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A New DNN Technique for Improving Relative Localization Accuracy Based on Distance Between Unmanned Swarm Nodes

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ABSTRACT
In an environment where multiple nodes move without fixed points, such as in swarms of unmanned robots, understanding the relative positions of the robots is crucial. This paper proposes a new relative positioning technology for understanding the relative positions of nodes in environments where GPS usage is difficult, such as indoors. Specifically, the proposed technology is a new deep neural network (DNN) technique that performs relative positioning using distance information between nodes. This paper proposes two new methods to enhance the performance of relative positioning based on existing DNN techniques. The first method ensures a minimum distance between reference nodes, and the second method involves selecting the optimal reference node. Through computer simulations, it was confirmed that coordinate estimation performance improves when a minimum distance between reference nodes is maintained. Based on these results, the method for selecting the optimal reference node was developed to choose nodes with greater distances between them. Using this method increases the accuracy of coordinate estimation compared to existing methods.

KEYWORDS

Swarm robot, Relative positioning, Formation prediction, Reference node, Deep Learning, DNN

1. INTRODUCTION
Swarm of unmanned robot systems can perform various tasks in harsh environments where human access is impossible or dangerous, such as search and rescue operations in disaster areas or military missions (Schranz et al., 2020; Navarro & Matía, 2013; Tan & Zheng, 2013). Furthermore, if these robot systems are utilized in various industrial settings, they can prevent disasters and reduce the occurrence rate of accidents (Kim & Lee, 2023). To efficiently operate swarm of unmanned robot systems, it is crucial to accurately track the positions of the robots (Chen et al., 2022). The most common method for determining the positions between robots is using GPS (Rashid et al., 2015). However, in indoor environments, there is an issue where GPS signals are blocked or reflected due to walls or ceilings, making it difficult to receive GPS signals properly (Al Nuaimi & Kamel, 2011; Kunhoth et al., 2020; Li, 2019). Furthermore, even in outdoor environments, the presence of GPS jamming signals makes it challenging to utilize GPS for positioning (Hu & Wei, 2009; Grant et al. 2009; Purwar et al. 2016). Research has been conducted using alternatives to GPS such as Wi-Fi signals, RFID, and others. However, these methods require fixed anchor nodes, making it difficult to apply them in swarm node environments where all nodes are mobile and there are no fixed nodes (Guidara et al., 2021; Abidin et al., 2021). In environments where GPS reception is difficult for operating swarm nodes, one alternative for relative positioning is the use of Deep Neural Network (DNN) technology, which utilizes only the distances between nodes to perform relative positioning (Yun et al., 2023). In (Yun et al., 2023), distance information between nodes is inputted into the DNN, and the DNN outputs the coordinates of each node. In this method, although three reference nodes are selected, achieving accurate positioning can be challenging due to symmetrical configurations or rotations of the reference nodes. To mitigate this issue, the technique imposes constraints on the three reference nodes to facilitate effective relative positioning. However, there is a problem with the

degradation of positioning performance when the reference nodes are clustered together or when the three reference nodes form a straight line. Therefore, there is a need for technological development to address these issues and reduce relative positioning errors. This paper proposes two approaches to improve the relative positioning performance of swarm robots in environments where fixed nodes do not exist. The first method involves setting a minimum distance between reference nodes. The second method involves selecting the optimal three nodes from the given cluster nodes and setting them as reference nodes. Both methods are technologies capable of enhancing the accuracy of relative positioning. Relative positioning employs DNN, where the input data comprises distance information between all nodes, and the output predicts coordinates $(\boldsymbol{x}, \boldsymbol{y})$ for all nodes. The performance of the proposed technique is confirmed through computer simulations. According to the simulation results, when a minimum distance of approximately 1m is maintained between reference nodes, regardless of the number of nodes, an average positioning error of approximately 0.82$\boldsymbol{m}$ is observed. Additionally, comparing the positioning performance based on the standard deviation of distance measurement errors in the second method of selecting optimal reference nodes, the proposed method shows an average positioning error approximately 0.92$\boldsymbol{m}$ smaller than the conventional method, regardless of the number of nodes. The structure of this paper is as follows: Section 2 explains the existing distance-based relative positioning methods, while Section 3 describes two proposed improvements for relative positioning systems. Section 4 elaborates on the relative positioning system. Section 5 presents the performance of the proposed two methods and the simulated experimental results compared to the existing method. Finally, Section 6 concludes the paper.

2. Conventional method

The conventional distance information-based relative positioning system estimates the relative coordinates based on the measured distances between all nodes existing on a coordinate plane. In situations where there are no fixed reference nodes, to resolve the ambiguity caused by symmetrical or rotated formations being misinterpreted as different formations, the following rules were applied to three reference nodes: The first node exists at the origin, the second node exists on the x-axis, and the third node is constrained to have a positive $\boldsymbol{y}$-value. There are no restrictions for the remaining nodes apart from these three. With N nodes present, ${}_{\boldsymbol{N}}\boldsymbol{C}_{\boldsymbol{2}}$ pieces of distance information are used as input, and $(\boldsymbol{2N-3})$ pieces of coordinate information, excluding zero values, are output. [Figure 1] illustrates examples of performance degradation in the conventional method's relative positioning when there are five nodes. When the first and second reference nodes are close to each other as depicted in (a) of [Figure 1], and when the value of $\boldsymbol{y_3}$ is small, leading to the three reference nodes forming a straight-line formation as shown in (b) of [Figure 1], there is an issue with degraded positioning performance. This paper proposes two methods to address these mentioned issues and improve the coordinate estimation performance, building upon the conventional relative positioning system.

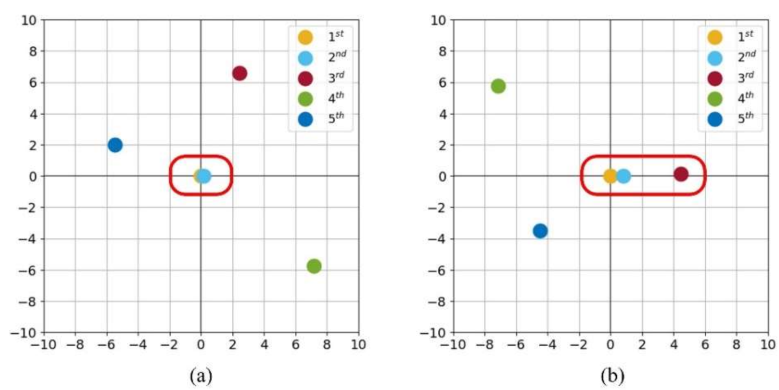

Figure 1. Problems with conventional methods

3. Proposed method

3.1. *Minimum Spacing Assurance Technique between Reference Nodes*

The technique for ensuring a minimum spacing between reference nodes is designed to address the issue arising when the values of $\boldsymbol{x_2}, \boldsymbol{y_3}$ are close to zero. This method incorporates spatial constraints to maintain sufficient distance between nodes, ensuring they are positioned within a specific range. The spatial constraint range for the reference nodes can be defined as follows in [Equation 1, Equation 2].

$$min_x \leq x_2 \leq 10 \quad (1)$$

$$min_y \leq y_2 \leq 10 \quad (2)$$

$\boldsymbol{min_x}, \boldsymbol{min_y}$ represent the minimum spacing values for the reference nodes along the $\boldsymbol{x}$ and $\boldsymbol{y}$ axes, respectively. $\boldsymbol{Bound_x}$, $\boldsymbol{Bound_y}$ denote the maximum boundary values set along the $\boldsymbol{x}$ and $\boldsymbol{y}$ axes of the coordinate plane, indicating the limits of the space within which the nodes can be positioned.

[Figure 2] serves as an example of ensuring minimum spacing between reference nodes in a scenario where five nodes exist. Here, $(\boldsymbol{x_i}, \boldsymbol{y_i})$ represents the coordinates of the $\boldsymbol{i^{th}}$ node. As illustrated in [Figure 2], the second node is positioned at a minimum distance from the origin to avoid adjacency with the first node. By setting a minimum spacing through this method, interference among the reference nodes can be minimized, thereby improving the accuracy of relative positioning. However, this can only be applied when there is sufficient spatial margin to secure an adequate minimum spacing between the reference nodes.

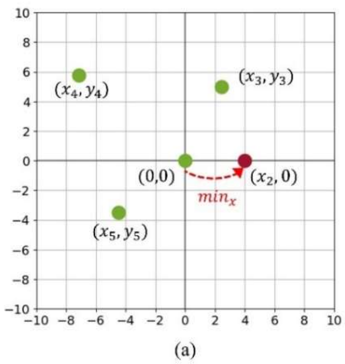

Figure 2. Techniques to ensure minimum spacing between reference nodes

3.2. *Optimal Reference Node Selection Technique*

In this section, we propose a method for selecting the optimal reference nodes while maintaining the formation of the swarm nodes. To achieve this, an additional process of selecting three optimal reference nodes is incorporated after measuring the distances between all nodes existing on the coordinate plane in the existing distance-based relative positioning system model. The selected three reference nodes are then rearranged according to the reference node rules, and the distance information between nodes is input into the DNN model to predict the coordinates of the nodes.

In [Equation 3], $\boldsymbol{a}, \boldsymbol{b}$, and $\boldsymbol{c}$ represent nodes, and $\boldsymbol{d_{a,b}}$ denotes the distance between node $\boldsymbol{a}$ and node $\boldsymbol{b}$. This equation signifies a method for selecting the combination of maximum distances. The maximum distance combination selection method chooses the reference nodes from among all possible combinations of three nodes on the coordinate plane, selecting the combination that yields the largest sum of distances. For $\boldsymbol{N}$ existing nodes, there are $_{\boldsymbol{N}}\boldsymbol{C_3}$ possible combinations. For each possible combination, the sum of distances is calculated, and the combination with the largest sum is chosen as the reference nodes.

$$argmax(d_{a,b}, d_{b,c}, d_{c,a}) \tag{3}$$

[Figure 3] is an example of applying the optimal reference node selection technique when there are five nodes present. In [Figure 3], using [Equation 3], the combination of three nodes that maximizes the sum of the distances between them is found and chosen as the reference nodes. In this example, nodes 2, 4, and 5 were selected as the reference nodes. After selecting the reference nodes, they are rearranged according to the rules, as shown in [Figure 3]. As can be seen in the figure, the formation of the nodes is maintained throughout the process of selecting and rearranging the optimal reference nodes.

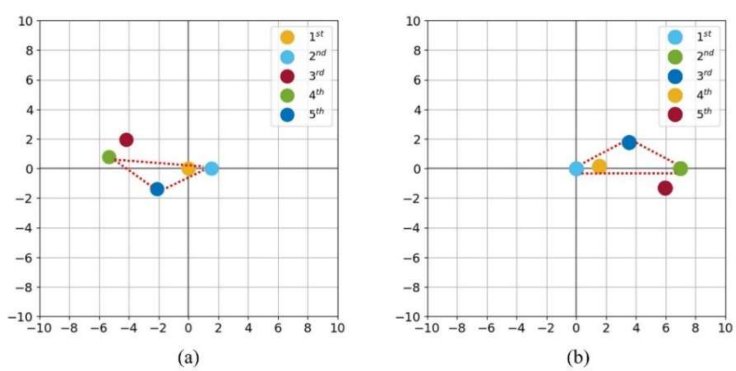

Figure 3. Optimal Reference Node Selection Technique

3.2.1. Considerations When Applying the Optimal Base Node Selection Method

[Figure 4] is an example where 5 nodes exist within a limited range of $\pm k$. As shown in [Figure 4], when selecting the optimal reference node, a node on the boundary of the Bound can be chosen as the reference node. In this case, when rearranging the formation according to the standard rule, there is a problem that the set node's limited range can be exceeded. Exceeding the limited range can affect the performance evaluation of the relative positioning algorithm, so it is necessary to consider this when training the artificial intelligence model. When the limited range in which nodes can exist is denoted as k, the maximum value that can exceed the limit is approximately $2k\sqrt{2}$, which is about 3 times. Therefore, it is necessary to train the artificial intelligence model considering a range that is 3 times the set node's limited range.

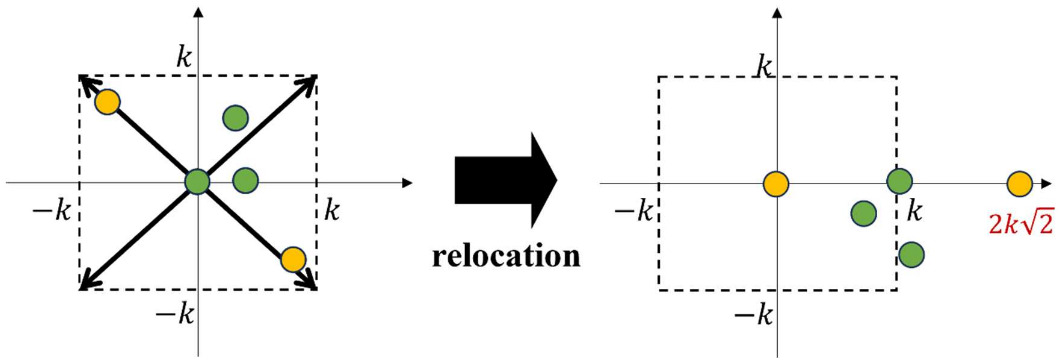

Figure 4. RMSE Performance with Optimal Reference Node Selection

4. DNN model Architecture

[Figure 5] illustrates the proposed DNN model structure, where $(\boldsymbol{x_i}, \boldsymbol{y_i})$ represents the coordinates of the $\boldsymbol{i^{th}}$ node, and the distance between the $\boldsymbol{i^{th}}$ and $\boldsymbol{j^{th}}$ nodes is denoted as $\boldsymbol{d_{i,j}}$. The proposed DNN structure can estimate the coordinates of all nodes existing on the coordinate plane, regardless of the number of nodes, using two deep neural networks. When there are $\boldsymbol{N}$ nodes, $(\boldsymbol{N-2})$ coordinate estimations are required. The first neural network uses the distance information between all reference nodes to estimate the coordinates of the third reference node. The coordinate estimation for the remaining nodes is performed by the second neural network. The second network uses the coordinates of the third reference node estimated by the first neural network and the distance information between the reference node and the node to be estimated as inputs. Through this process, the second neural network sequentially estimates the coordinates of all remaining nodes one by one.

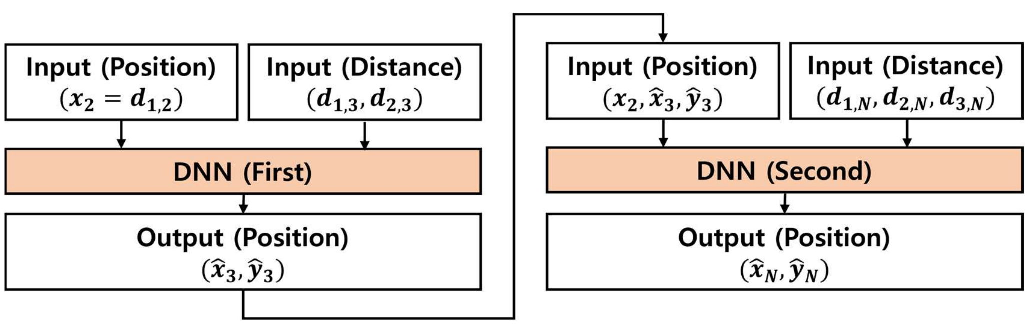

Figure 5. Proposed DNN Architecture

5. Simulation

5.1. Simulation environment

To validate performance, simulations are conducted using TensorFlow and MATLAB. The number of nodes existing within the coordinate plane range is set to between 4 and 8. The measurement error in the distance between nodes due to fading is assumed to be Gaussian noise within a standard deviation of $\boldsymbol{0.01\,m \le \sigma \le 0.10\,m}$. The primary metric used to evaluate the performance of positioning estimation is the root mean square error (RMSE), commonly employed in regression models, as shown in [Equation 4]. $\boldsymbol{N}$ represents the number of data, $\boldsymbol{k}$ denotes the actual value, and $\boldsymbol{\hat{k}}$ signifies the predicted value by the artificial intelligence model.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|\boldsymbol{k}_i - \hat{\boldsymbol{k}}_i\right|^2} \quad , \boldsymbol{k}_i = (x_i, y_i) \tag{3}$$

5.2. ***Training DNN models***

For the training of the artificial intelligence model, the standard deviation of the training data is randomly set within the range and 100,000 samples are generated. In this case, when the node is rearranged by selecting the reference node, the limit range of the node may be exceeded. Therefore, when learning the dnn model, the range of the 2D coordinate plane in which the node may exist is limited to $\pm 30\boldsymbol{m}$. The standard deviation of the test data is set at intervals of $0.01\boldsymbol{m}$ within the same range, and 25,000 data samples are generated within a coordinate plane range of $\pm\mathbf{10}\boldsymbol{m}$.

The hyperparameters required for model training in this paper were determined based on extensive simulations and a heuristic approach. The first DNN model consists of four hidden layers with 256, 256, 256, and 2048 units, respectively. The batch size for the first DNN model is set to 512, and the epoch to 4500. The activation function is the Rectified Linear Unit (ReLU), and the optimizer used is Adagrad, with a learning rate set to 0.01. The second DNN model consists of five hidden layers with 128, 128, 128, 64, and 64 units, respectively. The batch size is set to 128, and the epoch to 1000, with the activation function and optimizer being the same as those used in the first DNN model.

5.3. Simulation Result

5.3.1. Performance with Minimum Reference Node Spacing

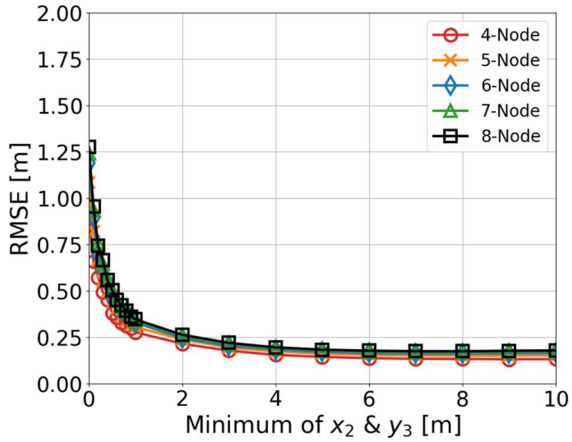

Figure 6. RMSE Performance with Guaranteed Minimum Spacing

[Figure 6] illustrates the RMSE performance in relation to the number of nodes during coordinate estimation, achieved by setting minimum values for $\boldsymbol{x_2}$ and $\boldsymbol{y_3}$ to enhance the accuracy of coordinate estimation. The $\boldsymbol{x}$-axis represents the minimum values for $\boldsymbol{x_2}$ and $\boldsymbol{y_3}$, while the $\boldsymbol{y}$-axis represents the RMSE performance, with lower values indicating superior coordinate estimation accuracy. The performance was evaluated with a fixed standard deviation of noise at $0.05\boldsymbol{m}$. In scenarios with five nodes, ensuring a minimum distance of at least $0.2\boldsymbol{m}$ between reference nodes resulted in an excellent positioning performance of approximately $0.42\boldsymbol{m}$, and securing a minimum distance of $0.8\boldsymbol{m}$ or more showed even better performance, approximately $0.75\boldsymbol{m}$. Regardless of the number of nodes, as the minimum distance between reference nodes increases, the performance of coordinate estimation improves. Therefore, setting the minimum distance between reference nodes is considered a crucial factor for enhancing the coordinate estimation performance of DNNs. Notably, after a certain minimum distance, the RMSE converges to a specific value. This indicates that securing additional distance does not indefinitely improve the performance of coordinate estimation. Thus, it is important to determine the optimal minimum distance between reference nodes, taking into account the limitations of the available space.

5.3.2. Performance with Optimal Reference Node Selection Applied

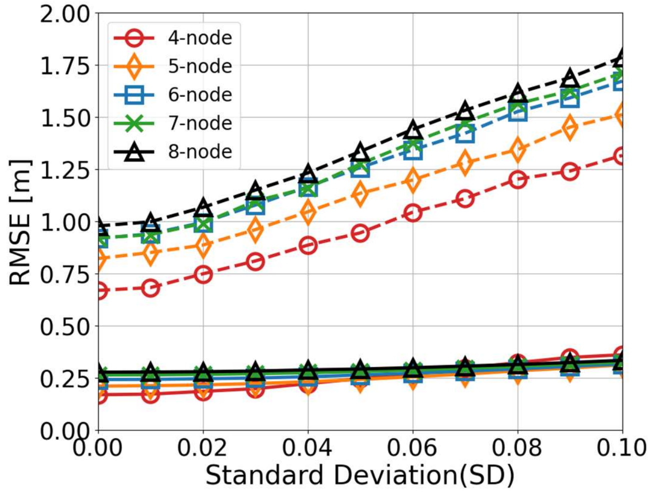

Figure 7. RMSE Performance with Optimal Reference Node Selection

[Figure 7] shows the coordinate estimation performance according to the standard deviation of noise when the optimal reference node selection method is applied. The $\boldsymbol{x}$-axis represents the standard deviation of noise, and the $\boldsymbol{y}$-axis represents the RMSE. The dotted line indicates the performance of the conventional method, while the solid line represents the performance when applying the proposed optimal reference node selection method. When the standard deviation of noise is $0.08\boldsymbol{m}$, the coordinate estimation performance improved by approximately 0.88 $\boldsymbol{m}$ for four nodes compared to the conventional method, and by about $1.26\boldsymbol{m}$ for seven nodes. As the number of nodes increases, the range of options for selecting the optimal combination of reference nodes expands, leading to significant improvements in coordinate estimation performance. Furthermore, while traditional methods show a tendency for the RMSE values to increase as the standard deviation of noise increases, the proposed technique exhibits minimal changes in coordinate estimation performance even with increased noise levels. This indicates that the proposed method can perform stable coordinate estimation in high-noise environments.

6. Acknowledgment

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7. CONCLUSION

In this paper, we proposed two relative positioning techniques that ensure superior performance compared to conventional methods when performing relative positioning using only distance information in swarm unmanned robot systems. The proposed methods estimate coordinates based on the DNN-based relative positioning method utilizing distance information proposed in existing research. The first method ensures a minimum spacing between reference nodes. Simulation results showed that, regardless of the number of nodes, securing a minimum spacing of about 1m between reference nodes improved the coordinate estimation performance by an average of about $0.82\boldsymbol{m}$. The second method involves selecting the optimal reference node using distance information to perform relative positioning. When applying the optimal reference node selection technique, it showed an average improvement of about $0.92\boldsymbol{m}$ over the conventional methods. This method demonstrates the same effect as ensuring a minimum distance of about 2m between reference nodes, meaning accurate positioning performance can be expected even in situations where it's difficult to secure a minimum spacing. This research anticipates that accurately understanding the relative positions between nodes in environments where all nodes are mobile without any fixed nodes will enhance the efficiency and stability of collaborative tasks among robots. It also foresees broad applications in future unmanned robot systems and related fields. As a future research direction, we plan to validate the coordinate estimation performance of the proposed methodology through actual field experiments using transmission and reception modules. Through this, we aim to develop a relative positioning technology that ensures better performance and stability in real-world conditions.

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