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Research on Simulated Center of Gravity Offset Localization Algorithm Based on RSSI Assistance

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Abstract

To enhance the accuracy of wireless sensor network localization algorithms without increasing computational overhead, a simulated center of gravity offset localization algorithm (SCG-DV-Hop) based on RSSI assistance is proposed. The algorithm utilizes the relative positional differences between the unknown node and its neighboring anchor nodes to classify other anchor nodes into minimum-hop difference groups relative to the unknown node and its neighboring anchor nodes. A Cartesian coordinate system is established centered on the neighboring anchor nodes to construct a comparison function and record the relative offset angles of the node to be localized. By employing a center-of-gravity-inspired computation method, the algorithm determines the unique offset angle. RSSI measurements are then used to estimate distances and assist in calculating the final solution coordinates. Simulation results demonstrate that the proposed algorithm significantly enhances localization accuracy while maintaining a lower time complexity.

Keywords: wireless sensor networks, node localization, RSSI, center of gravity calculation, complexity

1. Introduction

With the development of sensor technology and the concept of the Internet of Things (IoT), Wireless Sensor Networks (WSNs) are widely used in various applications such as smart ranching, environmental monitoring, natural disaster monitoring, military tracking, and more. What is required at these application levels is not only multi-sensor fusion of environmental sensing information, but also the geographic location of sensor nodes, which plays a crucial role in the effectiveness of environmental data. Ideally, sensor anchor nodes equipped with Global Positioning System (GPS) and BeiDou positioning modules can provide accurate node localization in low-interference environments. However, due to the random nature of the operating environments of wireless sensor networks, which are not easily subject to manual intervention, and the significant limitation of low energy consumption, it is not feasible to deploy a large number of anchor nodes. As a result, how to locate other unknown nodes through a limited number of anchor nodes has become a key area of current research.

The traditional localization methods for wireless sensor networks can be classified into ranging and non-ranging localization based on the ranging technique. Ranging-based localization methods primarily include Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), and Received Signal Strength Indication (RSSI), among others. These methods often require additional hardware, such as in the cases of TOA, TDOA, and AOA localization methods. These algorithms typically demand a high density of anchor nodes and exhibit poor localization accuracy when anchor node density is low (Huang, X., Han, D., Cui, M., Lin, G. & Yin, X., 2021). Common non-ranging localization algorithms include the APIT algorithm, center-of-mass algorithm, MDS-MAP algorithm, and the DV-Hop localization algorithm. Non-ranging localization algorithms do not require additional hardware support, and they generally perform better than ranging methods in dense networks and complex environments (Xiao, H., Zhang, H., Wang, Z. & Gulliver, T. A., 2017). Additionally, their low energy consumption and ease of deployment make them well-suited for the operational characteristics of wireless sensor networks, particularly in resource-constrained environments. The DV-Hop algorithm, as the most widely used non-ranging localization algorithm, provides ideal localization results even with a limited number of anchor nodes, and it is an efficient and cost-effective localization method compared to other non-ranging algorithms (Kumar, S. & Lobiyal, D. K., 2017).

The classical DV-Hop algorithm, whose localization process can be roughly divided into three phases, faces an issue where the minimum hop path between anchor nodes and the minimum hop path from the unknown node to the anchor node are not consistent. This inconsistency causes the average hop distance of the anchor nodes to not accurately reflect the average hop distance of the unknown node. This error is amplified in anisotropic networks, and as the minimum number of hops from the unknown node to the nearest anchor node increases, error accumulation also increases (Cao, Y. & Wang, Z., 2019). To further improve the localization performance of the DV-Hop algorithm, scholars have proposed various improvement schemes. Liu et al. proposed an adaptive average hop distance strategy to dynamically adjust the value of the average hop distance (Liu, X., Zhang, S., Wang, J., Cao, J. & Xiao, B., 2011). Although this method helps to improve localization accuracy in some cases, it is difficult to tune parameters and increases the risk of error propagation. Wang et al. proposed an optimal selection strategy for anchor nodes, which optimizes the number and location of anchor nodes (Wang, J., Hou, A., Tu, Y. & Yu, H., 2020). This method improves localization accuracy while reducing cost and energy consumption. However, it is more difficult to deploy the network, and there is a significant discrepancy between the theoretical optimal position and number of anchor nodes and those in the actual environment. Shu et al. introduced machine learning and optimization algorithms to re-estimate the distances between unknown nodes and anchor nodes, using particle swarm optimization to maximize the adaptive function of the original DV-Hop algorithm (Li, J., Gao, M., Pan, J.-S. & Chu, S.-C., 2021). However, this method is limited by the network topology, with insufficient localization accuracy in low-connectivity networks and a tendency to fall into local optima. Mohamed et al. proposed two localization methods that divide the network area into sub-regions, one of which uses anchor nodes within the same sub-region to localize the unknown node, and the other uses a fusion of leap-point counting and RSSI to compute the estimated distance from the unknown node to the anchor node (Mohamed, E., Zakaria, H. & Abdelhalim, M. B., 2017). This algorithm somewhat alleviates the issue of minimum hop count path mismatch, but it relies heavily on the selection of anchor nodes and the division of sub-regions, and there is considerable uncertainty in the parameter settings.

Currently, optimization schemes for the classical DV-Hop algorithm improve positioning accuracy to a certain extent, with most of the improvements focusing on correcting the average hop distance of anchor nodes as a whole. However, in the process, due to the increased algorithmic complexity, there is a considerable rise in time complexity compared to the classical algorithm. Therefore, this paper proposes a simulated center-of-gravity offset positioning algorithm based on RSSI assistance. The algorithm establishes a Cartesian coordinate system around the neighboring anchor nodes using the hop difference between the node to be localized and its neighboring anchor nodes, as well as other anchor nodes. A judgment function is constructed to record the relative offset angle of the node to be localized. The center-of-gravity-inspired computation method is then used to determine the unique offset angle. Finally, an auxiliary circle is used to determine the unique solution for the coordinates of the node to be localized.

2. Analysis of Classical DV-Hop Error Sources and Improvement Algorithm

2.1 Error Analysis of DV-Hop Localization Algorithm

Error analysis is done for each of the three localization stages of the classical DV-Hop localization algorithm:

(1) Calculate the minimum number of hops: Nodes convey node information by broadcasting and forwarding data within their communication radius. This process defines all the nodes within the communication radius to each other as one-hop. This data transmission method does not consider the actual distance between nodes; although it simplifies the calculation, it leads to a significant difference in actual distance between groups of nodes with the same one-hop. This difference is amplified when calculating the estimated distance of unknown nodes. In the classical DV-Hop algorithm, the average hop distance is calculated using unbiased estimation, which averages the hop distance error. However, the localization effect is not ideal for nodes with large differences in local node densities and poor local network communication environments.

(2) Calculate the average jump distance for unbiased estimation of anchor nodes: Classical DV-Hop uses the unbiased estimation of the neighboring anchor nodes of the to-be-localized node as the average hop distance of the to-be-localized node for the equation construction of the unknown node. The accuracy of this method greatly depends on the uniformity of the topology. However, the topology of the wireless sensor network is anisotropic, and the use of the unbiased estimation in place of the average hop distance between the to-be-localized node and a specific anchor node is not ideal. This scheme leads to error accumulation when the to-be-localized node is surrounded by network voids and when the number of hops from neighboring anchor nodes is too large, a phenomenon that becomes more pronounced in complex environments and low-density regions.

(3) Calculate the estimated coordinates of the unknown node: The position estimation of the nodes to be localized by the classical DV-Hop is done by solving the system of equations using the least squares method, in which the non-linear system of equations is converted into a linear model by pseudo-inverse computation. Linearization errors are inevitably introduced in this process, which becomes particularly obvious in environments where the distance between nodes is large and signal quality is poor. Furthermore, the anchor node coordinate error in the design matrix of the system of equations and the estimated distance error between the unknown node and a specific anchor node will cause error accumulation during the least squares calculation. Effectively controlling the linearization error and the distance estimation error becomes crucial to improving the positioning accuracy of the DV-Hop algorithm.

Aiming at the traditional DV-Hop algorithm with low positioning accuracy and average hop distance calculation, which is greatly affected by the anisotropy of the path with the minimum number of hops in the network, this paper proposes a simulated center of gravity offset positioning algorithm based on RSSI assistance. This algorithm utilizes the difference in the number of hops between the node to be positioned and the neighboring anchor nodes for the same other anchor nodes to perform regional fallout statistics. Then, the weighted relative outgoing angle between the node to be positioned and the neighboring anchor nodes is estimated by the normalized probability distribution function, and accordingly, the unique direction of the node to be positioned with respect to the neighboring anchor nodes is determined. The normalized probability distribution function is used to estimate the weighted relative outgoing angle between the node to be located and the neighboring nodes, and accordingly, the unique direction of the node to be located relative to the neighboring anchor nodes is determined. For nodes to be located with neighboring anchor nodes within one hop, the estimated distance using the weighted Gaussian-filtered RSSI is used to form a circle to determine the unique solution of the position coordinates. For neighboring anchor nodes not within one hop, the estimated distance is calculated using the unbiased average hop distance of the nearest anchor node, and the estimated distance is used to form a circle to determine the unique solution for the location coordinates.

2.2 Calculation of Regional Fallout and Simulated Center of Gravity

2.2.1 Regional Landing Site Statistics

There is a difference in the number of hops between the to-be-located node and the neighboring anchor nodes as well as the other anchor nodes. Using this difference, the relative direction of the to-be-located node is determined. A Cartesian coordinate system is established with the neighboring anchor node $(x_{n'}, y_{n'})$ as the origin, and Equation (1) determines the relative direction of the anchor node (x_j, y_j) with respect to the neighboring anchor node $(x_{n'}, y_{n'})$.

$$\theta_j = \tan^{-1}\frac{y_j - y_{n'}}{x_j - x_{n'}}, \quad (1)$$

where θ_j represents the relative position of the jth anchor node with respect to its neighboring anchor nodes. From the inter-node hop count matrix, which records the possible drop directions based on the hop count information between the to-be-located node and its neighboring anchor nodes as well as the other anchor nodes, the distribution matrix of the drop directions can be described as:

$$\lambda[a] = \begin{cases} \theta_j, & if \ HM_{nj} < HM_{n'j} \\ \theta_j \pm \pi, & if \ HM_{nj} > HM_{n'j} \end{cases}, \quad (2)$$

where $\lambda[a]$ represents the effective landing direction of the ath node to be localized, HM_{nj} is the minimum number of hops between the node to be localized and the non-neighboring anchor node, and $HM_{n'j}$ is the minimum number of hops between the neighboring anchor node and the non-neighboring anchor node.

2.2.2 Estimation of Exit Angle for Simulated Center of Gravity Calculations

The computation of the drop direction distribution matrix for the node to be localized is completed around the neighboring anchor node. The obtained node may have multiple exit angles, which need to be mapped to a unique direction. Inspired by the computation of the center of gravity of a non-uniform disk, the region is modeled as a regular circle centered around the neighboring anchor node, where the weight of the circle itself is ignored. There are i existing load-bearing materials with the same weight, which are added to the circle with the same weight according to the direction recorded by $\lambda[i]$. The formula for the center of gravity of the circle is obtained as:

$$(x_{cma}, y_{cma}) = \left(R \cdot \cos(\lambda[a]), R \cdot \sin(\lambda[a])\right), \quad (3)$$

$$\begin{cases} x_{cm} = \frac{1}{n}\sum_{a=1}^{n} R \cdot \cos(\lambda[a]) \\ y_{cm} = \frac{1}{n}\sum_{a=1}^{n} R \cdot \sin(\lambda[a]) \end{cases}, \quad (4)$$

where (x_{cmi}, y_{cmi}) is the coordinate of the ath material, R is the radius of the auxiliary circle, x_{cm} is the horizontal coordinate of the center of gravity, y_{cm} is the vertical coordinate of the center of gravity, and n is the length of the λ matrix. Then, the unique solution for the position coordinates of the node to be localized can be described as:

$$(x_n, y_n) = \left(R\cos(\tan^{-1}\frac{y_{cm}}{x_{cm}}), R\sin(\tan^{-1}\frac{y_{cm}}{x_{cm}}\right) \quad (5)$$

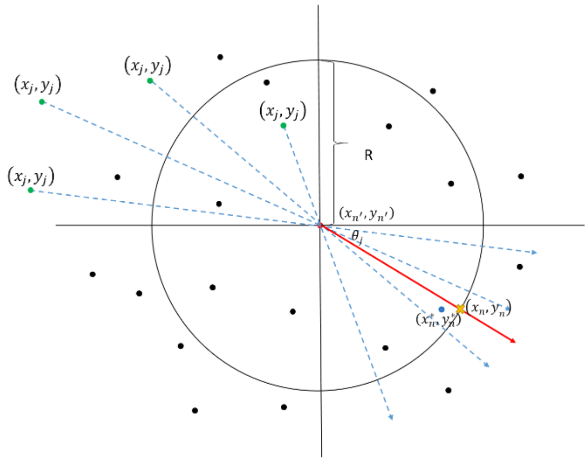

Figure 1. Estimation of exit angle for simulated center of gravity calculations

3. Simulation Analysis

To verify the feasibility and algorithm performance of the proposed scheme in this paper, Matlab R2022a is used to simulate the localization process of the SCG-DV-Hop algorithm. To visually reflect the performance of the algorithms, the following algorithms are compared with SCG-DV-Hop: DV-Hop, the improvements to DV-Hop1 (Zhang, W. & Yang, X., 2023), and the improvements to DV-Hop2 (Xue, D., 2019). Three sets of control experiments are set up in square uniform random topology and C-type random topology, respectively, to demonstrate the localization errors of different algorithms in environments with varying communication radii, anchor node ratios, and total numbers of nodes. The simulation area is set to 100×100 m². To avoid experimental result bias, all data involved in the algorithm are taken with the same parameters and the same network topology type, and the experiments are repeated 100 times.

To unify the evaluation index, the normalized error is used to measure the positioning accuracy of each algorithm, and the expression is:

$$ALE = \frac{\sum_{n=1}^{UN} \sqrt{(x_n - x_n^*)^2 + (y_n - y_n^*)^2}}{R \cdot UN}, \quad (6)$$

where UN denotes the number of unknown nodes and R is the maximum communication radius (x_n^*, y_n^*) denotes the nth unknown node real label.

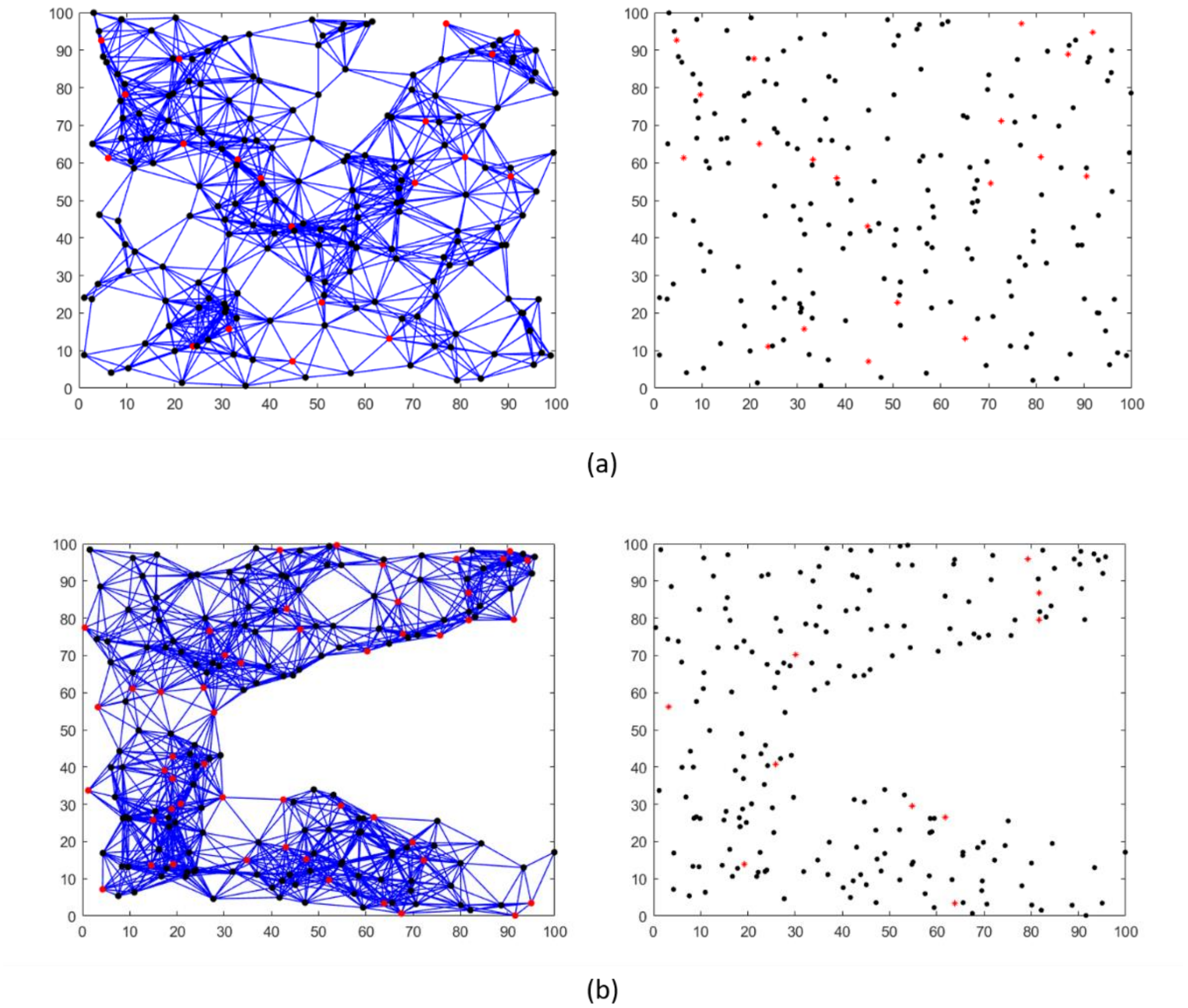

Figure 2. (a) Square uniform random topology; (b) C-shaped random topology structure

3.1 Total Number of Nodes Control Group

In this subsection, the anchor node ratio is set to 0.1, the maximum communication radius is 15 m, and the total number of nodes is incremented from 200 to 400. The experimental results are shown in Figure 3.

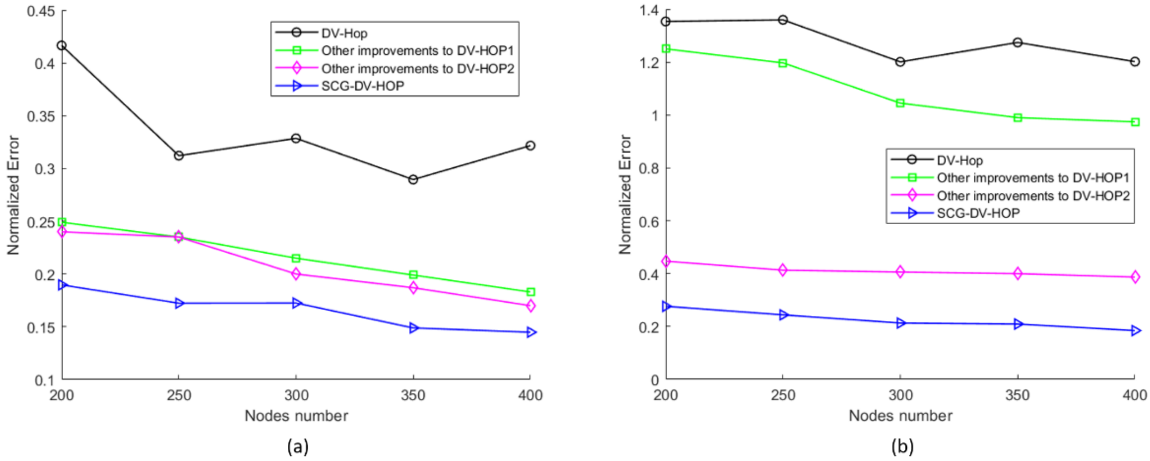

Figure 3. The effect of the total number of nodes on the normalization error for two different network random topologies: (a) Square uniform random topology; (b) C-shaped random topology

Figure 3 shows that for the same parameters of the square uniform random topology, the average normalization error decreases by 11.2% for other improvements to DV-Hop1, 12.1% for other improvements to DV-Hop2, and 16.6% for SCG-DV-Hop, compared to DV-Hop. Under the same parameters of C-type uniform random topology, compared to DV-Hop, the average normalization error of other improvements to DV-Hop1 decreases by 21.8%, the average normalization error of other improvements to DV-Hop2 decreases by 88.8%, and the average normalization error of SCG-DV-Hop decreases by 106.4%. The localization errors of all four algorithms show a decreasing trend with the increase of the total number of nodes, but the fluctuation of DV-Hop is the largest, with SCG-DV-Hop having the smoothest trend and the best robustness.

3.2 Anchor Node Ratio Control Group

In this subsection, the total number of nodes is set to 200, the maximum communication radius is 15 m, and the anchor node ratio is incremented from 0.05 to 0.25. The experimental results are shown in Figure 4.

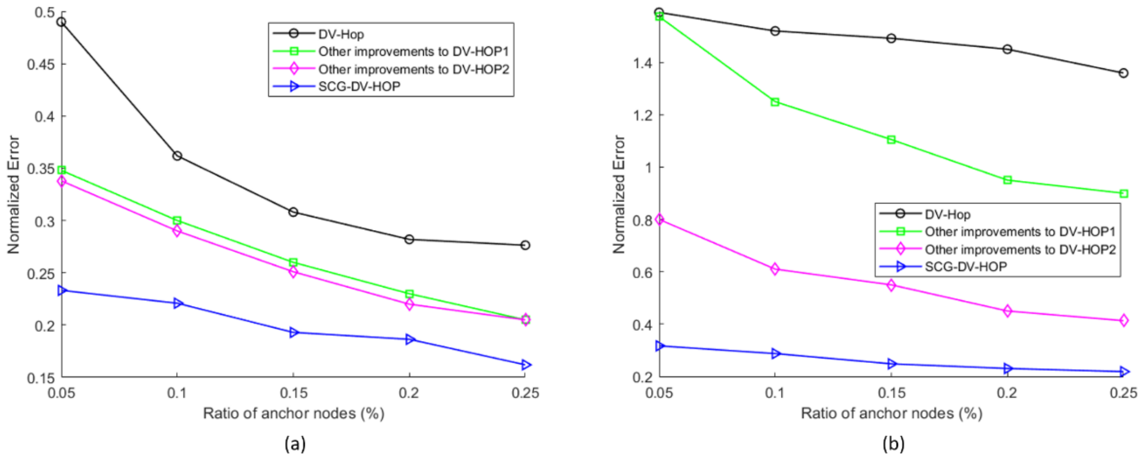

Figure 4. Effect of anchor node ratio on normalization error for two different network random topologies: (a) Square uniform random topology; (b) C-shaped random topology

Figure 4 shows that for the same parameters of the square uniform random topology, the average normalization error decreases by 7.40% for other improvements to DV-Hop1, 11.4% for other improvements to DV-Hop2, and 16.0% for SCG-DV-Hop, compared to DV-Hop. Under the same parameters of C-type uniform random topology, compared to DV-Hop, the average normalization error of other improvements to DV-Hop1 decreases by 36.4%, the average normalization error of other improvements to DV-Hop2 decreases by 94.2%, and the average normalization error of SCG-DV-Hop decreases by 126.4%. The localization errors of all four algorithms show a decreasing trend with the increase in the proportion of anchor nodes, and the decreasing trend of DV-Hop is most evident in the regular random topology. Among them, SCG-DV-Hop has the smoothest trend, and its accuracy is much higher than that of the other algorithms in non-regular topologies.

3.3 Maximum Communication Radius Control Group

In this subsection, the total number of nodes is set to 200, the anchor node ratio is 0.1, and the maximum communication radius is incremented from 15m to 35m. The experimental results are shown in Figure 5.

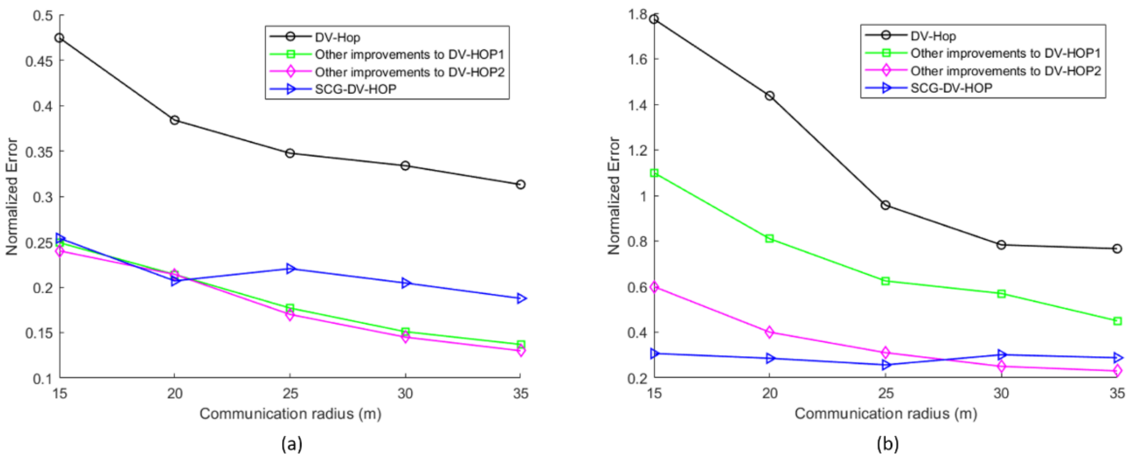

Figure 5. Effect of communication radius on normalization error in two different network random topologies: (a) Square uniform random topology; (b) C-shaped random topology

Figure 5 shows that for the same parameters of the square uniform random topology, the average normalization error decreases by 18.5% for other improvements to DV-Hop1, 19% for other improvements to DV-Hop2, and 15.2% for SCG-DV-Hop, compared to DV-Hop. Under the same parameters of C-type uniform random topology, compared to DV-Hop, the average normalization error of other improvements to DV-Hop1 decreases by 44.6%, the average normalization error of other improvements to DV-Hop2 decreases by 80.4%, and the average normalization error of SCG-DV-Hop decreases by 77.0%. Except for SCG-DV-Hop, the localization errors of all three algorithms show a decreasing trend with the increase in the proportion of anchor nodes. In the communication radius experiment, the error of SCG-DV-Hop increases to a certain extent with the increase of the maximum communication radius. This is because, as the radius increases, the difference in the number of hops between the node to be located and its neighboring nodes to the other anchor nodes becomes smaller, resulting in insufficient sample data for the simulated center of gravity when calculating the angle of ejection, thereby increasing the error.

3.4 Algorithm Complexity Analysis

Due to the low energy consumption of wireless sensor networks, time complexity is an important index to measure the performance of wireless sensor localization algorithms. To standardize the measurement, this paper does not consider the same necessary steps of the classical DV-Hop and the SCG-DV-Hop algorithms, such as the calculation of the adjacency matrix and the hopping matrix. Instead, we analyze only the complexity of the main body of the algorithm. For DV-Hop, it is necessary to traverse each unknown node (number of unknown nodes, UN), so the complexity of the outer loop is $O(UN)$. For each unknown node, it is necessary to use anchor nodes (number of anchor nodes, q) to construct the system of equations, and the complexity of the inner loop is $O(q)$. Therefore, the complexity of matrix construction and matrix solving is $O(q)$. Thus, the time complexity of the DV-Hop algorithm is $O(UN \times q)$. For the SCG-DV-Hop algorithm, the outer complexity is the same as DV-Hop, which is $O(UN)$, while the inner code of SCG-DV-Hop does not involve nested computations of anchor nodes. It will only be executed sequentially at the same level of traversal of the unknown nodes. Therefore, its overall time complexity is roughly $O(UN+q)$.

To verify this analysis, experiments were set up with a total of 200 nodes, an anchor node ratio of 0.2, and a maximum communication radius of 20 m. The running time of the main code of both algorithms was recorded in a uniform random topology network with 100 different square configurations, as shown in Figure 6. The localization time of the SCG-DV-Hop algorithm is significantly lower than that of the classical DV-Hop algorithm under the same parameters in the same network.

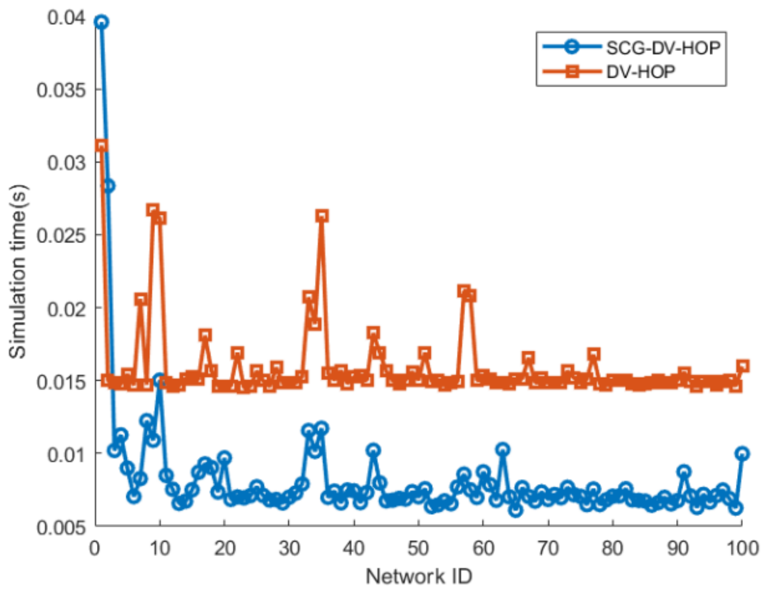

Figure 6. Running time of two algorithms in different uniform random topologies

4. Conclusion

In order to solve the problem of low positioning accuracy and poor stability of the classical DV-Hop positioning algorithm, inspired by the computation of the center of gravity of a non-uniform disc, this paper proposes an RSSI-assisted simulated center-of-gravity offset positioning algorithm, called SCG-DV-Hop. To verify the algorithmic performance of the proposed algorithms in different environments, SCG-DV-Hop was tested in the square uniform random topology and C-type uniform random topology, and its localization accuracy was compared with that of DV-Hop and other existing optimization algorithms. The simulation results show that, without adding additional hardware, SCG-DV-Hop, except for a slight accuracy degradation in the ultra-high communication radius environment, exhibits much higher localization performance than other algorithms in other regular and non-regular random topology networks. It has smaller normalization errors and smoother error curves, demonstrating superior localization accuracy and robustness. Compared with DV-Hop, its normalization error is reduced by 47.8% on average in square uniform random topology, and by 106.5% on average in C-type random topology networks. In addition, the current optimization algorithms for DV-Hop, such as some intelligent swarm optimization algorithms, while significantly improving positioning accuracy, inevitably increase the complexity of the algorithms. Through code analysis and experimental simulations, it is verified that SCG-DV-Hop not only has higher positioning accuracy but also lower time complexity under the same simulation environment. However, it is predicted that the algorithm in this paper will be affected to some extent in environments with low node density, low numbers of neighboring anchor nodes, and excessively large communication radii. Improving the algorithm's localization accuracy in such special environments will be the focus of future research.

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