Development of Relative Positioning Technique for Swarm Robots Using Distance Information Based on Deep Learning in Indoor Environments

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This paper proposes two DNNs for predicting the relative positions of mobile swarm nodes in real-time, utilizing only distance information. The first method simultaneously estimates the coordinates of each node using acquired distance information. The second method estimates the coordinates by grouping a total of four nodes, including three anchor nodes. To resolve the ambiguity of the estimated coordinates, constraints are applied to the nodes playing the role of anchor nodes. To compare the performance of the DNN, a grid-based algorithm is adopted as the conventional method. Limiting the number of nodes on the coordinate plane to 4 to 8 in simulated experiments, the results indicate a degradation in coordinate estimation performance as the standard deviation (SD) of noise increases, across all methods. Additionally, except for scenarios involving 8 nodes with an SD of 0.02 m, the proposed technique exhibits superior performance in all cases.

Keywords: Swarm robots, Indoor relative positioning, Formation prediction, Deep learning.

1. Introduction

A swarm robot system is a system in which multiple robots collaborate to perform intricate and diverse tasks with a performance surpassing that of an individual robot (La et al., 2011; Blach et al., 1998). By enabling each robot to communicate with neighboring robots and maintain a certain distance, a swarm robot system facilitates the execution of tasks that were challenging for an individual robot to perform alone (Kang et al., 2022; Oh et al., 2020). Integrating machine learning with swarm robot systems enables adaptive, intelligent behavior in collective robotics, paving the way for applications in diverse domains such as exploration, disaster response, agriculture, and industrial automation (Rani et al., 2022; Min et al., 2024; Na et al., 2024). Continued research and development in this field will drive advancements in autonomous robotics and distributed intelligence.

This type of system is utilized in a variety of application areas, including environmental reconnaissance, disaster relief, military operations, and others, as it enables smoother handling of high-risk tasks (Nayyar et al., 2018). In cases where multiple robots operate within constrained operational areas, precise awareness of each other's positions is vital to facilitate seamless collaboration (Heo et al., 2010). Therefore, as a pivotal technology for facilitating seamless task execution among robots, relative positioning is garnering significant attention. Through this, optimizing interactions among robots, including collision avoidance and movement path coordination, enables the maximization of stability and efficiency (Wee et al., 2012; Choi et al., 2022). Furthermore, seamless collaboration among robots allows for the efficient execution of complex tasks.

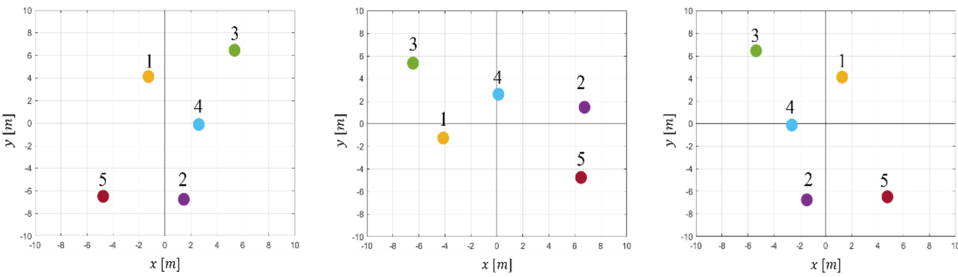
One of the most widely recognized indoor and outdoor relative positioning technologies is the Global Positioning System (GPS). GPS is a technology that determines positions based on calculated distance information from signals measured by at least four artificial satellites. One prominently recognized indoor and outdoor relative positioning technique is the GPS. GPS is a technology that employs distance calculations based on signals measured from a minimum of four artificial satellites to determine positions. However, when obstacles exist between satellites and mobile nodes or discrepancies in transmitter/receiver timing arise, the received distance information becomes subject to errors. The errors associated with the transmission and reception process between satellites and mobile nodes inherently present limitations in achieving complete elimination, and these errors significantly affect the accuracy of the data (Jeon et al., 2008). To mitigate the impact of errors on data accuracy, a configuration of three or more transmitting satellites and a minimum of one satellite for error correction is essential (Kim et al., 2011).

Technologies for calculating positions based on distance information observed from satellites include trilateration and grid-based positioning. Trilateration employs geometric triangulation to determine the relative position of a target object between anchor nodes and terminal nodes (Sohn et al., 2013). In a 2D coordinate plane, a minimum of three anchor nodes is required to accurately determine the relative positions between terminal nodes. Grid-based positioning computes the difference between anchor nodes and mobile nodes using the Euclidean distance formula (Laitinen et al., 2011). By considering the nearest grid point, this technique estimates the node's position as the grid point with the smallest difference. The accuracy of this method varies based on the grid spacing, with finer grids requiring more complex computations due to increased computational demands (Galčík et al., 2016). Both techniques utilize the distance information between anchor nodes, obtained from GPS, and terminal nodes to calculate positions. However, a drawback is that if anchor nodes move, the positions of all nodes must be re-estimated (Rhim et al., 2009). In scenarios where terminal nodes are mobile and lack fixed reference points, both of these methods are challenging to apply. Thus, a technology capable of positioning based solely on distance information is needed for situations involving mobile swarm nodes with moving reference points.

In this paper, a deep neural network (DNN) is proposed for estimating the relative coordinates of nodes and predicting the formation of nodes when only distance information between nodes. The introduced DNN framework consists of two distinct methods. The first method involves simultaneously estimating coordinate information for all nodes, referred to as the "Simultaneous estimation method.". The second method sequentially estimates the nodes on the coordinate plane, including anchor nodes, and is termed the "Group-wise estimation method.". Through computer simulations, we assess the performance of each method in terms of position estimation. Specifically, we compare the proposed DNN method with the grid-based positioning technique among existing localization algorithms. The measurement errors between nodes are assumed to be Gaussian noise with a standard deviation (SD) ranging from 0.00 m to 0.10 m. In simulated experiments with the number of nodes restricted to 4 to 8, the performance of coordinate estimation deteriorates as the standard deviation of noise increases across all methods. In most scenarios, except when 8 nodes are present, the performance of the DNN method surpasses that of the grid-based positioning technique.

Criteria Selection for Relative Positioning

In relative positioning that predicts locations based solely on distance information between nodes, there arises an ambiguity due to the existence of multiple potential solutions. Figure 1 provides examples of ambiguous scenarios that can occur during relative positioning.



(a) label (b) 90° Rotation (c) y-axis Symmetry

Fig. 1: Ambiguity in Formation

(a) to (c) in Figure 1 are all the same formations, but due to symmetry or rotation, it can be judged to be different formations. To address this ambiguity, three conditions are proposed when generating simulated experimental data. Firstly, the first node must be located at the origin. Secondly, the second node should lie along an axis. Thirdly, the third node must possess a positive value. These three nodes are collectively referred to as "Anchor node.". While anchor nodes typically denote nodes with known positions, in this paper, anchor nodes are designated within the moving node set without fixed positions, rendering their locations variable. Furthermore, no specific constraints are imposed on the remaining nodes apart from the anchor nodes.

2. Relative-Positioning Algorithms

2.1 Existing Relative Positioning Algorithms

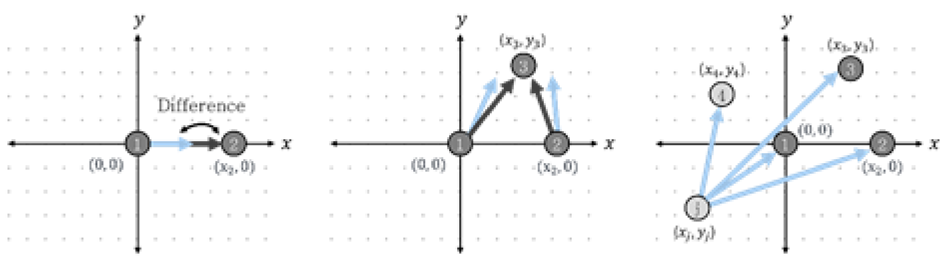
Among the conventional algorithms employed for relative positioning, there exists the grid-based positioning method, which divides the coordinate axes into segments based on the specified count within the node's operational range to estimate the most appropriate coordinates. In this paper, this method is referred to as the "Grid-based algorithm." Additionally, the designated count of divisions along the coordinate axes is termed the "Grid size." The Grid-based algorithm, in accordance with the criteria defined in this paper, systematically explores from the designated anchor nodes. In this process, the first node is anchored at the origin, and as the x-value of the second node is 0, it is excluded from the estimation procedure. When estimating the coordinates of the second anchor node, utilizing the distance information from the first node, it is possible to select the most suitable grid among the x-coordinates divided by the grid size. Starting from the third node, the estimation of coordinates relies on the distance information from the previous node and the coordinates of the preceding nodes, calculated in the earlier steps.

$$\hat{d}_i(x, y) = \sqrt{(x - \hat{x}_i)^2 + (y - \hat{y}_i)^2} \tag{1}$$

Equation 1 provides the formula for calculating d, which represents the distance $\hat{d}_i(x, y)$ between the i-th node and an arbitrary grid point (x, y). Here, x and y denote the coordinates of the i-th node estimated in the previous iteration.

$$(\hat{x}_i, \hat{y}_i) = \mathrm{argmin}_{(x,y)} \sum_{i=1}^{j-1} \left| \hat{d}_i(x, y) - d_{j,i} \right| \tag{2}$$

Equation (2) depicts the process of calculating $(\hat{x}_i, \hat{y}_i)$ when designating the node under estimation as j. In this process, candidate coordinates (x, y) for the j-th node are determined. This involves selecting coordinates that minimize the sum of discrepancies between actual distances and estimated distances from the j-th node to the $(j - 1)$-th node for a given candidate coordinate (x, y).



(a) Estimation of the 2nd Node (b) Estimation of the 3rd Node (c) Estimation of All Nodes on Coordinate Plane

Fig. 2: Grid-based Algorithm

2.2 Existing Relative Positioning Algorithms

In this paper, Deep Neural Network (DNN) is proposed for estimating relative coordinates using only distance information between nodes. The estimation method comprises two distinct methods. Both methods adhere to the criteria defined during dataset generation, where the values of the first and second anchor nodes, which serve as the origin, are omitted from the output data.

2.2.1 Simultaneous Estimation Method

The simultaneous estimation method entails feeding the DNN model with distance information between all nodes, resulting in the generation of estimated x and y values for every node. Consequently, as the count of nodes to be estimated increases, the dimensions of both input and output escalate, necessitating the design of distinct models for each case. The simultaneous estimation method is illustrated in Figure 3.

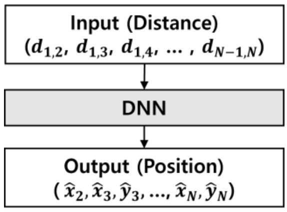


Fig. 3: Simultaneous Estimation Method

The input data for the DNN incorporates distance information between all nodes present in the coordinate plane. Through this distance information, simultaneous estimation of all coordinates for each node is achieved. When there are N nodes to be estimated, the input data consists of ${}_{\mathrm{N}}\mathrm{C}_2$ entries, and the output data comprises $(2\mathrm{N}-3)$ entries.

2.2.2 Group-wise Estimation Method

The group-wise estimation method involves sequential estimation of values for all nodes, starting from the anchor node, while iteratively estimating coordinates for a total of four nodes, including the anchor node and the node intended for estimation. In this method, two distinct Deep Neural Networks are employed. When there are N nodes, this method requires $(\mathrm{N}-2)$ rounds of coordinate estimation.

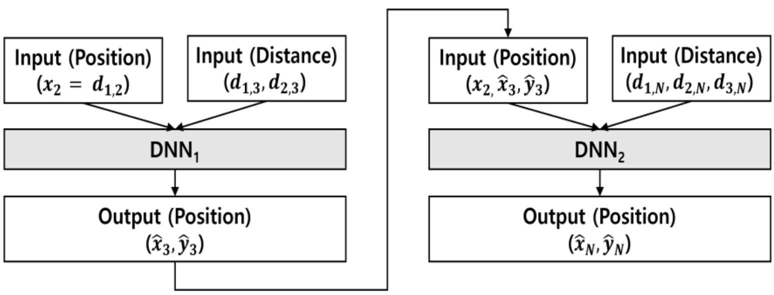


Fig. 4: Group-wise Estimation Method

The process of coordinate estimation is illustrated in Figure 4. Initially, the x-value of the second anchor node is determined using distance information from the first node. The first Deep Neural Network estimates the coordinates of the third anchor node. For this, the input data comprises distance information between the first and second anchor nodes as well as the coordinates of the second anchor node. The second Deep Neural Network sequentially estimates coordinates for the remaining nodes excluding the anchor nodes. The input for the second network includes distance information between anchor nodes and the nodes intended for estimation, along with the coordinates of the third anchor node estimated through the first neural network. The group-wise estimation method has the advantage of being able to estimate the coordinates of all nodes through two deep neural networks without needing each model even if the number of nodes changes.

3. SIMULATED EXPERIMENTS

3.1 Simulation Environment

Data for the simulated experiments is generated using MATLAB, while training and performance validation of the DNN are carried out using TensorFlow. The number of nodes present on the coordinate plane varies from 4 to 8, and the restricted range for both x and y is set at ±10 m. The grid size for the grid-based algorithm is consistently set at 300 for all simulation experiments. The simultaneous estimation method is trained with tailored and optimized networks corresponding to the specific number of nodes involved. Moreover, the group-wise estimation method employs an optimized network designed for scenarios involving four nodes on the coordinate plane.

3.2 DNN Model Training

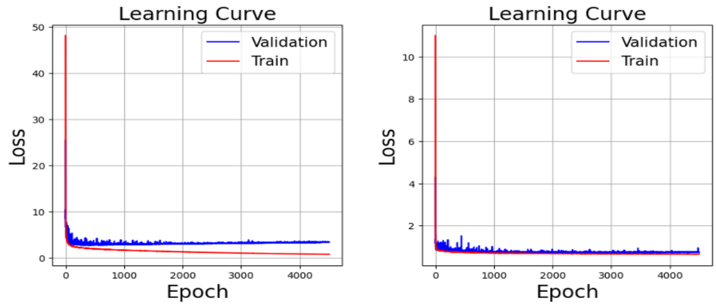
The training data used for AI model training consists of 100,000 samples, while the test data comprises 25,000 samples. The standard deviation (SD) of the noise σ is randomly generated within the range of $0.01\,\mathrm{m} \leq \sigma \leq 0.10\,\mathrm{m}$, following the formula presented in Equation (3). Here, $\tilde{d}_{m,n}$ represents the distance information between the m-th node and the n-th node. z signifies Gaussian noise with a variance of 1, and σ denotes the standard deviation.

$$\tilde{d}_{m,n} = \tilde{d}_{m,n} + \sigma z \tag{3}$$

The hyperparameters required for model training are as follows. The optimizer utilized consistently across all models is AdaGrad, with a learning rate of 0.01. For the simultaneous estimation method, when there are 4 nodes present, a batch size of 512 and 4500 epochs are set for training. For scenarios with 5 to 8 nodes, a batch size of 128 and 2000 epochs are used for training. In the case of the group-based estimation method, a previously optimized network is employed when 4 nodes are present, with a batch size of 512 and 4500 epochs for training. The training objective involves minimizing the Mean Squared Error (MSE), represented by the loss function given by Equation (4).

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(k_i - \hat{k}_i)^2, \qquad k_i = (x_i, y_i) \tag{4}$$

Through Figure 5, it can be observed that after rapid convergence, a gradual decrease in the loss function occurs.



(a) Simultaneous Estimation Method

(b) Group-wise Estimation Method

Fig. 5: Learning Curve of DNN

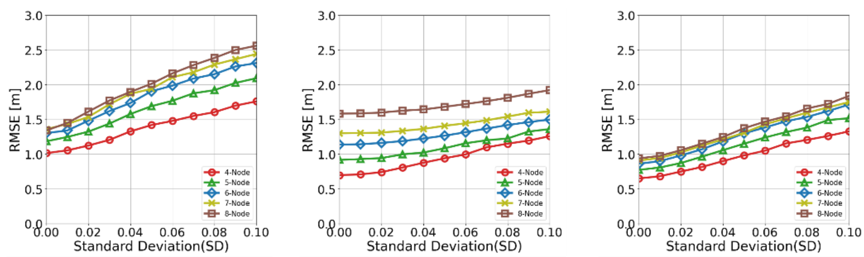
3.3 Simulation Results

The performance evaluation metric for the simulated experiments is the Root Mean Squared Error (RMSE), as defined in equation (5).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(k_i - \hat{k}_i\right)^2}\ , \qquad k_i = (x_i, y_i) \qquad (5)$$

3.3.1 Performance Variation with Standard Deviations of Noise

Figure 6 illustrates the performance with respect to different noise standard deviations for each algorithm. Subfigures (a), (b), and (c) represent the grid-based algorithm, simultaneous estimation method, and group-wise estimation method, respectively. The x-axis of the graph represents the standard deviation of noise, and the y-axis represents the performance metric. In the graph, red circles (○) correspond to scenarios with 4 nodes, green triangles (△) to 5 nodes, blue diamonds (◇) to 6 nodes, yellow crosses (X) to 7 nodes, and brown squares (□) to 8 nodes.



(a) Grid-based Algorithm

(b) Simultaneous Estimation Method

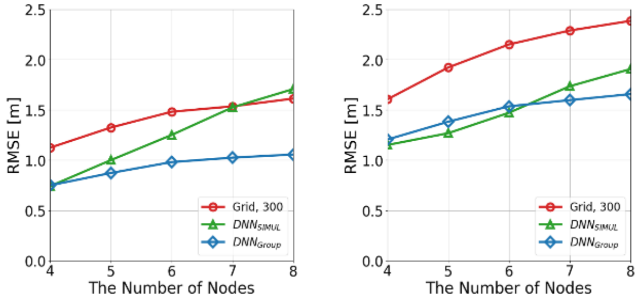
(b) Group-wise Estimation Method

Fig. 6: Performance Variation with Standard Deviation of Noise

Based on the results of the simulation experiments, it is evident that the estimation error increases as the standard deviation of the noise grows, across all methodologies. Moreover, better estimation performance is achieved when the number of nodes present in the coordinate plane is lower.

3.3.2 Performance Variation with Number of Nodes

Figure 7 depicts the performance of algorithms based on the number of nodes. Subplots (a) and (b) in Figure 7 illustrate performance variations with number of nodes for SD of 0.02 m and 0.08 m, respectively. In the graphs, the red (○) markers represent the grid-based algorithm's performance, the green (△) markers denote the simultaneous estimation method, and the blue (◇) markers indicate the performance of the group-wise estimation method.



(a) SD=0.02 m (b) SD=0.08 m

Fig. 6: Performance Variation with Number of Nodes

In the scenario with a noise standard deviation of 0.02 m, it is observed that the performance of the simultaneous estimation method is directly proportional to the number of nodes, regardless of the noise standard deviation. Additionally, the performance of the simultaneous estimation method is superior to the grid-based algorithm for all node counts except when there are 8 nodes based on the RMSE criterion. Moreover, among the three methods, the group-wise estimation method exhibits the highest performance. In the case of a noise standard deviation of 0.08 m, simultaneous estimation method performs best for scenarios with 6 or fewer nodes, while the group-wise estimation method outperforms for scenarios with 7 to 8 nodes.

4. CONCLUSION AND FUTURE WORK

In this paper, we propose two deep neural network-based methods for predicting the positions of nodes in a network solely based on distance information among nodes. The first method is the simultaneous Estimation method, which simultaneously outputs coordinate information for all nodes. The second method is the group-wise estimation method, which sequentially estimates the coordinates of nodes grouped in sets of four, including anchor nodes. Through simulation experiments conducted in environments with 4 to 8 nodes on a 2D coordinate plane, we found that both the proposed methods and conventional relative positioning algorithms exhibit improved localization performance as the number of nodes decreases on the coordinate plane. Additionally, across all methods, increasing noise standard deviation is observed to degrade the coordinate estimation performance. By employing the proposed relative positioning algorithms, it is expected that operating swarm robots would be more convenient due to accurate relative positioning between swarm robots. Future research will focus on predicting the future positions of nodes that change over time at regular intervals and studying scenarios involving partial updates of distance information.

Acknowledgments

This work was supported by the research fund of Hanbat National University in 2023.

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