DNN Based Relative Localization Technique for Real Time Positioning of Moving Unmanned Swarm Robots

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Abstract – The unmanned swarm robot system, which enables multiple robots to collaborate and perform a variety of tasks, is extensively researched for its potential applications. Accurate determination of the location of swarm robots during operation is of paramount importance, and various positioning algorithms are employed to achieve this. Specifically, in situations where global positioning system (GPS) signals are unavailable, fixed anchor nodes with known location information can be utilized for localization. However, in scenarios where fixed anchor nodes are not present, and the robots operate in a swarm, applying this technology poses challenges, necessitating a localization technique that relies solely on distance information between the robots. This paper proposes a deep neural network (DNN) technique that utilizes only the distance information between moving nodes to predict the real-time relative coordinates of each node. It is assumed that the distances between nodes are updated sequentially and periodically according to a predetermined measurement cycle. A grid-based localization technique is used as the existing method for performance comparison. Computer simulation results demonstrate that the proposed DNN-based relative Localization technique exhibits superior localization performance compared to the existing Grid-based method. Furthermore, the proposed technique shows similar performance regardless of the distance measurement cycle, indicating that it is not significantly affected by the cycle. Therefore, applying the proposed relative Localization algorithm to swarm robots could enable real-time and accurate relative positioning, facilitating precise location tracking of the swarm.

Keywords – Relative Localization, Deep Neural Network, Distance, Swarm Robots, Moving Nodes.

I. INTRODUCTION

Unmanned robot systems are widely utilized for unmanned operations in various fields such as environmental exploration, military operations, and agricultural management [1-4]. As the application areas for robots expand, research is being conducted to operate unmanned swarm robots that exceed the performance of single robots [5]. In particular, the unmanned swarm robot system involves a system where multiple robots collaborate to perform complex and diverse tasks [6]. In this paper, unmanned swarm robots are referred to as 'nodes'. The unmanned swarm robot system is resilient to unexpected situations such as the failure of several robots within the system, maintaining normal operation and allowing for versatile task performance by simply changing the robots' behavior rules according to the given task [7]. In situations where multiple robots operate within a limited area, accurate determination of each other's location is crucial for smooth collaboration, making the research on location estimation of swarm robots a critical field to be addressed in unmanned swarm robot systems [8].

Systems for determining location indoors and outdoors use geometric techniques or pattern recognition algorithms to identify the user's location. When determining location, characteristics of the transmission signal such as received signal strength (RSS) or Time of Arrival (ToA) can be utilized [9]. Algorithms that use received signal strength base their estimation on the principle that RSS values decrease with distance, employing a path loss model to estimate distance from the signal. Location is then estimated through techniques such as fingerprint mapping [10]. Algorithms that use ToA measure the time it takes for a wireless signal to travel from the transmitter to the receiver to estimate distance. The distance information estimated through ToA is used to predict the node's location using methods such as trilateration and grid-based algorithms. Trilateration uses triangle geometry to determine the relative position of an object based on the distances between anchor nodes and the terminal node [11]. Grid-based localization finds a grid that matches the distance between anchor nodes and moving nodes through the Euclidean distance formula [12]. The accuracy of grid-based localization varies with the grid interval; a narrower grid interval improves localization accuracy but increases computation complexity [13]. Both methods using received signal strength and ToA rely on anchor nodes, which are typically fixed and their locations known [14]. Therefore, when the anchor node moves, the positions of all nodes need to be re-estimated. [15]. Thus, in scenarios where all nodes are moving without fixed anchor nodes, a technology that can perform localization using only distance information is required.

In this paper, we propose a deep neural network (DNN)-based relative Localization technique that utilizes only the distance information between nodes to predict the relative 2D (x, y) coordinates of each node in real-time as they move. The positioning process of the proposed technique involves measuring the distance between all moving nodes using Time of Arrival (ToA). These distances are measured and updated at specific time intervals. If all distances are measured at once, the distance measurement interval is considered to be $0s$; otherwise, pairs of distances are measured at specific intervals in a sequential manner. This technique employs distance information to estimate the coordinates of the nodes through a DNN. Specifically, among all nodes, three are selected as reference nodes, around which coordinate realignment is performed. These reference nodes serve the role of anchor nodes. Subsequently, the distance between these reference nodes and the node of interest is used to estimate the coordinates of the interest node through the DNN. The root mean square error (RMSE) is used as a performance evaluation metric for Localization. A grid-based Localization technique is selected among existing methods for performance comparison with the proposed technique. According to computer simulation results, the proposed technique demonstrates superior Localization accuracy compared to existing methods, regardless of distance measurement error and the number of operating nodes. Furthermore, the proposed method exhibits minimal performance deviation based on the distance measurement interval, indicating that frequent measurements of the distance between nodes are unnecessary.

II. DISTANCE-BASED LOCALIZATION

The overall process of localization based on distance information is illustrated in **Fig 1**. The conventional localization technique adopted is the grid-based method, which divides the area of interest into a grid to carry out localization. The proposed localization technique is based on a DNN. The processes other than Localization are identical for both the conventional and proposed localization techniques.

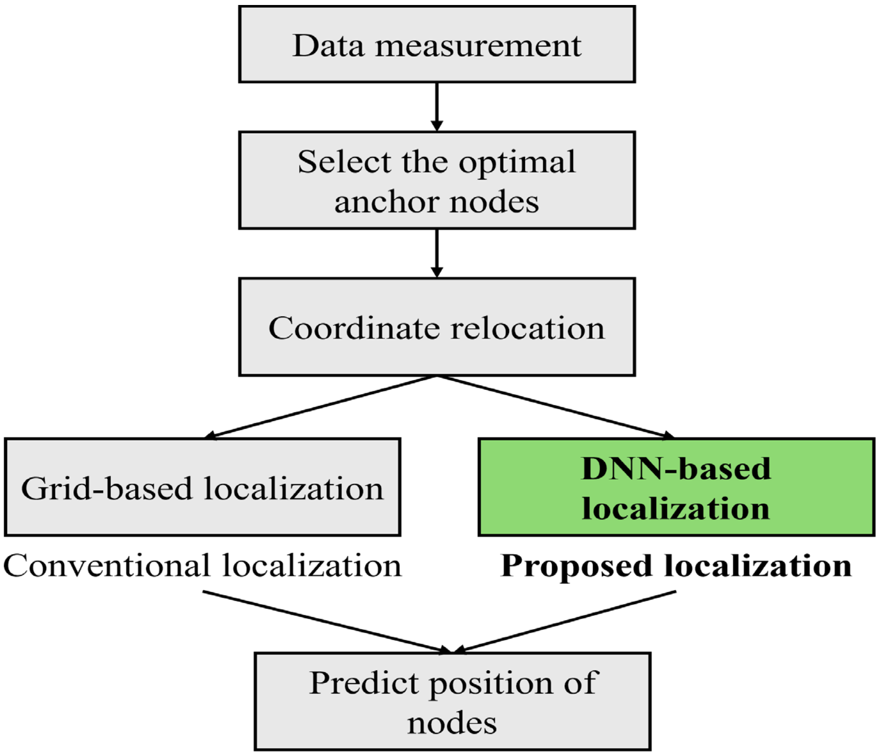

Fig 1. Distance-Based Localization Process

Distance Information Collection

Distance measurement for relative Localization is conducted using the ToA method. ToA refers to the time taken for a signal to reach from the transmitter to the receiver, and when the propagation speed of the signal, such as light or sound, is known, it is used to calculate the distance between the transmitting and receiving objects. The process of distance measurement is illustrated in **Fig 2.**

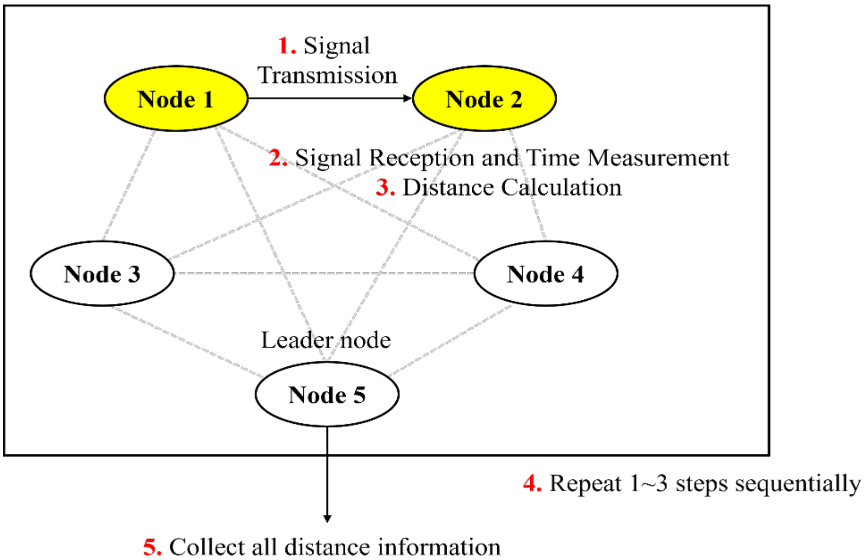

Fig 2. The Process of Collecting Distance Information

Fig 2 illustrates an example of the process by which each node measures and collects distance information. There are two methods of distance measurement: a parallel measurement method where all nodes measure distance simultaneously, and a sequential measurement method where distance measurement is conducted in sequence. This paper assumes that distance measurements are conducted sequentially. In the case of parallel measurement, the distance measurement interval is considered to be 0 seconds, while for sequential measurement, intervals of 0.01 seconds, 0.1 seconds, and 1 second are assumed. Assuming the presence of five nodes, a random node initiates the process by transmitting a signal to a target node for signal reception. The receiving node measures the time of arrival of the signal to calculate the distance, and once the distance calculation is complete, another random node transmits a signal. The order of signal transmission and reception among the nodes is independent of the node numbers. This process is repeated until the distance measurement between all nodes is completed, at which point a leader node collects all the distance information.

Selection of Reference Nodes for Relative Localization

In relative Localization, where the prediction of an entity is based solely on distance information between nodes, ambiguity arises due to the presence of various possible solutions when estimating the entity. [Figure 2] provides examples of ambiguous scenarios that may occur during Localization.

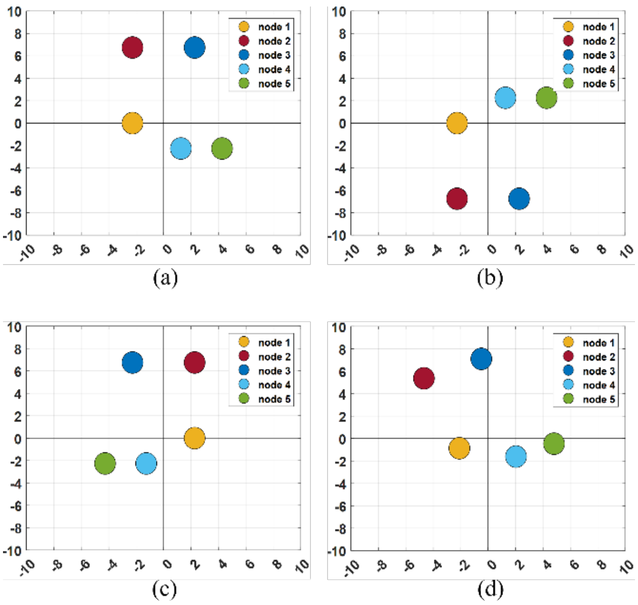

Fig 3. Ambiguity in Formation (a) Label (b) $\boldsymbol{y}$-axis Symmetry (c) $\boldsymbol{x}$-axis Symmety (d) Rotation

In **Fig 3**, (a), (b), (c), and (d) represent the same formation, but due to symmetry or rotation, they could be perceived as different formations, leading to ambiguity in performance evaluation. To resolve this ambiguity, three reference nodes, acting as anchor nodes, are required, and three conditions are proposed. First, the first node must be located at the origin. Second, the second node must reside on the x-axis. Third, the third node must have a positive y-value. The positions of the reference nodes are not fixed but designated within the moving nodes, making the positions of the reference nodes variable. Moreover, there are no constraints for the other nodes, excluding the reference nodes. However, problems in accurately predicting the formation can arise if the distance between the first and second reference nodes is too short, or if the three reference nodes align linearly.

Optimal Selection of Reference Nodes

To address the issues that may arise during the selection of reference nodes, a process for choosing the optimal reference nodes is necessary. The optimal reference nodes should form combinations that are sufficiently distant from each other while resembling an equilateral triangle rather than a straight line. The number of combinations of three nodes out of N nodes is given by ${}_{N}C_{3}$.

In the selection of optimal reference nodes, the mean absolute deviation (MAD) is used. MAD indicates how far the data points are from the mean. Here, the mean represents the equilateral triangle formed by the three reference nodes, and the deviation indicates how close the combination of three nodes is to an equilateral triangle. Through this, we can select nodes among the existing ones that form combinations resembling an equilateral triangle, which can be expressed as [Equation 1].

$$MAD = \frac{1}{3}\left(\left|d_{a,b} - m\right| + \left|d_{b,c} - m\right| + \left|d_{a,c} - m\right|\right),\ m = \frac{d_{a,b}+d_{b,c}+d_{a,c}}{3} \tag{1}$$

[Equation 1] represents the formula for calculating the mean absolute deviation for each side with respect to the average of three sides. Here, each side denotes the distance between three anchor nodes. Considering three nodes, a, b, and c, on the coordinate plane, where $d_{a,b}, d_{b,c}, d_{a,c}$represent the distance information between the three reference nodes, and m represents the mean of the three sides. To reselect the three reference nodes that form an equilateral triangle, we calculate the mean absolute deviation for each combination of the average of three sides. It is essential to consider the relative sizes of the three sides formed by the three reference nodes, thus normalization of the mean absolute deviation is conducted. The three anchor nodes with the smallest normalized mean absolute deviation are ultimately selected. Normalization can be expressed as [Equation 2].

$$MAD_{normalization} = \frac{MAD}{(d_{1,2}+d_{1,3}+d_{2,3})} \tag{2}$$

Formation Relocation

As mentioned in Section 2.3, after selecting the three optimal reference nodes from the existing formation, it is necessary to reposition the formation to align with the reference node conditions for relative Localization as discussed in Section 2.2.

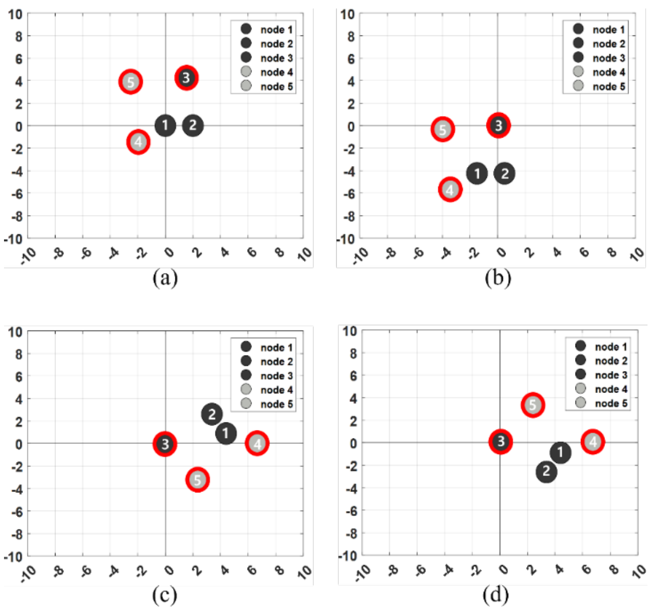

Fig 4. Process of Relocation (a) Original Formation and Reference Node Selection (b) Origin Relocation (c) Rotational Displacement (d) Symmetric Displacement

Fig 4 depicts the process of relocation the formation in accordance with the reference node rules based on the reselected optimal reference nodes. (a) shows the three reselected reference nodes from the original formation, while (b) to (d) illustrate examples of the formation undergoing translation (parallel shift), rotational movement, and symmetrical movement centered around the reference nodes, respectively. Upon reselection, the three nodes become reference nodes in the order of their original node numbers. Once the three optimal reference nodes are reselected, the formation undergoes a parallel shift centered around the reference nodes according to the first rule of the reference node rules. Based on the translated formation, the formation then undergoes rotational movement with the origin node fixed, in accordance with the second rule of the reference node designation rules. After the rotational movement, a symmetrical movement along the x-axis is performed to apply the third rule of the reference node designation rules. During this process, the formation may exceed the designated boundary limits for the nodes. Therefore, considering the maximum potential value for cases where nodes exceed the allowable range, which is $2 \times k \times \sqrt{2}$, where k represents the limit of node existence, it's essential to set the node's restriction range accordingly.

Localization Technique

Conventional Localization Technique (Grid-based Localization)

In this paper, the conventional Localization technique adopted is the grid-based Localization method widely used in Localization systems. The grid-based Localization method divides the area of interest (AoI) into predefined grids, where the AoI represents the restricted range of nodes, and the number of grids is referred to as the 'grid size'. The accuracy varies depending on the grid size, and as the grid size decreases, resulting in narrower grid intervals, the computational complexity increases. After dividing the area of interest into grids based on the specified grid size, the method compares the collected signals in each grid cell with those obtained from the target object to estimate the object's position. By determining the grid cell with the highest similarity, the position of the target object is estimated. Since Time of Arrival (ToA) signals are used, the method compares the measured distance values at each grid point with the actual distance measurements to estimate the object's position.

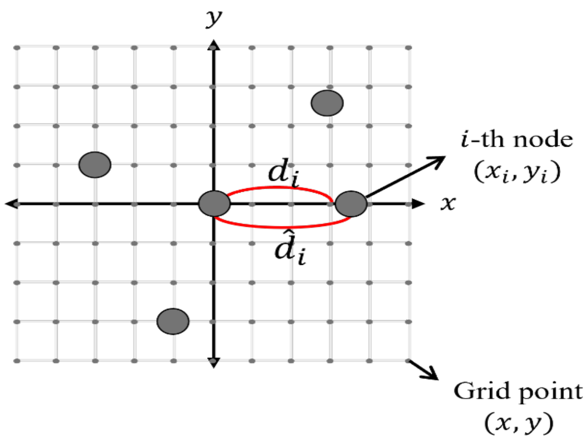

Fig 5. Grid-Based Localization

In grid-based Localization, it sequentially searches from the specified criteria starting from the designated anchor node. Here, the first anchor node serves as the origin, and the y-coordinate of the second anchor node is excluded from estimation as it is set to 0. For estimating the x-coordinate of the second anchor node, the distance information from the first node is utilized to select the most suitable grid among the coordinates divided according to the grid size. From the third node onwards, the coordinates are estimated using the distance information from the previous node and the coordinates information of the preceding nodes obtained in earlier steps.

$$\hat{d}_i(x, y) = \sqrt{(x - \hat{x}_i)^2 + (y - \hat{y}_i)^2} \tag{3}$$

[Equation 3] represents the formula for calculating the distance $\hat{d}_i(x, y)$ between the i-th node and an arbitrary grid point (x, y). Here $\hat{x}_i$ and $\hat{y}_i$ denote the coordinates of the i-th node previously estimated.

$$(\hat{x}_i, \hat{y}_i) = argmin_{(x,y)} \sum_{i=1}^{j-1} \left|\hat{d}_i(x, y) - d_{j,i}\right| \tag{4}$$

[Equation 4] describes the process of determining the coordinates of node $(\hat{x}_i, \hat{y}_i)$ of node j to be estimated. This involves selecting the coordinates $(\hat{x}_i, \hat{y}_i)$ as the answer, which minimize the sum of errors between the actual distances from first node through $j - 1$ and the estimated distances for candidate coordinates $(\hat{x}_j, \hat{y}_j)$.

Proposed Localization Technique (DNN-based Localization)

The proposed DNN-based Localization predicts the relative coordinates of each node solely based on the distance information between the nodes. The problem of predicting relative coordinates through inter-node distance information can be seen as a non-linear relationship. DNN, one of the deep learning techniques, exhibits excellent performance in modeling complex non-linear relationships. Therefore, this problem employs DNN for Localization. As the number of nodes to be estimated increases, the size of the inputs and outputs grows, necessitating the design of different DNN models for each case. **Fig 6** is a block diagram of the proposed DNN.

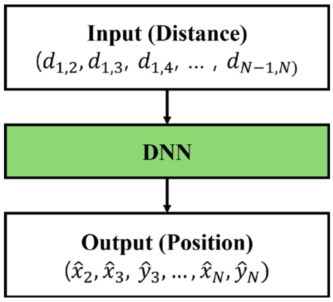

Fig 6. DNN-Based Localization

Fig 6 illustrates that the distance information between all nodes present in the coordinate plane is used as input data for the deep neural network. This distance information is utilized to simultaneously estimate the 2D (x, y) coordinates of each node. When there are N nodes to be estimated, the input data consists of ${}_N C_2$ combinations, and the output data, following the clustering node placement rule, excludes the y-values of the first and second reference nodes, resulting in $(2 \times N - 3)$ data points.

III. SIMULATED EXPERIMENTS

Simulation Environment

Data for the simulation is generated using MATLAB, while DNN training and performance evaluation are conducted in TensorFlow. The number of nodes existing on the coordinate plane is assumed to be between 4 to 8. When estimating nodes, the input data consists of ${}_N C_2$ distance information pairs, and the output data includes $(2 \times N - 3)$ pieces of coordinate information for each node. The DNN model employs an optimized network for each node count for training. The boundary range for nodes is set to $\pm 10m$. In line with considerations mentioned in section 2.3, the boundary range for nodes during DNN model training is specified as $\pm 30m$, with the dataset comprising 100,000 data points. For model validation, the node boundary range is set to $\pm 10m$, with the dataset consisting of 25,000 data points. The distance measurement intervals for the nodes are assumed to be $0s$, $0.01s$, $0.10s$, and $1.00s$, where $0s$ represents the case where all distances are measured simultaneously, and the other intervals represent cases where distances are measured sequentially. The distance measurement error between nodes is assumed to be Gaussian noise with a standard deviation (SD) ranging from $0.00m$ to $0.10m$. The root mean squared error (RMSE) is used as the metric for evaluating coordinate estimation performance.

Simulation Environment

Fig 7 and **Fig 8** display graphs representing the performance of the conventional grid-based Localization technique versus the proposed DNN-based Localization technique. The dashed line represents the grid-based Localization, while the solid line represents the DNN-based Localization. Through both graphs, it can be observed that the proposed DNN-based Localization technique exhibits superior Localization accuracy compared to the grid-based Localization technique. Furthermore, since both techniques show minimal performance deviation with respect to the distance measurement intervals, frequent measurements of the distance between nodes are not necessary.

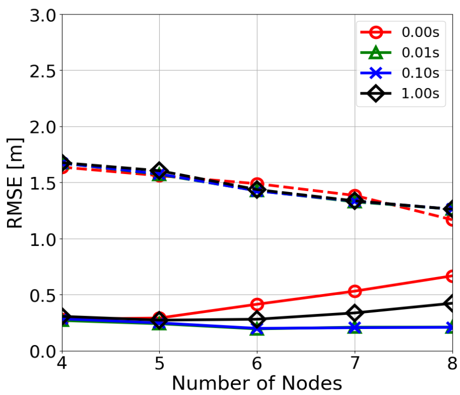

Fig 7. Performance According to the Number of Nodes

Fig 7 presents a performance graph based on the number of nodes existing on the coordinate plane. With the standard deviation of noise fixed at $0.05m$, a comparison of performance across different distance measurement intervals reveals that the grid-based Localization technique exhibits a decrease in RMSE as the number of nodes increases. Conversely, for the DNN-based Localization technique, an increase in the number of nodes corresponds to an increase in RMSE. Meanwhile, for the grid-based Localization technique, the trend in coordinate estimation performance appears similar regardless of the distance measurement interval, while for DNN-based Localization, the best coordinate estimation performance is observed at a distance measurement interval of $0.10s$.

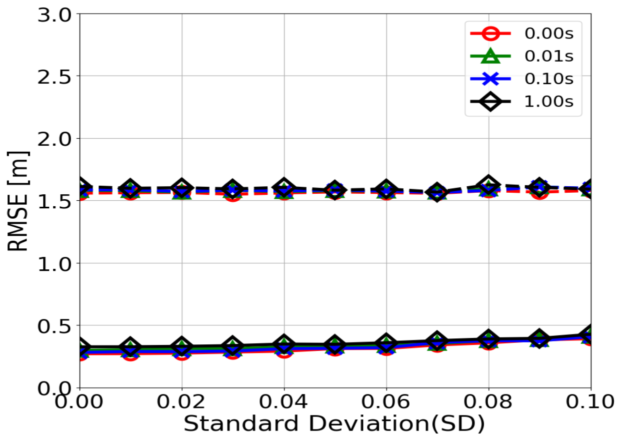

Fig 8. Performance According to Standard Deviation

Fig 8 is a performance graph based on the standard deviation of noise. With the number of nodes fixed at 5 to assess performance, both the grid-based and DNN-based Localization techniques exhibit similar RMSE, regardless of the noise's standard deviation. Furthermore, the trend in coordinate estimation performance is similar for both Localization techniques, irrespective of the distance measurement interval. This indicates that both techniques are capable of stable coordinate estimation in high-noise environments.

IV. CONCLUSION

In this paper, we propose a DNN-based Localization technique that can predict the coordinates of each node using only the distance information of nodes moving in real-time, thereby understanding their relative formation. According to the simulation results, the proposed DNN-based Localization technique demonstrates superior coordinate estimation performance compared to the conventional Grid-based Localization technique. Additionally, the proposed technique is not significantly affected by the distance measurement interval, showing similar performance. Therefore, applying the proposed relative Localization algorithm to swarm robots could enable accurate real-time relative Localization of the swarm robots, allowing for precise determination of their locations. Future work will involve extending the node coordinate space from 2D to 3D to further research the DNN-based Localization technique.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

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Competing Interests

There are no competing interests.

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