - 1 \) is the degree of freedom of the ratio \( e_j \). \( 6k \times 2 \) denotes the degree of freedom of the cluster statistics vectors \((\mu_j, \Sigma_j)\), where the states possess six degrees of freedom.

\( N(\mathbf{s}_i|\mu_j, \Sigma_j) \) is the likelihood by substituting the \( i \)th particle \( \mathbf{s}_i \) into a multivariate normal distribution with average vector \( \mu_j \) and variance matrix \( \Sigma_j \), which are derived from the statistical values of the \( j \)th cluster. To reduce the required communication size, the covariance is not considered here. Alternatively, the detail of the original particles are expressed by incrementing the cluster size. As each particle of the AUV is composed of six parameters, the degree \( m \) is six.

\[
\theta_{\text{opt}} = \arg \min_{1 \leq k \leq k_{\text{max}}} \text{AIC}_c.
\]

The AIC returns \( L(\theta) \) and \( F(k) \), expressing the goodness of fit and the penalty function, respectively. The penalty discourages overfitting as the number of free parameters is increased in the approximation. The smaller the AIC value, the better the statistical model. Based on the AIC, the steps in Figure 8 are repeated to construct an optimal approximated model. Assumed that the latest AIC value is \( \text{AIC}_n \) and the current optimal model’s AIC value is \( \text{AIC}_o \), the latest model is recorded as the new optimal model if \( \text{AIC}_n < \text{AIC}_o \).

3 | SYSTEM DESCRIPTION

3.1 | Positioning and communication device

A positioning and communication device was developed to realize the method. The system is called an Acoustic Localization and Communication (ALOC) shown in Figure 9. The ALOC, which comprises one transmitter and four receivers, enables communication among multiple underwater platforms. It also enables platforms to calculate their relative positions from acoustical measurements using a short base line (SBL) technique. Transmitted waves are chirp signals and communication signals. The latter are transmitted using multiple-value frequency-shift keying at a data rate of 100 bits per second with a data size of 8 bytes. The beam pattern of the ALOC is horizontally omnidirectional. As all the AUVs are located at almost the same depth in the ALN, such a beam pattern is suitable for the ALN.
3.2 AUVs

The method is implemented on the AUV "Tri-Dog 1" (TD) and AUV "Tri-TON" (TT). Both AUVs are hovering-type AUVs with thrusters that can independently control surge, sway, heave, and yaw motions. Photographs and specifications of the AUVs are shown in Figures 10 and 11 and Tables 1 and 2, respectively. Ground velocity is measured by a Doppler velocity log (DVL), and yaw angular velocity is measured by a single-axis fiber optic gyro (FOG). The ALOC is mounted on the top center of each AUV. Each AUV is also equipped with landing gear.

4 SEA EXPERIMENT

This section describes the sea experiments for verifying the performance of the ALN using two AUVs (TD and TT).

4.1 Outline

4.1.1 Objectives

- To realize a wide area survey using two AUVs with the ALN in a sea environment,
- To evaluate the performance of the ALN in a sea environment, and
- To compare the ALN with a conventional navigation method using sea experimental data.

4.1.2 Experimental site

The series of experiments were conducted in August, 2014 at "OKI SEATEC" in Uchiura Bay in Japan (Fig. 12) and was supported by the staff of "OKI SEATEC." Figure 13 shows the appearance of the experimental station in "OKI SEATEC." The terrain of the experimental site is almost flat.

4.1.3 Conditions

The experiments were conducted under the following conditions. The setup of the experiments is illustrated in Figure 14.

- TD is the first moving AUV and TT is the first landmark AUV.
- The moving AUV takes photographs of the seafloor.
- The moving AUV estimates the states using measurements from the DVL, the FOG, and the ALOC.
High-grade super short base line (SSBL) (iXBlue) was fixed on the experimental station to measure the GPS-based position of the AUVs for ground truth (0.06% accuracy of slant range).

Particle reconstruction was not used.

The positions obtained by the SSBL were just used for off-line performance evaluation.

### 4.1.4 Parameters

The sensor errors and the parameters of the particle filter were set as shown in Table 3. Sensor errors were determined through tank tests or sea experiments. The number of particles was determined based on the performance of the CPU mounted on each AUV. The examinations for determining clustering parameters are detailed in Ref. 25.

### 4.1.5 Procedure

First, the initial landmark AUV, TT, was deployed. Next, the initial moving AUV, TD, was deployed. After the two AUVs had dived, they surveyed the seafloor, alternately taking on the landmark role. The AUV in the moving role surfaced first after completing the mission.
FIGURE 33  Particle locations of TD and TT during the first half of TT’s second moving role (TT-2). Each symbol is same as in Figure 32

4.2 Outline of the results

Four dives were conducted. Dives 1 and 2 were for short distance navigation. Dives 3 and 4 were for long distance and wide area navigation. The outline of each dive is explained below.

- **Dive 1 and 2**
  Two AUVs made a seafloor observation within a 30-m area. They exchanged the landmark role when the moving AUV was 15 m apart from the landmark AUV.

- **Dive 3**
  Two AUVs performed long distance navigation. They navigated more than 100 m. They succeeded in a seafloor mapping, with each AUV alternately becoming the landmark. The AUVs exchanged the landmark role when the moving AUV was 30 m ahead of the landmark AUV.

- **Dive 4**
  Almost all settings were the same as in Dive 3. The AUVs exchanged the landmark role when the moving AUV was 40 m ahead of the landmark AUV. The AUVs succeeded in performing 200 m navigation.

Here, we focus on the results of Dive 4.
4.3 | Results of Dive 4

4.3.1 | Estimated trajectories

Figure 15 plots the horizontal trajectories of the two AUVs, indicating the roles of the AUVs and the procedural events. The blue solid and red dotted paths show the trajectories of TD and TT, respectively. TD-\(i\) and TT-\(i\) indicate the \(i\)th moving role of TD and TT, respectively. The yellow circle and star indicate the landing position of TD and TT, respectively. At its first landing point, TT remained stationary on the seafloor and awaited the arrival of TD. As TD arrived at its first landing point, it located TT using the ALOC, and then moved to its second landing point (event “TD-1”). TD landed on the seafloor, and then transmitted compressed information about the states to TT. After receiving this information, TT started moving to the second landing point (event “TT-1”), and the process repeated. From the figure, it is found that both AUVs alternatively moved to the next landing point.

Figure 16 shows the estimated trajectories of the two AUVs in real time and SSBL measurements. Each number shows the landing number of the AUVs. SSBL measurements were transformed from a GPS coordinate system into the AUV’s coordinate system based on the first landing position of the two AUVs, and TD’s first moving direction. From this figure, the estimated trajectories are in agreement with the SSBL measurements during TD-1 and TT-1. However, errors increased gradually. The reason for this is examined in Section 4.4.

4.3.2 | Sensor measurements

Figure 17 shows the horizontal ground velocities of both AUVs during the mission. From this figure, we observe that while one AUV was
moving, the other remained stationary (ground velocity was around 0). The surge velocities (\(V_x\)) of TD and TT when they are in the moving role were around 0.15 m/s, which is the reference value. It is clear that the two AUVs alternately moved.

Figure 18 shows the altitude measurements of both AUVs. We observe that while one AUV was moving at the reference altitude, the other remained on the seafloor. Offset values when they are landed indicate the height of the landing gear.

Figure 19 shows the heading angles and angular velocities of the AUVs. When each AUV was in the landmark role, values of magnetic sensors were stable. However, during the time period marked by the red circle, TD’s heading changed and the angular velocity of TD’s FOG was about 1.0 deg/s.

Figure 20 shows the enlarged figure of Figure 19. From TD’s heading angle from the magnetic sensor and the FOG, measurements were changed (magnetic sensor: from 35° to 65°, FOG: from 348° to 11°). As both sensors changed in a short period (from 3100 s to 3200 s), it is evidenced that TD’s heading was changed during this time period. The change in the magnetic sensor was bigger than that of the FOG. Accuracy of the magnetic sensor is likely to be affected by environments. Although FOG measurements have a sensor drift, accuracy in a short period is reliable. So it was estimated that the change of TD’s heading was 23° (from 348° to 11°) from the change of the FOG. In the ALN, as the moving AUV estimates the states and could not notice the state change of the landmark AUV in real time, this change could cause great estimation errors. In the performance evaluation through postprocessing simulations (Section 4.4), this heading change was considered.

4.3.3 Analysis of landing stability based on seafloor pictures

This section examines the stability of the AUVs when they are at the landing position based on seafloor pictures obtained by their cameras. For pictures taken just after landing and just before landmark exchange, local features are detected based on scale-invariant feature transform (SIFT). Corresponding features are compared to evaluate displacement of features.

Figure 21 shows the pictures obtained by TT’s downward-looking camera when it was landed. The upper, center, and lower panels show the pictures obtained when TT was at the first, second, and third landing positions, respectively. These positions correspond to TT’s landing positions in Figure 15. The left and right panels show the pictures obtained immediately when TT became, and then completed, the landmark role, respectively. Each line shows corresponding features detected by SIFT. Table 4 shows the averages and standard deviations of the displacements of the corresponding features. As displacements are around 1 pixel for each landmark time, it is obvious that TT kept stable during the time when it was landed.

Next, TD’s case is examined. Figure 22 shows the pictures obtained by TD’s forward-looking camera when it was landed on the seafloor. The pictures are transformed to gray-scale pictures. The upper and lower panels show the pictures obtained when TD was at the first and second landing positions, respectively. These positions also correspond to TD’s landing positions in Figure 15. However, as the battery of TD’s camera ran down when it was at the second landing position, pictures were obtained only until then. From Table 4, it is also obvious that TD remained stable when it was at the first and second landing positions.

From both the results of sensor measurements and seafloor pictures, it was verified that both AUVs kept stable on the seafloor except for the time when TD was at the third landing position.
Performance analysis: Estimation accuracy

To support discussion of the performance of the ALN, postprocessing state estimation was carried out based on measurements from the DVL, the FOG, and the ALOC obtained in the experiments. Through the simulation, the horizontal position, and the heading angle of the AUVs were recalculated in different conditions and compared with the positioning results obtained by the SSBL. The performance of the ALN was compared with that of a conventional navigation method (dead reckoning).

Case 1. ALN: Both AUVs estimated the states based on the measurements from the ALOC as well as from the DVL and the FOG. They performed both prediction and observation phases. The former is based on measurements from the DVL and the FOG. The latter is based on measurements from the ALOC.

Case 2. Dead reckoning (DR): Both AUVs estimated the states based on the measurements from the DVL and the FOG. They performed only the prediction phase.

Case 2 also performed the observation phase based on the measurements from the ALOC for the first 200 s to equalize initial position errors with Case 1. 10 trials were conducted for each case.

4.4.1 Conditions

The simulations were carried out under the following conditions:

- The number of particles increased from 300 (TD) and 500 (TT) to 5000 to enhance the accuracy of the state estimation.
- The parameters of the particle filter were set to the same values as those shown in Table 3.
- The change in TD’s heading angle at the third landing position was revised based on the change in TD’s FOG measurements from Figure 20.
- Particle reconstruction shown in Section 2.3.4 was used in the simulation.

The parameter setting of particle reconstruction is shown in Table 5. The determination of the parameters is shown in Ref. 31.
4.4.2 Results (Dive 4)

Figure 23 shows the estimated trajectories of the two AUVs in the case of the ALN. Blue solid and red dotted lines show the trajectories of TD and TT, respectively. The estimated trajectories are the averages of the results of the 10 trials. Each number indicates the number of the landing position.

Figure 24 shows the comparison of the estimated trajectories and SSBL measurements in the case of the DR as well as the ALN. The light blue and magenta dots show the positions of TD and TT, respectively, measured by the SSBL. It was found that estimated trajectories in the ALN were in good agreement with the SSBL measurements, whereas those in the DR deviated from the SSBL measurements, implying that heading errors occurred and might cause position errors.

Figures 25 and 26 show the estimation errors of the AUVs in the cases of the ALN and the DR, which were the averages of the results of 10 trials. The errors are calculated from the difference between estimated positions of the AUVs and SSBL measurements at each time. The blue dots, red crosses, and green x-marks show the errors of the X position, Y position, and distance, respectively. Variations of errors are also shown in every 30 measurements of the SSBL by boxplots. A boxplot is a way of graphically depicting a set of numerical data through their quartiles. The bottom and the top of the box are the first and third quartiles, respectively. The band inside the box is the median. Dotted lines extending vertically from the boxes indicate variability outside the upper and lower quartiles. Each range of the whisker is 1.5 times the interquartile range. Data outside the whisker are plotted as circles.

Finally, the distance errors of the ALN were suppressed to be within 5 m, whereas those of the DR expanded to about 10 m. The errors of the ALN were about 2.5% of the distance traveled (200 m), whereas those of the DR were 5.0% of the distance traveled. This indicates that the ALN enables AUVs to estimate the states with more than twice the accuracy of the DR. By comparing the boxplots of the ALN and the DR, as they do not overlap, it is obvious that there is a statistically significant difference between the results of the ALN and the DR. In the DR, TD’s errors have greater variations than TT’s errors. This is because the observation phase was also performed for the first 200 s in the DR, and errors were affected by this process.
Figure 27 shows the positioning measurements for each moving role. Trajectories and landing positions are the same as the above figures. The black and green lines show positioning measurements from TD and TT, respectively. The black squares and red circles show the positions where positioning was succeeded by both AUVs and only a moving AUV, respectively. Positioning results mainly correspond to the estimated position of the landmark AUV for each case. However, TD could not succeed in stable positioning during the latter half of the second moving role (TD-2).

Figures 28 and 29 show the standard deviations (SDs) of the particles in the cases of the ALN and the DR, respectively, which were the averages of the results of the 10 trials. The blue, red bold, and green dotted lines show the SDs of the X position, Y position, and heading angle, respectively. The upper and lower panels show the SDs of TD and TT, respectively. Variations of the SDs are also shown every 300 s by boxplots.

The initial SDs of X and Y are set to be 1.0 m, and that of the heading angle is set to be 2.0°. The SDs in the case of the DR increased by up to around 10 m of the X and Y positions, which correspond to the position errors shown in Figure 26, and 8° of the heading angle. On the other hand, in the case of the ALN, the SDs of the X and Y positions were decreased to be within 0.5 m and that of the heading angle was decreased to be around 2.0°. However, these uncertainties were smaller than the errors shown in Figure 25. This is because the particles were converged incorrectly, and they exchanged the landmark role with errors. As they exchanged the landmark role, position errors for both AUVs occurred.

Figures 30 and 31 show the comparison of the SDs and errors of the estimated states in the case of the ALN and the DR, respectively. From Figure 30, it can be seen that differences between SDs and errors increase from the latter half of TD-2 to TT-2. The estimation errors also increase during this time. From Figure 31, it can be seen that errors are the same or within the SDs except for the X error of TT. TT moved mainly in the X direction, so the error of the DVL measurement was greater than expected.

Figures 32–34 show particle locations of TD and TT during TD-2 and TT-2. From Figure 32, it is found that particles of TD expanded due to lack of positioning measurements. TD’s SDs in the ALN increased during this time [Fig. 28(a)]. This also caused the increase of TD’s position errors during TD-2 shown in Figure 25(a). From Figures 33 and 34, it can be seen that particles of TD converged gradually, and particles locations deviated from SSBL measurements. This incorrect convergence increased the error between the estimated position and the SSBL measurement.

In real-time navigation, estimation errors increased greatly during TD-2, TT-2, and TD-3 (Fig. 16). The following three items are considered as a cause.

- The number of particles
  Since the number of particles was smaller than postprocessing simulation for computational cost, the state distribution cannot be expressed accurately and localization failure was likely to occur.
- The recovery method from localization failure
  During TD-2, estimation uncertainty increased due to lack of positioning measurements. As the recovery method from localization failure (particle reconstruction) was not used in real-time navigation, incorrect convergence during TT-2 caused great errors.
- Heading change of TD
In addition, heading change of TD caused errors during TT-2 and TD-3. In the ALN, as the moving AUV estimates the states and cannot notice the state change of the landmark AUV in real time, this change can cause great errors.

4.4.3 Results (Dive 1–3)

To evaluate the robustness of the ALN, postprocessing state estimation was also carried out against Dive 1–3.

Figures 35, 39, and 43 show the estimated trajectories of the ALN in Dive 1, 2, and 3, respectively. The estimated trajectories are the averages of the results of the 10 trials. Again, each number indicates the number of the landing position.

Figures 36, 40, and 44 show the comparison of the estimated trajectories and SSBL measurements in the case of the DR as well as the ALN. It was found that all estimated trajectories in the ALN were in better agreement with the SSBL measurements than those in the DR.

Figures 37, 38, 41, 42, 45, and 46 show the estimation errors of the ALN and the DR from Dive 1 to 3, which were the averages of the results of 10 trials. Graph legends are the same as in the results of Dive 4. For all cases, estimation errors in the ALN were smaller than those in the DR. From these results, the robustness of the ALN was statistically verified.

4.4.4 Application example of the ALN

The AUVs obtained seafloor pictures in the experiments. Figure 47 shows a photomosaic of the seafloor in Dive 4, which was obtained based on the estimated trajectories in the postprocessing simulation. The techniques proposed in Ref. 39 were used. Plants, benthoses, and objects were observed. Figure 48 shows all trajectories of the experiments in the global map, which were estimated in the postprocessing simulation. From these results, it is clear that detailed information about environments near the seafloor can be obtained using the ALN. More information can be obtained by implementing another
observation sensor, which measures chemical or physical parameters, on the AUVs.

5 | COMPARISON: ALN AND CONVENTIONAL METHODS

5.1 | Conditions

In Section 4, the performance of the ALN was compared with the DR. Comparison with the other typical navigation methods was performed in this section. A series of simulations of long distance navigation were performed. The following cases were compared. The states were estimated by the particle filter (Case 1–4). The number of particles was set to 5000. The parameters of the particle filter were set to the same values as those shown in Table 3.

Case 1. ALN-1.
Both AUVs navigated based on the ALN and estimated the states using the measurements from the ALOC as well as from the DVL and the single-axis FOG. The AUVs performed both prediction and observation phases. This is the same as in Case 1 in Section 4.4.

Case 2. ALN-2.
The navigation conditions are almost the same as in Case 1. It is assumed that AUVs have a high-grade positioning sensor for relative positioning (Teledyne Benthos). The performance of this sensor is shown in Table 6. AUVs used this sensor for positioning instead of the ALOC.

Case 3. Dead reckoning (DR) (navigation with the DVL and the single-axis FOG).

| TABLE 6 | Performance of the high-grade positioning sensor (Teledyne Benthos) |
|----------|-----------------------------|
| Angular accuracy | 0.3° (moving) |
| | 0.18° (being landed) |
| Distance accuracy | 0.5% of distance |

FIGURE 42 Estimation errors of the DR (Dive 2)
The AUV performed only the prediction phase. This is same as in Case 2 in Section 4.4

Case 4. High-grade navigation (HN) (triple-axis FOG with the DVL).
The AUV estimated the states based on the measurements from the DVL as well as the triple-axis FOG. As the triple-axis FOG can measure true north, the heading error is assumed to be 0. The AUV performed only the prediction phase.

Case 5. Long base line (LBL).
Typical accuracy is up to 1 m.40

Case 6. Super short base line (SSBL) from the ship.
Typical accuracy is about 1–2% of the depth.11

Figure 49 shows the navigation condition. In Cases 1 and 2, both AUVs exchange the landmark role. The landmark interval is \( L \) (m) (shown in right panel of Fig. 49). In Case 1, \( L \) is set to 50 m because the performance of the ALOC becomes worse as the distance increases above 50 m. In Case 2, two cases were simulated (\( L \) is set to 50 m or 200 m). The distance between AUVs D is set to 10 m. In Cases 3 and 4, the AUV navigates based on its navigation sensors (shown in left panel)

**Figure 43** Estimated trajectories of the AUVs in the case of the ALN (Dive 3)

**Figure 44** Estimated trajectories of the AUVs and SSBL measurements. Left are the results of the DR and right are those of the ALN (Dive 3)
of Fig. 49). Finally, AUVs navigate 1050 m in all cases. All cases were simulated 10 times.

### 5.2 Results

Figures 50–54 show the results. Errors in the ALN are shown every landmark exchange. Errors in the other cases are shown every 1000 s.

First, in Case 1 (Fig. 50), errors increased gradually as the AUVs alternate the landmark role. Compared with Case 3 (DR), estimation errors in Case 1 were smaller than those in Case 3 because localization was accurately measured with both AUVs landed before exchanging the landmark role. In Case 3 (Fig. 53), since DVL and FOG measurements contain errors, the errors of the position and the heading increased with time. In Case 2 (Figs. 51 and 52), estimation accuracy is greatly improved compared with Case 1 thanks to high-grade positioning sensors. The variations of the results in Figure 52 are smaller than those in Figure 51. By lengthening the landmark interval, it reduces the risk of increasing errors. By nature of the ALN, estimation errors increase as AUVs perform the landmark exchange. Thus, the errors of the ALN depend on the trial number of the landmark exchange as well as the accuracy for each landmark exchange. Compared to the ALOC with the high-grade positioning sensor, difference in performance is great in angular accuracy and this will cause the difference in heading accuracy. Heading accuracy also causes great difference in accuracy of the position.
In Case 4 (Fig. 54), as the triple-axis FOG can measure true north, thereby eliminating the heading error, errors were suppressed around 1.0 m. However, positioning errors remained due to errors from DVL measurements.

From the simulation, it was found that the performance of the ALN depends on the accuracy of the positioning sensors of the AUVs. Even if the performance of the positioning sensor is not so high grade, the errors of the ALN is better than those in the DR. If a high-grade positioning sensor can be used, the performance of the ALN is comparable to those of high-grade navigation methods such as navigation with the triple-axis FOG and the DVL, one with the LBL, or one with the SSBL. However, these conventional methods have several drawbacks such as time-consuming calibrations and system costs. As the ALN does not require these support systems, it provides a promising method in AUV navigation.

**6 | DISCUSSION**

Throughout the experiments and simulations, it was verified that the ALN provides a stable and accurate survey of the seafloor. From the experiments, postprocessing simulations and long distance simulations, the following items are important for the ALN to improve positioning accuracy in real-time navigation.

- To improve AUV’s stability during the landmark period.

In the ALN, the landmark AUV is kept on the seafloor by its own weight. There is possibility that the landmark AUV is moved by disturbances, such as currents. As the moving AUV estimates the states and cannot notice the state change of the landmark AUV in real time, this change can cause great errors. Thus, a method where the landmark AUV keeps its stability is necessary.
• To implement high-grade positioning sensors. Although it requires sensor cost, estimation errors through landmark exchange can be reduced. It can also reduce trial numbers of the landmark exchange.

• To recover from state estimation failure (particle reconstruction). The recovery method will reduce the risk of increasing errors through the landmark exchange.

• To ensure a sufficient quantity of particles. This will reduce the risk of estimation failure.

• To converge state uncertainties sufficiently before the landmark exchange.

From Figures 28 and 32–34, it was found that the particles were converged incorrectly, as the AUVs exchange the landmark role without
converging particles. From this result, it is necessary to monitor how many particles are converged before exchanging the landmark role to prevent increasing position errors.

By considering these items, the performance of the ALN will conduct sufficient performance in real-time navigation.

7 | CONCLUSIONS AND FUTURE VISIONS

This paper reported the performance verification of the ALN for wide area surveys of the seafloor using multiple AUVs. For self-localization, AUVs are typically supported by LBL or SSBL of the support system. Because of the ALN, where one AUV remains stationary on the seafloor as a landmark and the other AUVs observe the seafloor based on the landmark AUV, AUVs can perform stable survey without these support systems.

The required techniques, which consist of state estimation and state communication, were implemented on two hovering type AUVs, "Tri-Dog 1" and "Tri-TON." The performance of the method was examined through sea experiments using the AUVs. In the experiments, the AUVs succeeded in four dives, performing completely autonomous surveys without any support. In particular, in Dive 4, they succeeded in 200 m distance navigation and obtained environmental data near the seafloor. Through postprocessing simulation using sensor data obtained from the experiments, it was found that the estimation errors in the ALN were twice as accurate as those of the dead reckoning (DR). Through the simulation against all dives, it was statistically verified that the ALN has robust performance. In addition, it was also shown that the performance of the ALN is comparable to high-grade conventional navigation methods such as LBL or SSBL through simulation for long distance navigation.

As a result, it was verified that the ALN has the performance to conduct wide seafloor surveys with high positioning accuracy, enabling applications such as accurate seafloor photomosaicking, without any support. The ALN can be applied to several types of surveys such as bathymetry mapping, monitoring of seafloor life, resource surveys, searching for lost objects, and so on. The ALN will be a new observation technology of the seafloor and will contribute to enhance our understanding of the seafloor.

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