International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1–22

https://doi.org/10.70917/ijcisim-2026-0212
Article

Research on node position estimation method for wireless sensor networks based on artificial neural network

Xinrui Chen*

* Department of Electronic and Information Engineering, Beihai Vocational College, Beihai, Guangxi, 536000, China; xinrui89@126.com

Abstract: In this paper, classical wireless sensor network self-localization algorithms (e.g., ranging algorithms vs. non-ranging algorithms) and position computation are firstly described. For the challenge of node localization in three-dimensional space, a model of RSSI ranging system in three-dimensional space is constructed, and a position estimation model based on RSSI ranging by the great likelihood method is established on this basis. In order to further improve the accuracy and robustness of the model, a node localization algorithm based on convolutional neural network for wireless sensor networks is innovatively proposed. The results show that: the algorithm in this paper can maintain high localization accuracy under different numbers of working nodes, and the prediction error of the nodes of the model is less than 13% under different heights from 20m to 200m, and the model has a good high degree of adaptability; at the same time, the algorithm effectively reduces the communication and computation overhead of the nodes, and significantly prolongs the survival time of the wireless sensor network.

Keywords: wireless sensor; node localization; convolutional neural network; three-dimensional space

1. Introduction

A wireless sensor network (WSN) is a dynamic, self-organizing, low-power wireless network composed of hundreds or even thousands of low-power sensor nodes with self-computing and communication capabilities [1]. It is characterized by taking sensors as the core, using sensing devices to sense multiple information carried by the external environment or targets, converting this information into data, and realizing the transmission, processing, and storage of this information through wireless communication technology, which has achieved application value in a variety of fields such as military, industry, agriculture, smart home, healthcare, environmental science, biomonitoring, target tracking, and intelligent transportation and security [2-6].

In many WSN applications, the localization of sensor nodes is an essential part. The acquisition of node location information is a prerequisite to ensure that WSNs can work effectively in complex and changing environments, and the lack of location information may directly or indirectly lead to the decline or even disappearance of the value of the data information collected by the sensor nodes, and at the same time, the location information also plays an important role in the process of construction, management and maintenance of WSNs [7-10]. Global Positioning System (GPS) is an early satellite positioning technology, GPS technology can obtain the location information of devices or events within a certain accuracy range; however, in practical applications, the WSN sensor nodes are huge in size, limited in computational capability, and the GPS module is expensive, unstable in positioning performance, and susceptible to the influence of the surrounding environmental factors, and the effect of the GPS technology application in WSN is not unsatisfactory [11-13]. Therefore, it has been in high demand and research significance to develop WSN localization technology with high accuracy, robustness, and low power consumption and cost.

The goal of network node localization is to estimate the coordinates of that network node in a coordinate system, and there are several types of information that can be used to estimate a node's network location - Time Difference of Arrival (TDOA), Angle of Arrival (AOA), and Received Signal Strength Indicator (RSSI), among others [14]. In addition to this, hybrid algorithms can also achieve good localization results. However, in the actual WSN system utilization, the arrival signal strength has a strong uncertainty due to many environmental factors such as physical occluders such as walls, electromagnetic interference such as wireless devices, weather, and signal transceiver distance [15-17]. And artificial neural network (ANN) is a kind of algorithmic mathematical model that imitates the behavioral characteristics of animal neural network and carries out distributed parallel information processing [18]. By virtue of its excellent environmental adaptability and dynamic optimization ability, ANN shows great superiority in the field of digital signal processing and automatic control, and it has been successfully applied to adaptive control, system identification, signal detection, adaptive filtering processing and parameter estimation, etc. These practical applications provide practical references for WSN node position estimation [19-22].

In recent years, many WSN localization algorithms and corresponding improved algorithms have been developed and put into practical applications, the classical WSN localization algorithms can be divided into ranging-based WSN node localization algorithms and non-ranging-based WSN node localization algorithms, while different localization algorithms are affected by different factors, thus there are many differences in terms of performance, accuracy, and overhead, and therefore researchers are are committed to develop more cost effective and high accuracy localization methods [23-26]. In WSN node localization technique, sensor nodes interact with each other through information and estimate the position information of unknown nodes by combining known information through localization algorithms and environmental parameters [27].

Ranging-based node localization algorithms collect distance or angle metrics between sensor nodes, and calculate and estimate the location of unknown nodes based on the collected information. Landolsi et al [28] (2019) performed sensor localization under iterative maximum likelihood estimation (IMLE) based on TDOA measurement measurements, and the localization performance of the method in the presence of actual interference and timing estimation errors outperforms the traditional weighted least squares (LS) approach. Zou and Liu [29] (2020) proposed a semidefinite programming-based localization algorithm for joint source localization and propagation velocity MLE using TDOA measurements in the presence of errors in sensor locations. Wang et al. [30] (2020) formulated a joint synchronization and localization method for asynchronous WSNs in three steps that specifically employs TDOA measurements for LS estimation of relative clock deviations, then MLE of nodes using time-of-flight deviations, and then LS estimation of relative clock offsets to compensate for TDOA deviations caused by heterogeneous time differences. Adeyelu et al [31] (2020) shared an enhanced TDOA technique for estimating the location of mobile stations in WSNs that solves on TDOA hyperbolic and linear LS with the signal reception time difference between the mobile station and the neighboring base stations to achieve the position estimation with the lowest localization error up to 189 m. Zheng et al [32] (2018) for AOA-based localization methods, the measurement accuracy of AOA significantly affects the final localization performance, evaluates the estimation accuracy of different AOA algorithms in the environments with different multipath interferences Meanwhile, a weighted AOA-based localization method was proposed to quantify the AOA estimation accuracy by deriving a closed expression for the asymptotic variance of the AOA estimation error. Arbula and Ljubic [33] (2020) designed a new infrared angular sensor for improving the AOA estimation accuracy, which connects to the application through a server-side application programming interface for indoor localization. Monfared et al [34] (2020) established a non-data-assisted iterative algorithm based on AOA measurements, which is able to utilize more non-data samples, thus improving the location estimation accuracy of low-energy IoT sensor networks. Bianchi [35] (2018) proposed an RSSI-based indoor localization algorithm, which can be used in the field of smart home to achieve room-level localization with user's location estimation. However, Dolha et al [36] (2019) pointed out that variations in distance, geometric orientation of sensors, and environmental features affect the estimation of RSSI values and thus the positioning accuracy. While Gautam et al [37] (2023) set an isosceles layout based on Jaya's algorithm, which fixes the localization target in the transmission range of nodes, which can reduce the interference problem of RSSI values and improve the localization accuracy.

In addition, scientists have developed many algorithms with better performance on the traditional methods, which is more representative of the fusion of multiple techniques to design a hybrid technology-based localization algorithm with excellent performance. Zhang et al [38] (2019) used Gauss-Markov three-dimensional mobility model for single mobile anchor node mobile operation, and the joint ranging MLE of TOA and RSS respectively re proximal and distal ranging to determine the exact distance between the anchor node and the location node for WSN node localization. Chen et al [39] (2020) proposed a node localization algorithm implemented by combining three techniques of TDOA, Phase Difference of Arrivals (PDOA), and Particle Swarm Optimization algorithm, which firstly obtains the initial position estimation by optimizing the TDOA cost function, and then PDOA or hybrid TDOA-PDOA cost function is optimized using Particle Swarm Optimizer and finally the final target position estimate is obtained. Several studies on ranging-based node localization algorithms have shown that the advantages of this type of localization method are high accuracy, low cost, and a broader scope of application, but it still has some shortcomings, such as the sensing equipment is susceptible to the influence of ambient noise, and there is a delay in localization, which needs to be further optimized by the researchers.

In contrast to ranging-based node localization techniques, non-ranging-based node localization algorithms utilize connectivity information between nodes for position estimation of unknown nodes, e.g., the count of inter-node hops can indicate the tight connectivity between two sensors, and the number of neighboring nodes of a node indicates the importance of a single node in the whole WSN. The common non-ranging based localization algorithms are center of mass position localization algorithm, convex position estimation algorithm (CPE), approximate point triangulation (APIT), and distance vector hopping algorithm (DV-Hop), etc. Jiang et al [40] (2018) proposed an improved center of mass localization algorithm assisted with RSSI based technique, in the proposed algorithm, the beacon nodes that are connected into a closed graph of the center of mass is considered as a virtual beacon node, and the virtual beacon node can be used to replace the beacon with the weakest RSSI value among all the beacon nodes connected to the target node to be localized, which narrows the possible location area of the target node and improves the localization accuracy. Fan et al [41] (2017) utilized the irregular topology in 3D WSNs to perform an approximate convex segmentation, which splits the network into multiple sub-networks and utilized a multi-dimensional scaling based algorithm to locate each sub-network, thus realizing joint WSN localization and improving the localization accuracy. And Jain et al [42] (2017) proposed a fusion localization algorithm combining APIT algorithm with RSSI and particle swarm optimization algorithm, using APIT algorithm combined with the information of RSSI value between beacon node and target node, with the help of particle swarm optimization algorithm, to obtain the coordinates of the unknown node or the desired node. Liu et al [43] (2019) proposed an improved DV-Hop localization algorithm based on correcting the average hop size, which corrects the estimated distance between the unknown node and different anchor nodes based on the hop information and the relatively accurate anchor node coordinate information, and uses an improved differential evolutionary algorithm to obtain the estimated position of the unknown node, which effectively reduces the node localization error. At present, the research focus of non-ranging based positioning algorithms is to reduce the computational complexity and computational cost while improving the positioning accuracy of the algorithm and the convergence speed, the development and optimization of more non-ranging node positioning algorithms with excellent performance is also a key research and development direction of the WSN technology in the future.

With the continuous development and popularization of machine learning technology, the application of ANN in WSN node localization is promising. On the one hand, ANN can optimize the relevant localization data; on the other hand, ANN can facilitate the construction of accurate localization models. Sun et al [44] (2018) designed an ANN-based WSN device-less wireless localization system, which inputs RSS matrix difference into the ANN, determines the known location information, and obtains the localization estimation results directly in the online phase, while in the offline phase formulates the nonlinear function of RSS matrix difference and location information to obtain the localization results. Rama and Murugan [45] (2020) utilized RSSI data of mobile nodes processed by principal component analysis to input into ANN model based on firefly algorithm and combined with affine propagation clustering technique to reduce the positional error to determine the accurate localization of mobile nodes, which has 95% of the localization accuracy. Madagouda and Sumathi [46] (2019) applied RSSI to obtain static sensor node localization estimation results from three fixed anchor nodes under Multilayer Perceptron (MLP) and Radial Basis Function (RBF) in the ANN model, and MLP outperforms RBF. Annepu et al [47] (2021) stated that Compared to the WSN localization model based on the MLP method with Sigmoid activation function, the effectiveness of the RBF method based on the RBF method with Gaussian activation function can be improved by up to 70%. While Madagouda and Sumathi [48] (2021) proposed an indoor localization method for WSN nodes based on ANN-based neural feedback network, which uses only one mobile anchor node and achieves the dual benefits of low energy consumption and low cost. Esheh and Affes [49] (2024) used an unknown node location estimated by the DV-Hop algorithm and modified this position result with Gaussian noise based to form a new dataset to enhance the effect of the original data, and input the original data with the new dataset into a deep neural network to realize a WSN localization method with reduced computational cost.

In this paper, we integrate the ranging and non-ranging self-localization algorithms to construct a three-dimensional ranging system model with RSSI, and use the great likelihood method to estimate the initial position of wireless sensor network nodes. In order to solve the difficult problem that sensor nodes cannot communicate and obtain ranging information directly when the linear distance between nodes exceeds a certain threshold, a three-dimensional spatial node localization method based on convolutional neural network is proposed. The method uses the UAV as the data collector and processor of the wireless sensor network, assists in realizing the ranging between the farther nodes in the sensor monitoring area, takes the ranging information between the anchor node and the node to be localized as the input data, and uses it for neural network modeling, and finally realizes the node localization through the neural network model. Finally, the application effect of the localization method of this paper in three-dimensional space node localization is verified through experiments.

2. Convolutional neural network based node localization algorithm for wireless sensor networks

2.1. Self-localization algorithms for wireless sensor network nodes

2.1.1. Ranging based localization algorithm

The distance information between nodes can be obtained by both direct and indirect means, and the typical methods are as follows:

(1) RSSI Ranging Technique

The principle of RSSI ranging technique [50] is as follows: a node sends an RF signal with a known transmit signal power to the nodes within its communication range, and the receiving node measures the RF signal power after receiving the RF signal and determines the distance between it and the sending node according to the relationship between signal energy loss and propagation distance in the signal propagation model. loss and propagation distance in the signal propagation model to determine the distance between the node and the sending node. This technique is a cheap and low-cost distance measurement method, but its distance measurement results will produce a large error.

(2) TOA Ranging Technique

TOA ranging technique usually uses acoustic signals, the transmitting node records the time when it transmits the signal, and the receiving node also records the time corresponding to the received signal, and the distance between the nodes is obtained by multiplying the propagation time with the speed of the acoustic signal. The principle of the TOA ranging technique is shown in Fig. 1. Where T_0 is the time when the transmitting node transmits the signal, T_1 is the time when the signal reaches the receiving node, T_2 is the time when the receiving node sends back the signal to the transmitting node and T_3 is the time when the signal is returned to the transmitting node. The formulas for calculating the distance by TOA and RTOF are as follows respectively:

$$d_{TOA} = \left(T_1 - T_0\right) \times V \tag{1}$$

$$d_{RTOF} = \frac{\left[\left(T_3 - T_0\right) - \left(T_2 - T_1\right)\right] V}{2} \tag{2}$$

where V is the signal propagation velocity.

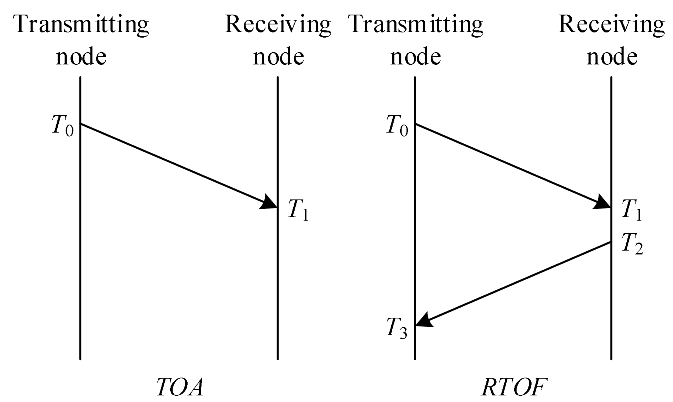


Figure 1. Schematic diagram of transmission time ranging

(3) TDOA Ranging Technique

In TDOA ranging technique, the transmitting node needs to transmit two signals with large differences in speeds, which are generally RF signals and ultrasonic signals, and the ranging schematic of TDOA ranging technique is shown in Fig. 2.

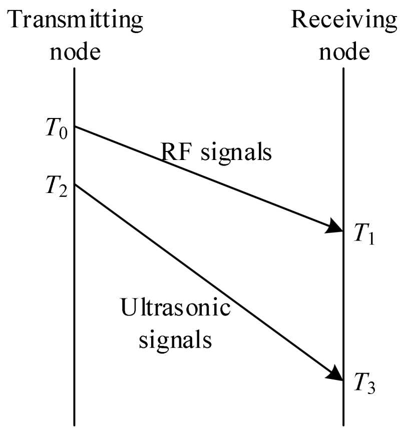


Figure 2. Time difference distance measurement diagram

Immediately after transmitting the RF signal at T_0 an ultrasonic signal is transmitted at T_2. When the signal is received at the receiving node, the reception time of the RF signal T_1 and the reception time of the ultrasonic signal T_3 are recorded. The propagation speeds of both the RF signal and the ultrasonic signal are known as V_{RF} and V_{US}, respectively, and hence the distance d from the transmitting node to the receiving node can be obtained by the following equation:

$$d = \left[(T_3 - T_1) - (T_2 - T_0) \right] \times \frac{V_{RF} V_{US}}{V_{RF} - V_{US}} \tag{3}$$

When there is no obstacle between the transmitting node and the receiving node, the transmission of the signal is line-of-sight transmission, at this time the TDOA technology can achieve a more ideal positioning effect, but the TDOA ranging technology itself has some defects.

(4) AOA ranging algorithm

The principle of the AOA ranging algorithm is that the unknown node measures the angle of the reached signal relative to the axis through the antenna array, and then estimates the node coordinates through triangulation. The AOA ranging schematic diagram is shown in Fig. 3. The coordinates of the unknown node B are assumed to be (x, y), and the coordinates of A_1, A_2 and A_3 are the anchor nodes with known coordinates, whose coordinates are $(x_1, y_1), (x_2, y_2)$ and (x_3, y_3), respectively. The relative angle of the received signals measured through the antenna is respectively are θ_1, θ_2 and

θ_3 . The system of equations can be obtained from the angle relationship:

$$\begin{cases} \angle A_3BA_1 = 2\pi - \theta_3 + \theta_2 \\ \angle A_1BA_2 = \theta_2 - \theta_1 \\ \angle A_3BA_2 = \theta_3 - \theta_2 \end{cases} \tag{4}$$

Combining the system of equations (4) and the coordinates of the anchor node, and then according to the triangulation method, the coordinates of the node can be calculated. The AOA ranging algorithm has a high localization accuracy, but it needs to install expensive antenna equipment on the node, which increases the cost, and is suitable for some special scenarios, and is not suitable for large-scale WSNs.

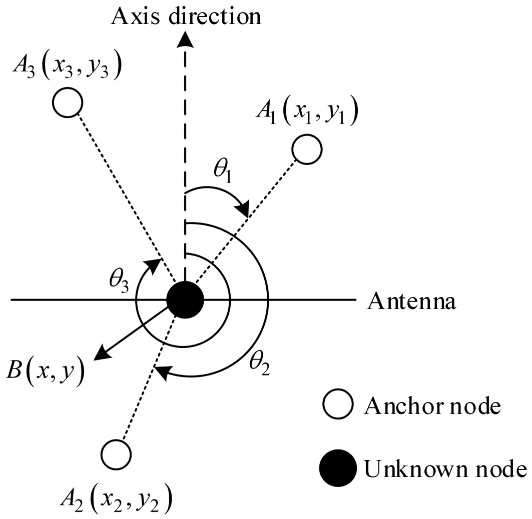


Figure 3. AOA distance measurement schematic

(5) Indirect Ranging Methods Based on Network Connectivity

Since the direct ranging technique is sensitive to environmental factors, it is difficult to achieve better localization results in some poor environmental conditions, and at this time, indirect ranging methods play its role. For example, the distance calculation method in the DV-Hop algorithm, the DV-Hop distance estimation schematic is shown in Figure 4.

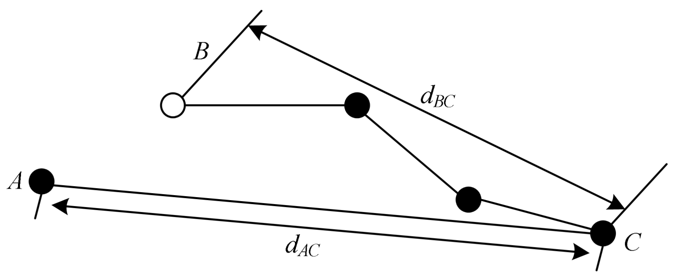


Figure 4. DV-Hop distance estimation diagram

Assume that node A and node C are anchor nodes and the distance between them is d_{AC} and the hop count is h_{AC}. node B is an unknown node, A is its nearest anchor node, and the hop count between node C and node B is h_{BC}. The distance d_{BC} is computed as follows:

$$d_{BC} = \frac{d_{AC}}{h_{AC}} \times h_{BC} \tag{5}$$

2.1.2. Non-ranging based localization algorithms

(1) DV-Hop Localization Algorithm

DV-Hop algorithm is one of the localization methods with wider range of applications at present.

The advantages of DV-Hop algorithm are its simplicity, feasibility, low cost and large localization coverage and the main disadvantage is its poor localization accuracy. In DV-Hop algorithm, the unknown node obtains its minimum hop count from the anchor node and then calculates the distance to the anchor node by multiplying the minimum hop count with the average hop distance. Finally, the node estimates its location using an algorithm such as maximum likelihood estimation.

(2) MDS-MAP algorithm

The MDS-MAP algorithm is a distributed sensor localization method based on multidimensional scales. The algorithm calculates the relative coordinates of the unknown through the information such as connectivity between nodes, and then converts the relative coordinates of the unknown nodes to absolute coordinates through reference nodes. However, the complexity of this algorithm is high, and in large-scale practical application scenarios, the high complexity will lead to an increase in localization time and node energy consumption. This will not only bring the result of reduced localization efficiency but also have adverse effects such as shortening the life cycle of the sensor network.

(3) Center of Mass Localization Algorithm

The center of mass localization algorithm is an algorithm for node localization without ranging based on network connectivity. The position of the node to be localized in this algorithm is calculated from the positions of several reference nodes. First, the node to be localized determines its own anchor nodes that it can communicate with directly, and then forms a polygon with these anchor nodes as vertices. Finally, the position of the center of mass of this polygon is used as the estimated position of the node to be localized, thus completing the process of localizing the current node. The center of mass algorithm is directly related to the density of anchor nodes in the sensor network. When the density of anchor nodes is low, the accuracy of the unknown node position obtained by the center of mass localization algorithm is also reduced.

(4) Approximate Triangle Interior Point Test Algorithm

The Approximate Triangle Interior Point Test (APIT) localization algorithm utilizes the idea of solving for the set of triangles composed of different reference nodes to locate the target node. Using whether the unknown node is within each triangle composed of reference nodes as a solution condition, in order to calculate the polygon that satisfies the condition, and then calculate the center of mass of the polygon, that is, the location coordinates of the unknown node. Because of the overlap of multiple triangles as the constraints of the polygon, the geometric center of mass calculated by this method is closer to the real position than the polygon center of mass position solved directly by the traditional center of mass algorithm. However, the APIT localization algorithm is more dependent on node density, and the algorithm has lower localization accuracy in sensor networks with sparse node distribution.

In summary, the accuracy of the ranging-based localization algorithm is directly related to the accuracy of ranging, which is easily affected by multipath effect, sound speed variability and other factors resulting in localization errors; while the accuracy of the node localization algorithm without ranging depends on the conditions of node communication range, network connectivity and other conditions, and is also affected by the impact of the complex environmental factors.

2.1.3. Position calculation

The trilateral measurement localization method, triangulation localization method, great likelihood estimation method [51], and Min-max localization method are the most commonly used ways to calculate the coordinates of an unknown node after obtaining the distance to each known node. The main ideas are as follows:

(1) Trilateral measurement localization method

For an unknown node to calculate its position using the trilateral measurement localization method, it needs to obtain the position information and distance information of three or more anchor nodes. The principle of trilateral measurement localization method is shown in Fig. 5, L_1, L_2 and L_3 are three anchor nodes within the communication range of unknown node i. Their position information and distance information are obtained through information exchange. Assuming that their coordinates are $(x_1, y_1), (x_2, y_2)$ and (x_3, y_3), and the distances between unknown node i and them are d_1, d_2 and d_3, respectively. taking L_1, L_2 and L_3 as the center of the circle, and d_1, d_2 and d_3 as the radius to make a circle, the position of unknown node i is at the intersection of the three circles.

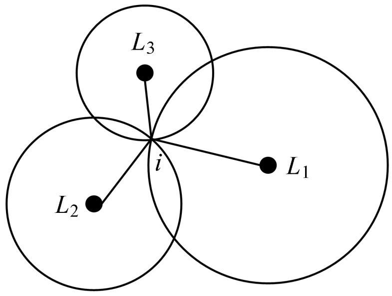


Figure 5. Schematic diagram of trilatcration

The following equation can be obtained from the distance relationship:

$$\begin{cases} \sqrt{(x-x_1)^2+(y-y_1)^2}=d_1 \\ \sqrt{(x-x_2)^2+(y-y_2)^2}=d_2 \\ \sqrt{(x-x_3)^2+(y-y_3)^2}=d_3 \end{cases} \tag{6}$$

Unknown coordinates of node i:

$$\begin{bmatrix} x \\ y \end{bmatrix}=\begin{bmatrix} 2(x_1-x_3) & 2(y_1-y_3) \\ 2(x_2-x_3) & 2(y_2-y_3) \end{bmatrix}^{-1}\begin{bmatrix} x_1^2-x_3^2+y_1^2-y_3^2-d_1^2+d_3^2 \\ x_2^2-x_3^2+y_2^2-y_3^2-d_2^2+d_3^2 \end{bmatrix} \tag{7}$$

(2) Triangulation localization method

Triangulation localization method is a method to complete the position estimation based on the geometric relationship between the unknown node and the anchor node position, mainly suitable for the unknown node to obtain to the known node's angular information in the case of the triangulation localization method, the principle of the triangulation localization method is shown in Fig. 6.

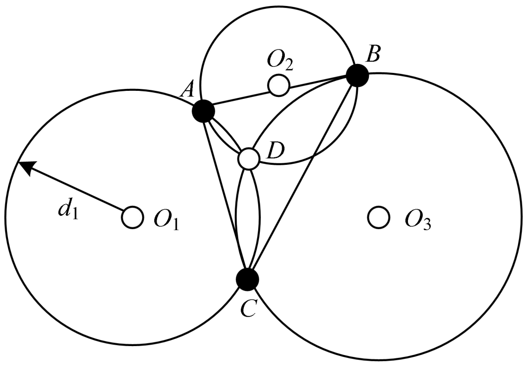


Figure 6. Schematic diagram of triangulation

Assume that the coordinates of the unknown node D are (x,y), and the coordinates of the three anchor nodes A,B and C are known to be (x_1,y_1), $(x_2,y_2),(x_3,y_3)$. The angles from the unknown node to each of the anchor nodes are $\angle ADB,\angle ADC$ and $\angle BDC$. For the nodes A,C and $\angle ADC$ a circle can be determined with center $O_1(x_{o1},y_{o1})$ and radius d_1. Let $a=\angle AO_1C=2\pi-\angle ADC$, which can be obtained by the relationship of angles and distances between the nodes:

$$\begin{cases} \sqrt{(x_{O1}-x_1)^2+(y_{O1}-y_1)^2}=d_1 \\ \sqrt{(x_{O1}-x_3)^2+(y_{O1}-y_3)^2}=d_1 \\ (x_1-x_3)^2+(y_1-y_3)^2=2d_1^2-2d_1^2\cos a \end{cases} \tag{8}$$

The unique circle with radius d_1 and center O_1 coordinates (x_{O1}, y_{O1}) can be obtained from the above equation. Similarly, for nodes A, B and $\angle ADB$, nodes B, C and $\angle BDC$ the corresponding circle center $O_2(x_{O2}, y_{O2})$ and radius d_2, and circle center $O_3(x_{O3}, y_{O3})$ and radius d_3 can be obtained, respectively. Finally, the three circle centers are treated as three anchor nodes in the trilateration measurement method, and the position of the unknown node D is calculated.

(3) Great Likelihood Estimation Method

In practical applications, the nodes in the wireless sensor network can estimate the unknown node position by the great likelihood estimation method after obtaining the information of more than three anchor nodes, the great likelihood estimation method is schematically shown in Fig. 7.

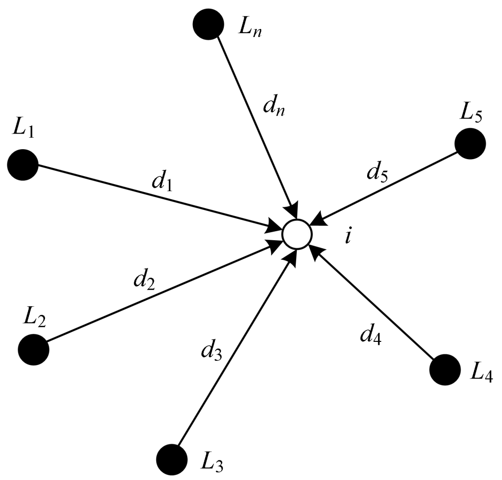


Figure 7. Maximum likelihood estimation diagram

Assuming that the coordinates of the anchor node $L_1, L_2, L_3, \cdots, L_n$ are $(x_1, y_1), (x_2, y_2), (x_3, y_3), \cdots, (x_n, y_n)$, the coordinates of the unknown node i are (x, y), and the distance from each anchor node to the unknown node is $d_1, d_2, d_3, \cdots, d_n$, the following equation exists:

$$\begin{cases} (x_1-x)^2+(y_1-y)^2=d_1^2 \\ \vdots \\ (x_n-x)^2+(y_n-y)^2=d_n^2 \end{cases} \tag{9}$$

The above equation can be expanded as:

$$\begin{cases} x_1^2-x_n^2-2(x_1-x_n)x+y_1^2-y_n^2-2(y_1-y_n)y=d_1^2-d_n^2 \\ \vdots \\ x_{n-1}^2-x_n^2-2(x_{n-1}-x_n)x+y_{n-1}^2-y_n^2-2(y_{n-1}-y_n)y=d_{n-1}^2-d_n^2 \end{cases} \tag{10}$$

The conversion to matrix form is as follows:

$$AX = b \tag{11}$$

Where, $A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ \vdots & \vdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{bmatrix}, b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_n^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix}, \ X = \begin{bmatrix} x \\ y \end{bmatrix}.$

Thus the coordinates of the unknown node i can be derived:

$$X = \left(A^T A\right)^{-1} A^T b \tag{12}$$

(4) Min-max localization method

The principle of Min-max localization method is shown in Fig. 8:

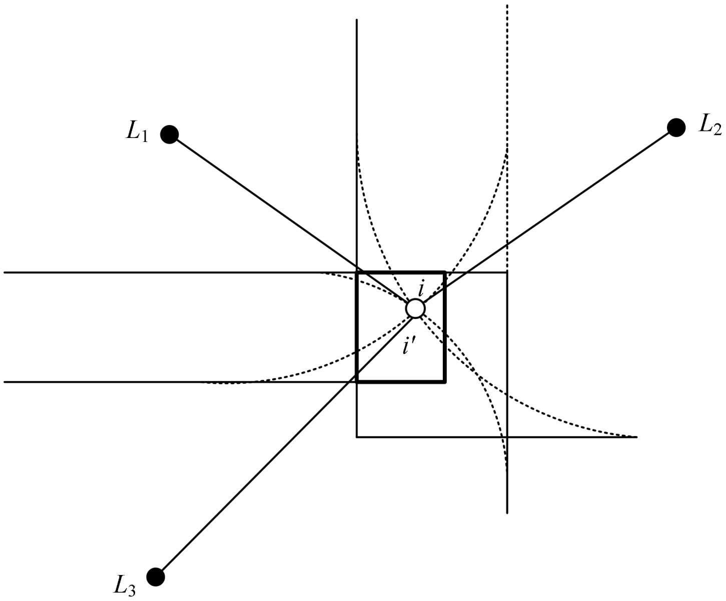


Figure 8. Min-max positioning principle diagram

The coordinates of the anchor nodes L_1, L_2 and L_3 are $(x_1, y_1), (x_2, y_2)$ and (x_3, y_3), and their distances to the unknown node i are d_1, d_2 and d_3. Taking the horizontal and vertical coordinates of the anchor nodes as the reference values, the unknown node is within the bounding box of the coordinate values with the added or subtracted distance values, and the bounding box is calculated by the formula: $[x_i - d_i, y_i - d_i] \times [x_i + d_i, y_i + d_i]$.

Taking the minimum of $[x_i + d_i, y_i + d_i]$ and the maximum of $[x_i - d_i, y_i - d_i]$ on all the bounding lines, the bounding intersecting rectangle box is: $[\max(x_i - d_i), \max(y_i - d_i)] \times [\min(x_i + d_i), \min(y_i + d_i)]$. Calculate the center of mass i' of this rectangle, which is the estimated location of the unknown node i. The formula is as follows.

$$\begin{cases} x = \dfrac{\max(x_i - d_i) + \min(x_i + d_i)}{2} \\ y = \dfrac{\max(y_i - d_i) + \min(y_i + d_i)}{2} \end{cases} \tag{13}$$

2.2. 3D Localization Algorithms for Wireless Sensor Networks

Since most of the application areas of wireless sensor networks are concentrated in three-dimensional space, such as forests, mountains, air, underwater, etc., the study of three-dimensional spatial localization is more in line with the application of actual nodes. Therefore, this paper takes three-dimensional space as an example, and combines ranging and non-ranging algorithms to construct a three-dimensional space node localization model to estimate the initial position of wireless sensor network nodes.

2.2.1. Modeling of RSSI Ranging System

In this paper, the RSSI ranging model is established through the mutual communication between the UAV and the unknown sensor node, with the UAV as the transmitter of the signal and the unknown sensor node as the receiver of the signal. Assuming that the maximum communication range of the UAV is R and the relative distance between the UAV and the unknown sensor ranging is l. If the UAV wants to realize the information interaction between the UAV and the unknown node, it should satisfy the $l \le R$. By means of the propagation loss model, the establishment of the ranging model can be expressed as follows:

$$P_r(d) = P_i(d_i) - 10\gamma \lg\left(\frac{d}{d_i}\right) + W_\delta \tag{14}$$

Where d denotes the relative measured distance between the transmitter and receiver, $P_r(d)$ is the actual signal strength received by the receiver, and d_i is the reference distance near the ground. $P_i(d_i)$ is the signal strength received at d_i, γ is the attenuation factor of the signal in the path, whose magnitude depends on the specific environment in which the signal is propagated, and W_δ is a normally distributed Gaussian random variable. This model is used to calculate the relative distance between the UAV and the unknown sensor node.

2.2.2. Great Likelihood Approach Position Estimation Model Based on RSSI Ranging

When the UAV flies to the area of the unknown sensor node, the UAV moves vertically above the unknown sensor with a set altitude z and speed v. The vertical plan view of the UAV and the unknown sensor node is shown in Fig. 9.

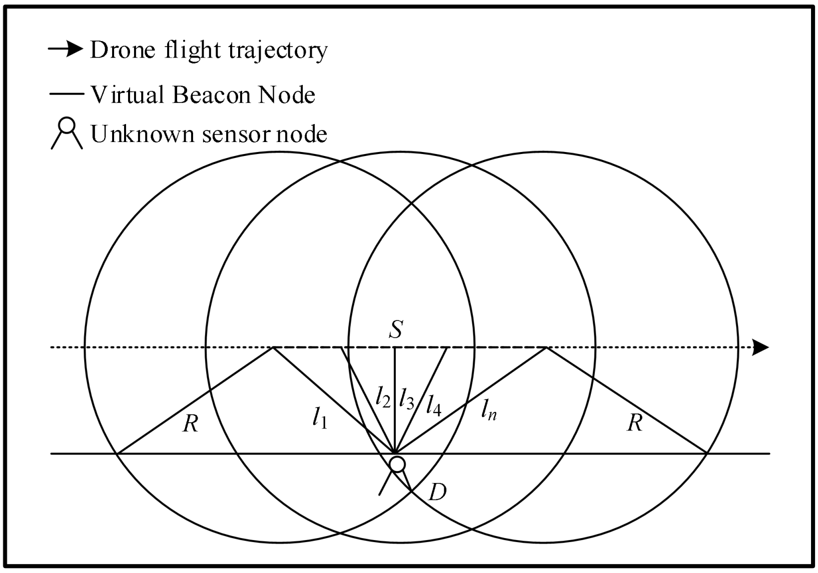


Figure 9. Vertical plan view of drones and unknown sensor nodes

Where R is the communication radius of the drone, the size of its communication radius depends on the size of the signal transmitter power and the specific environment, now make the drone broadcast its own position information every fixed period T, i.e., every after period T the drone produces a virtual beacon, S is the distance flown in the process of the drone broadcasting the virtual beacons, the virtual beacons contain the drone's actual position at that moment, from the figure It can be seen that the communication range of all virtual beacons satisfies that its communication radius is greater than or equal to the relative distance between the virtual beacon and the unknown sensor, i.e., $l \le R$, assuming that the UAV passes through n virtual beacons, i.e., set to $\{M1, M2, \ldots\ldots Mn\}$, the UAV's coordinates in the perpendicular of the node of each virtual beacon corresponding to the unknown sensor node are $(x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), \cdots (x_n, y_n, z_n)$; From the figure, it can be seen that $l_1, l_2, l_3, l_4 \cdots l_n$ is the relative distance between the virtual beacon to the unknown sensor, and their relative distances can be measured by the RSSI ranging model. Since the UAV on-board GPS module flies on a fixed trajectory over the unknown node, the vertical coordinates of the UAV over the unknown node, $(x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), \cdots (x_n, y_n, z_n)$, can be measured by RSSI, and it can be known additionally that when the UAV is directly vertically above the unknown sensor node, the distance l_3 between the virtual beacon generated by the UAV and the unknown sensor node is known. In addition, it can be known that when the UAV is directly above the unknown sensor node, the distance l3 between the virtual beacon and the unknown sensor node is known. Assuming that the coordinates of the unknown sensor node are (x, y, z_0), and since the vertical elevation z_1 of the UAV is known, then the height z_0 of the unknown sensor node is known, i.e. $z_0 = z_1 - l_3$, and the heights of the other unknown sensor nodes can be introduced in accordance with this. Then only the (x, y) coordinates of the unknown sensor node need to be obtained to determine the initial position of the unknown sensor node, then after RSSI ranging, so that the distance between the UAV and the unknown sensor node D is $d_1, d_2, d_3, \ldots . d_n$, respectively, and according to the Euclidean distance formula there is the following relational equation:

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = d_1^2 \\ \vdots \\ (x_n - x)^2 + (y_n - y)^2 = d_n^2 \end{cases} \tag{15}$$

The above equation can be expressed as a linear equation; $AX = b$, where:

$$A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ \vdots & \vdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{bmatrix}, b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix}, X = \begin{bmatrix} x \\ y \end{bmatrix} \tag{16}$$

Using the minimum mean square error estimation method for the above formulas, the two-dimensional coordinates of the position of the unknown sensor node D can be expressed as: $\hat{X} = (A^T A)^{-1} A^T b$, and the coordinates of the three-dimensional preliminary localization can be expressed as $(\hat{X}, z_0)$.

2.3. Convolutional neural network based node localization algorithm for wireless sensor networks

2.3.1. Fundamentals of Convolutional Neural Network Architecture

Convolutional neural network [52] is a special neural network structure for processing data with a grid structure. The basic structure of convolutional neural network consists of several layers, including convolutional layer, pooling layer and fully connected layer.

(1) Convolutional Layer: The convolutional layer is the most important layer in a convolutional neural network, which extracts features by applying a series of convolutional kernels to the input data. Convolutional kernels are usually a set of small matrices that perform element-by-element multiplication and summation operations on localized regions of the input data to generate an output feature map. By varying the number and size of convolution kernels, different types of features can be extracted, and the convolution kernels are the trainable weight parameters in the convolutional neural network.

(2) Pooling layer: The pooling layer is used to reduce the size of the feature map and reduce the amount of computation in the output of the convolutional layer. Common pooling operations include maximum pooling and average pooling, which can take the maximum and average values of the local

regions in the input data, and use them as output features; because pooling operations can lead to the loss of some of the network feature data, the pooling operation is not used in the convolutional neural network structure involved in this paper.

(3) Fully connected layer: the fully connected layer connects all the feature maps and inputs them into a standard feed-forward neural network. This network usually consists of one or more fully connected layers, which output the computed results in the form of one-dimensional vectors.

2.3.2. Principles of node localization algorithm based on convolutional neural network

In the proposed convolutional neural network-based node localization model approach in this section, the node localization network model needs to collect the results of multiple ranging measurements among the ground sensor nodes as inputs to the network. The UAV is set to fly over the wireless sensor network monitoring area for M cycles, and during the m -th cycle, the set of RSSI vectors corresponding to all nodes on the ground, denoted as R^m , is collected, and the RSSI similarity $Sim_{ij}^m, i \in [1, N_a], j \in [N_a+1, N_b]$ between all anchor nodes and unknown nodes is calculated based on the collected information, and the estimated distance $\hat{d}_{ij}^m$ between the corresponding nodes is calculated for the corresponding nodes in that flight cycle, and the node N_j is to be localized to the node, and the UAV flight cycle with all the complex nodes to form a distance estimation vector $\hat{d}_j^m$, rearrange the obtained distance estimation vectors to form a gridded distance estimation matrix, and then form a feature map f_j^m , and the feature maps collected in all the flight cycles of the UAV collectively form the input layer $input_j$ of the convolutional neural network. in the above process, in order to ensure that the collected distance estimation vectors are easy to be meshing, the number of anchor nodes N_a is usually set as a perfect square number, and the above process is expressed as:

$$
\begin{aligned}
\hat{d}_j^m &= \left\{\hat{d}_{1j}^m, \hat{d}_{2j}^m, \ldots, \hat{d}_{Naj}^m\right\} \\
f_j^m &= \begin{bmatrix} \hat{d}_{1j}^m & \hat{d}_{2j}^m & \cdots & \hat{d}_{\sqrt{Na}\,j}^m \\ \hat{d}_{(\sqrt{Na}+1)j}^m & \hat{d}_{\left(\sqrt{N_a}+2\right)j}^m & \cdots & \hat{d}_{\left(2*\sqrt{N_a}\right)j}^m \\ \vdots & \vdots & \ddots & \vdots \\ \hat{d}_{\left(N_a-\sqrt{N_a}+1\right)j}^m & \hat{d}_{\left(N_a-\sqrt{N_a}+2\right)j}^m & \cdots & \hat{d}_{N_a j}^m \end{bmatrix} \\
input_j &= \left[f_j^1 \quad f_j^2 \quad \cdots \quad f_j^M\right]
\end{aligned} \tag{17}
$$

$input_j$ in the above expression is a three-dimensional data, in the convolutional neural network structure, the input layer is often a three-dimensional tensor, and the three dimensions are length*width*number of channels, in the input layer structure of the proposed network, the number of UAV flight cycles M corresponds to the number of channels of the input layer of the network, and the length and width are the square root of the number of anchor nodes $\sqrt{N_a}$, using $input_j$ as the input to the convolutional neural network. A convolutional neural network node localization model is constructed, which contains one input layer $input_j$, three hidden layers $z^{(1)}, z^{(2)}, z^{(3)}$, and one output layer $\hat{N}_j$. The number of neurons, the type of network layer, the size of convolutional kernel, and the corresponding activation function are the parameters of each layer inside the neural network. The internal structure of the convolutional neural network node localization model is shown in Table 1.

Table 1. Internal structure of the convolutional neural network node positioning model

Network layer name	Network layer type	Network layer size	Convolution kernel size	Activation function
Input layer	Convolution Layer	$M*\sqrt{N_a}*\sqrt{N_a}$	$M*\left(\sqrt{N_a}-1\right)*\left(\sqrt{N_a}-1\right)$	ReLU
Hidden Layer 1	Convolution Layer	18*2*2	18*2*2	ReLU
Hidden Layer 2	Fully connected	30	-	Sigmoid

	layer			
Hidden Layer 3	Fully connected layer	18	-	Sigmoid
Output layer	Fully connected layer	2	-	-

In the node localization method based on convolutional neural network proposed in this section, the computer randomly generates a large number of node coordinates in the sensor monitoring area as training data, and in the actual experimental process, the distance measurement data obtained from simulated drone-assisted ranging algorithms are used, and the simulated ranging results are rearranged to form the form of a three-dimensional tensor as the input to the network, and the actual coordinates of the nodes are used as the training labels of the network, and the appropriate The actual coordinates of the nodes are used as the training labels of the network, and appropriate network training parameters are selected to train and optimize the network. Once the network is trained, it can predict the position of nodes in different environments, with high robustness and overcoming the influence of error, at the same time, the neural network model improves the positioning accuracy of nodes, and can adjust the number of ranging times assisted by UAVs according to the actual needs and thus adjust the structure of the network, so that the algorithm has a higher degree of flexibility.

3. Performance analysis of wireless sensor node localization algorithm

3.1. Performance analysis of the number of working nodes of the algorithm

3.1.1. Effect of different anchor node ratios on node localization

In fact, wireless sensors (WSNs) are generally deployed in large areas, so there are more sensor nodes in the monitoring area, and considering the cost of manually deploying the nodes, it is common to randomly scatter the sensor nodes in a certain area by using airplanes and so on. In order to avoid the phenomenon of regularity in the node arrangement, a random function is used in the simulation process. Figure 10 shows the random distribution of nodes. The distribution of each node is given in the figure and the distribution is randomized. The horizontal and vertical distance of this experimental site is 1000 meters, and there are 200 nodes in this experimental site, and each node is randomly distributed, and among these nodes there are beacon nodes and unknown nodes, which are indicated by the black and red signs, respectively. From the practical cost point of view, due to the high cost of beacon nodes, not too many of these nodes will be selected, so the total ratio is relatively low, and the location of these nodes is known, in the whole experimental process, they act as the main task is the role of reference.

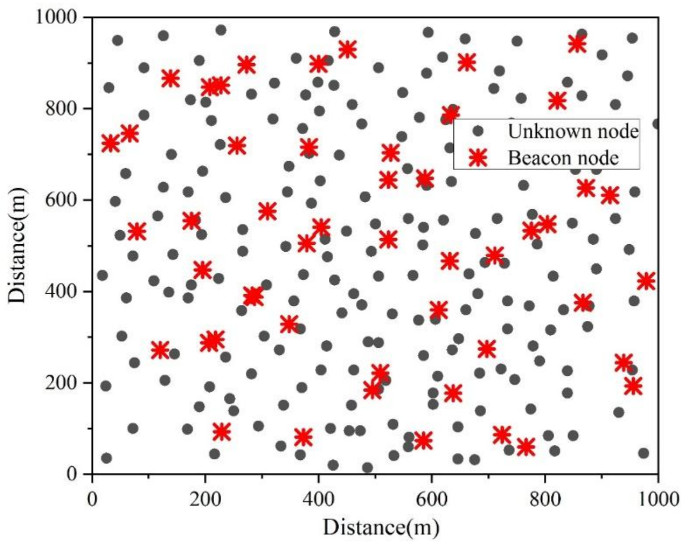
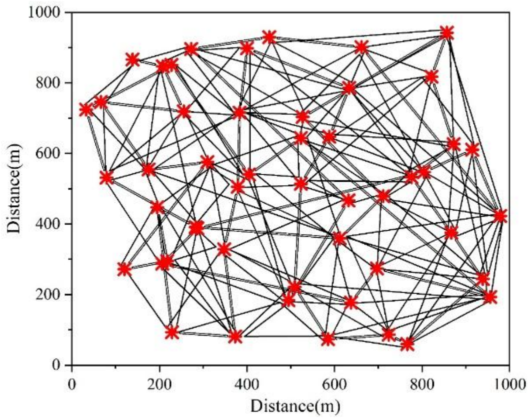


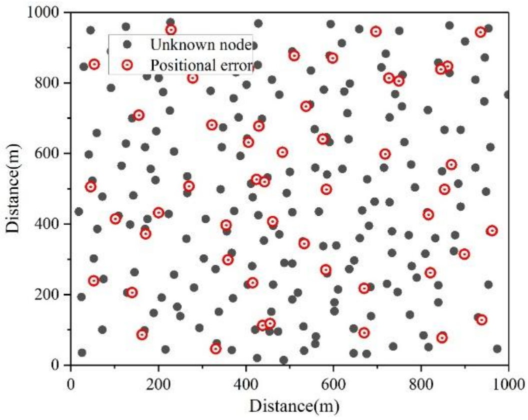
Figure 10. Node random distribution diagram

When the beacon nodes account for 25% of the total node proportion and the size of the parameter R is 200m, the three-dimensional spatial node localization results of the convolutional neural network are shown in Fig. 11, where (a) represents the network connectivity graph of the nodes in the localization area of 1000m*1000m, (b) is the localization error graph of the unknown nodes, and (c) is the localization error of each node. The relationship between the proportion of beacon nodes with a communication radius of 200m and the positioning accuracy is shown in Table 2.

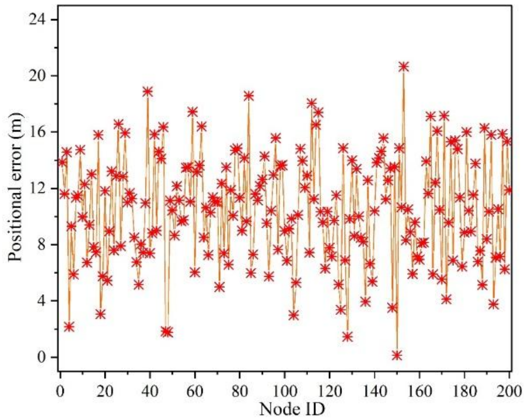
It can be found through simulation that when the communication radius R maintains a fixed value, the localization results will change with the change of the ratio of beacon nodes, and the size of the ratio increases from 5% to 35% (each time increasing by 5%), the corresponding localization accuracies are, in order: 37.0856, 35.7758, 34.055, 32.1797, 34.7395, 34.7919 and 34.8121.When the proportion of beacon nodes is less than 25%, the localization accuracy improves proportionally more as the proportion of beacon nodes decreases. When the proportion of beacon nodes is small, the unknown node can only refer to fewer nodes in the localization process, and conversely, it can refer to more nodes for localization and the accuracy is improved. When the proportion of beacon nodes in the network is increased to more than 25%, the localization accuracy of this paper's algorithm basically reaches saturation. Therefore, the number of beacon nodes should be limited in practical applications, which can ensure the cost optimization and also make the localization accuracy larger.



(a)Network connectivity map of the location



(b)Unknown node positioning error map



(c)Positioning error of each node

Figure 11. 3D spatial node localization results of convolutional neural networks

Table 2. Relationship between beacon node ratio and positioning accuracy

Beacon node ratio (%)	5	10	15	20	25	30	35
Positioning accuracy (%)	37.0856	35.7758	34.055	32.1797	34.7395	34.7919	34.8121

3.1.2. Effect of different shape sensing regions on node localization

In order to explore the differences of the wireless sensor network node localization algorithm introducing convolutional neural network for different sizes and shapes of the sensing area, this paper uses the wireless sensor network node localization algorithm before adding convolutional neural network optimization (Optimize) and after optimization (Postoptimality) to carry out experimental analysis.

The simulation experimental environment is: the proportion of anchor nodes is 10%, the node communication radius is 200m, the node sensing area side length is changed from 200m to 1000m respectively. Figure 12 shows the effect of the sensing area size on the average localization error. It can be seen that the localization error of the algorithm in this paper is lower than that of the comparison algorithm, but the localization error will be bigger with the increase of the size of the sensing area. The reason is the effect of the node communication radius, if the communication radius is too small, most of the unknown nodes and their anchor nodes used to localize the number of jump segments between the relatively large, due to the increase in the number of jump segments and thus lead to the accumulation of error, thus affecting the localization accuracy.

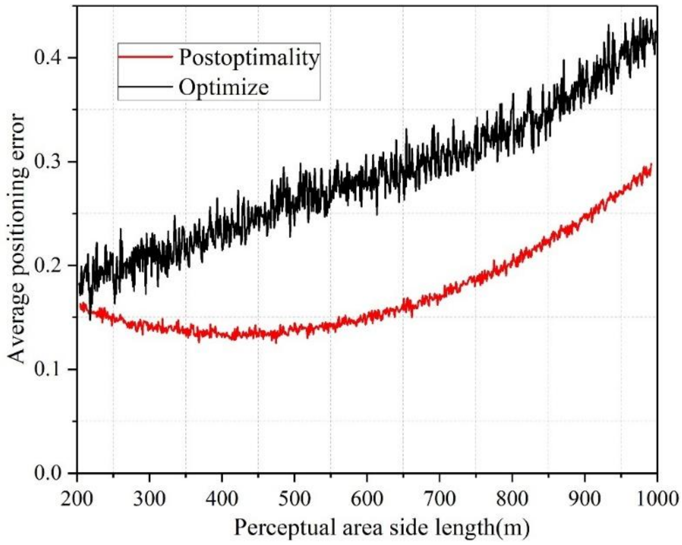


Figure 12. Effect of perceptual area size on average positioning error

3.2. Effect of different UAV altitudes on node localization

The optimized values for the number of nodes at different heights are shown in Fig. 13. Overall, the curve is in the shape of an upper open parabola, the RMSE value monotonically decreases at the beginning and then monotonically increases, the optimal heights correspond to 112m, 148m, 187m, 225m, and 266m when setting the heights to 20m, 50m, 100m, 150m, and 200m, respectively. From the lateral view, the RMSE value decreases due to the increase in height, however, with the increase in the distance making the ranging error to increase. Vertically, as the height increases, the optimal height that maximizes the accuracy can be located due to a certain height difference. The optimal height increases as the set height increases.

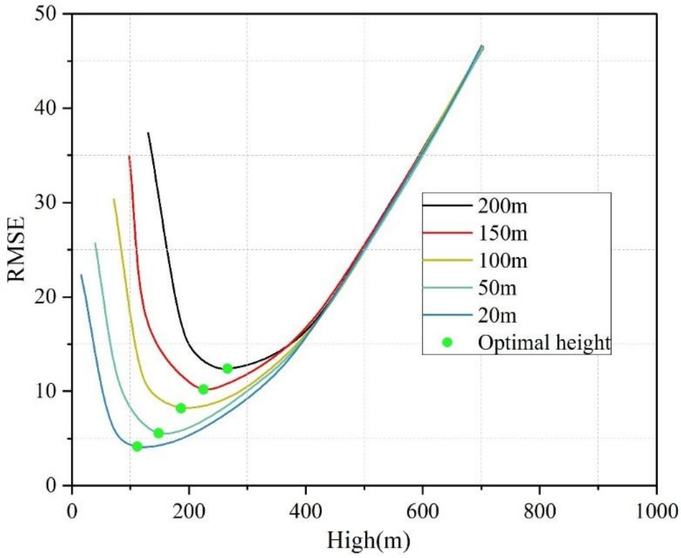


Figure 13. Optimized node count at different heights

The results of the localization rate of the nodes at different heights are shown in Fig. 14. The results show that the localization rate of the model to the nodes decreases gradually with the increase of the setting height. At a height of 20m, the model's localization rate reaches 100%, while when the height is increased to 200m, the localization rate decreases to 84.1%, but its localization rate is much higher than that of the 3D spatial node algorithm without the addition of convolutional neural network. Especially when the height is set to 200m, the localization rate of the 3D spatial node algorithm with convolutional neural network is 17.8% higher than that without convolutional neural network, and the localization rate of the node by the optimized algorithm in this paper under this condition is still above 80%, which shows that the introduction of the convolutional neural network algorithm is more effective in the estimation of the position of the nodes of the wireless sensor network.

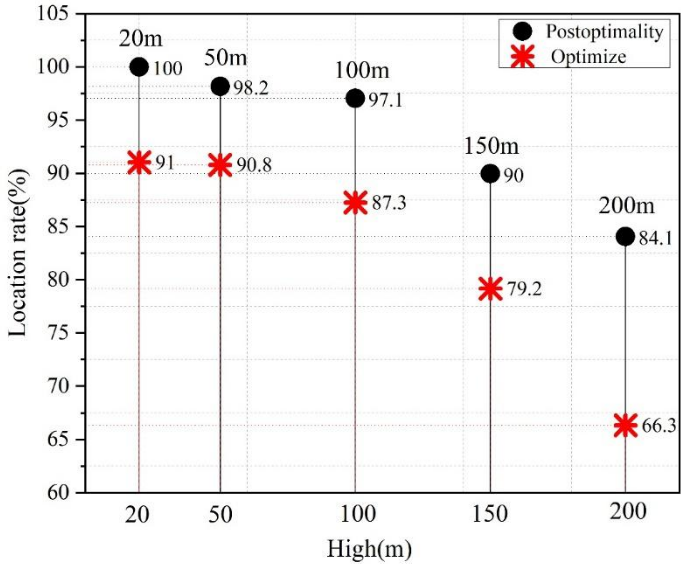


Figure 14. Node positioning rate results at different heights

3.3. Survival Time Performance of Wireless Sensor Networks

In wireless sensor networks, due to the different frequency of each sensor node to send and receive data, when the network works for a period of time the energy difference between the nodes is large, if the residual energy of the nodes is not considered to select the set of working nodes, it will result in some nodes continue to work, resulting in unbalanced energy consumption of nodes, which affects the survival time of the network, and then increase the difficulty and energy consumption of node location estimation of the wireless sensor network. Therefore, it is of great importance to consider the residual energy of nodes for node localization estimation in 3D space for wireless sensor networks.

In this subsection, in addition to the above node localization algorithm for wireless sensor networks with the addition of Convolutional Divine Networks before optimization (Optimize) and after optimization (Postoptimality), the existing Genetic Algorithm (GA) is also added for the comparative analysis of the survival time performance of the wireless sensor networks.

3.3.1. Failure time of the first node in the network

The results of the time comparison of the first node failure of the network under the three algorithms are shown in Fig. 15. It can be seen that the first node death appears in 47 rounds under this paper's algorithm, 27 rounds under the pre-optimization node set work, and 22 rounds under the GA algorithm; when the number of deployed nodes is increased to 100 points, the three algorithms' first node death rounds are increased in order to 96 rounds, 65 rounds, and 29 rounds; and when the number of nodes is increased to 200 points, it becomes 129 rounds, 84 rounds, and 30 rounds. Obviously as the number of deployed nodes increases, the first node death time increases for all of them, but the effect of the increase is quite different. This is due to the fact that the GA algorithm caused some nodes to work continuously and die quickly. The wireless sensor network node localization algorithm switches the work in the set of disjoint working nodes to equalize the node energy consumption and avoids the premature death of certain nodes due to continuous work. The wireless sensor network node localization algorithm based on convolutional neural network optimization has the strongest global optimization seeking ability, obtains the lowest number of nodes in the set of working nodes, and can rotate more node sets than the GA algorithm, effectively suppresses node death, and obtains the maximum survival time under the network survival time expressed by the first node death time.

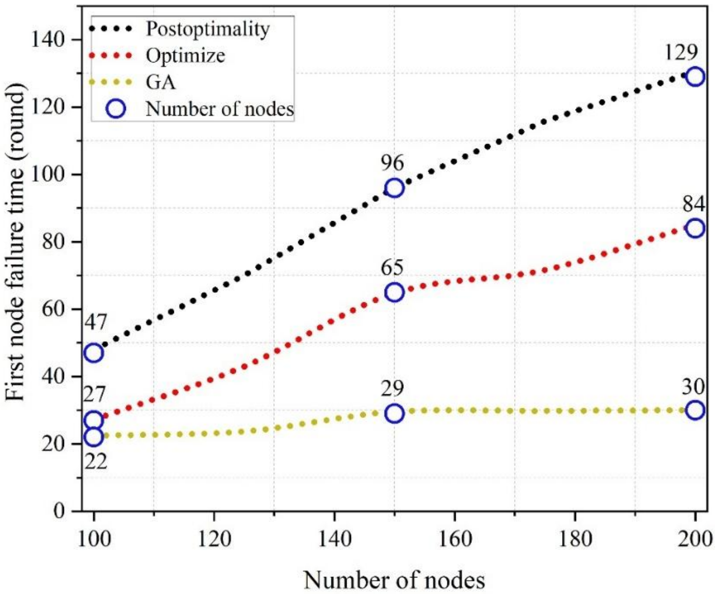


Figure 15. The time when the first network node fails

3.3.2. Coverage versus network survival time

The relationship between coverage and network survival time under the three algorithms is shown in Fig. 16. It can be seen that under the optimized 3D spatial localization algorithm based on the convolutional neural network algorithm, the coverage rate has been maintained above 98.09% when the network runs up to 174 rounds. When the network runs up to 174 rounds, the network coverage has been lower than 22.54% under the GA algorithm, and has been lower than 18.62% under the 3D spatial localization algorithm before optimization. Based on the convolutional neural network optimization of wireless sensor network node localization algorithm coverage curve decline gently, the network survival time is the longest, and this paper's algorithm than the GA algorithm and convolutional neural network optimization of the algorithm before the scheduling extension of about 60 rounds or more. It can be seen that the algorithm in this paper effectively extends the network survival time while better ensuring the coverage quality of the network. This is mainly due to the fact that, the convolutional neural network optimization based node localization algorithm for wireless sensor networks has the least number of nodes in the working node set, which can dormant a large number of nodes. In addition, its disjoint working node set scheduling effectively inhibits node death, equalizes network energy consumption, and reduces the node death rate, thus obtaining the maximum network survival time.

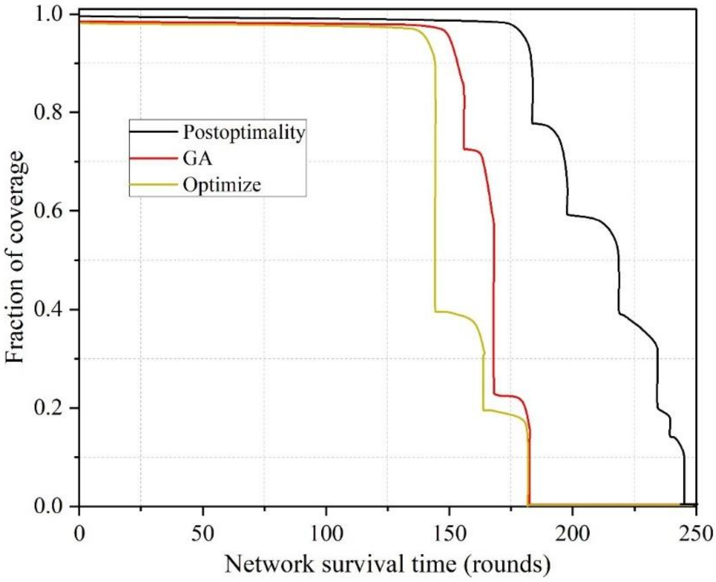


Figure 16. Dynamic coverage and network survival time relationship

3.3.3. Proportion of surviving nodes versus network survival time

The relationship between surviving nodes in the network and network survival time under the three algorithms is shown in Fig. 17. It can be seen that the node failure of the pre-optimization algorithm starts at the beginning of the network work. 86 rounds of surviving nodes are rapidly reduced, resulting in a sharp decrease in coverage. 134 rounds of surviving nodes are rapidly reduced under the GA algorithm, which is delayed by 48 rounds compared to the pre-optimization algorithm cycle scheduling. The trend of reduction of surviving nodes under the algorithm based on convolutional neural network optimization is smoother, node death is the slowest, and the obtained network survival time is prolonged by 68 and 97 rounds respectively compared to other methods, which fully reflects the superiority and effectiveness of the node localization algorithm based on the optimization of convolutional neural network for wireless sensor networks.

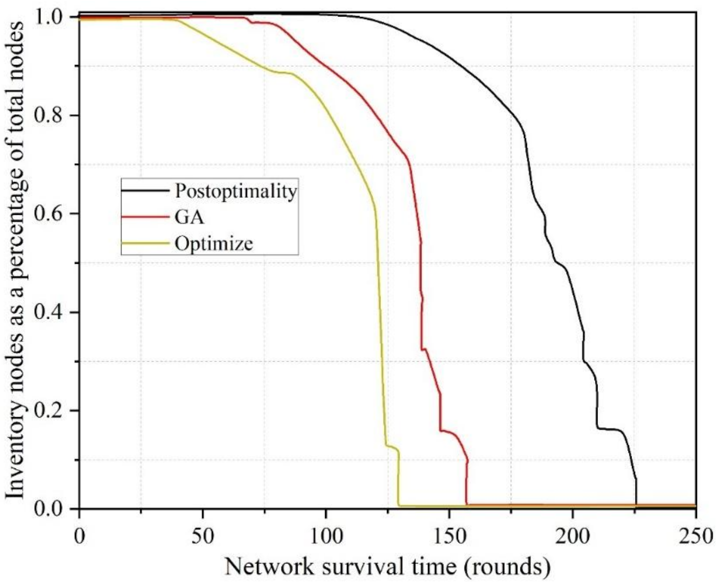


Figure 17. Relationship between active nodes and network survival time

4. Conclusions and outlook

4.1. Conclusion

In order to improve the localization performance of wireless sensor networks in complex environments, this paper proposes a node localization algorithm for wireless sensor networks based on convolutional neural networks, and explores the performance of the algorithm. The results show that:

When the proportion of beacon nodes in the network is increased to more than 25%, the localization accuracy of this paper's algorithm will remain basically stable, but its localization error will become larger and larger as the area of the sensing area increases, so it is necessary to control the number of hop segments between the unknown node and the localization anchor node when it is practically applied.

When the positioning height is increased from 20m to 200m, the positioning error of the model is still low, and its positioning accuracy remains above 80%, which shows that the model has good adaptability to different heights.

The model in this paper optimizes the selection and rotation of the working node set, and the working node set obtained has the advantages of small number of nodes, high coverage, and balanced energy consumption, which reduces the energy consumption and balances the energy consumption of the network, and effectively prolongs the survival time of the network.

4.2. Outlook

(1) In the node localization algorithm based on convolutional neural network modeling used in this paper, the neural network models are modeled using fully supervised training, the generation of the network's training dataset as well as the network's offline training phase will consume a certain amount of time and computational cost, and the future work can focus on the development of a semi-supervised learning neural network node localization model, in order to achieve excellent node localization performance.

(2) In the node localization algorithm based on deep learning neural network modeling studied in this paper, fixed anchor nodes are used, and the position of anchor nodes in the actual localization process must be strictly consistent with the network training process, and the anchor nodes are deployed in a certain regular distribution in the node monitoring area of the wireless sensor network, and in the future research work, it can be considered whether it is possible to realize the node localization algorithm by random anchor node design. node localization algorithm.

Funding

Key project of vocational education and teaching reform in Guangxi in 2021 “Exploration and practice of talent training mode of electronic information technology specialty group in Higher Vocational Colleges under the background of new generation artificial intelligence” (Project's number: GXGZJG2021A003); Research project of Beihai Vocational College in 2019 “Environmental information acquisition system based on ESP32” (Project's number: 2019HX04).

References

1. Nurlan, Z., Zhukabayeva, T., Othman, M., Adamova, A., & Zhakiyev, N. (2021). Wireless sensor network as a mesh: Vision and challenges. IEEE access, 10, 46-67.
2. Pragadeswaran, S., Madhumitha, S., & Gopinath, S. (2021). Certain investigation on military applications of wireless sensor network. International Journal of Advanced Research in Science, Communication and Technology, 3(1), 14-19.
3. Abdollahi, A., Rejeb, K., Rejeb, A., Mostafa, M. M., & Zailani, S. (2021). Wireless sensor networks in agriculture: Insights from bibliometric analysis. Sustainability, 13(21), 12011.
4. Baghezza, R., Bouchard, K., Bouzouane, A., & Gouin-Vallerand, C. (2021). From offline to real-time distributed activity recognition in wireless sensor networks for healthcare: A review. Sensors, 21(8), 2786.
5. Mabrouki, J., Azrour, M., Dhiba, D., Farhaoui, Y., & El Hajjaji, S. (2021). IoT-based data logger for weather monitoring using arduino-based wireless sensor networks with remote graphical application and alerts. Big Data Mining and Analytics, 4(1), 25-32.
6. Verma, S., Zeadally, S., Kaur, S., & Sharma, A. K. (2021). Intelligent and secure clustering in wireless sensor network (WSN)-based intelligent transportation systems. IEEE Transactions on Intelligent Transportation Systems, 23(8), 13473-13481.
7. Chaudhary, M., Goyal, N., Benslimane, A., Awasthi, L. K., Alwadain, A., & Singh, A. (2022). Underwater wireless sensor networks: Enabling technologies for node deployment and data collection challenges. IEEE Internet of Things Journal, 10(4), 3500-3524.
8. Li, H., & Lin, Z. (2017). Study on location of wireless sensor network node in forest environment. Procedia Computer Science, 107, 697-704.
9. Mao, J., Jiang, X., & Zhang, X. (2019). Analysis of node deployment in wireless sensor networks in warehouse environment monitoring systems. EURASIP Journal on Wireless Communications and Networking, 2019(1), 288.
10. Sadeghi Ghahroudi, M., Shahrabi, A., Ghoreyshi, S. M., & Alfouzan, F. A. (2023). Distributed node

deployment algorithms in mobile wireless sensor networks: Survey and challenges. ACM Transactions on Sensor Networks, 19(4), 1-26.
11. Fuhrmann, D. R., Stomberg, J., Nooshabadi, S., McIntire, D., & Merill, W. (2014, October). Node synchronization in a wireless sensor network using unreliable GPS signals. In 2014 IEEE Military Communications Conference (pp. 630-636). IEEE.
12. Rychlicki, M., Kasprzyk, Z., & Rosiński, A. (2020). Analysis of accuracy and reliability of different types of GPS receivers. Sensors, 20(22), 6498.
13. Eledlebi, K., Hildmann, H., Ruta, D., & Isakovic, A. F. (2020). A hybrid Voronoi tessellation/genetic algorithm approach for the deployment of drone-based nodes of a self-organizing wireless sensor network (WSN) in unknown and GPS denied environments. Drones, 4(3), 33.
14. Sneha, V., & Nagarajan, M. (2020). Localization in wireless sensor networks: a review. Cybernetics and Information Technologies, 20(4), 3-26.
15. Foong, L. Y., Lim, S. Y., & Chan, K. S. (2023). Measurement and Prediction of Signal Strength of Wireless Sensor Network. Measurement, 2023, 11-03.
16. El Houssaini, D., Khriji, S., Besbes, K., & Kanoun, O. (2018, March). Performance analysis of received signal strength and link quality in wireless sensor networks. In 2018 15th International Multi-Conference on Systems, Signals & Devices (SSD) (pp. 173-178). IEEE.
17. Ganev, Z. (2020). Analysis of factors influencing communication and energy consumption in wireless sensor networks. TEM Journal, 9(2), 442-448.
18. Wu, Y. C., & Feng, J. W. (2018). Development and application of artificial neural network. Wireless Personal Communications, 102(2), 1645-1656.
19. Jamsheed, F., & Iqbal, S. J. (2023). Simplified artificial neural network based online adaptive control scheme for nonlinear systems. Neural Computing and Applications, 35(1), 663-679.
20. Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Umar, A. M., Linus, O. U., ... & Kiru, M. U. (2019). Comprehensive review of artificial neural network applications to pattern recognition. IEEE access, 7, 158820-158846.
21. Beheshti Aval, S. B., Ahmadian, V., Maldar, M., & Darvishan, E. (2020). Damage detection of structures using signal processing and artificial neural networks. Advances in Structural Engineering, 23(5), 884-897.
22. Jamili, E., & Dua, V. (2021). Parameter estimation of partial differential equations using artificial neural network. Computers & Chemical Engineering, 147, 107221.
23. Li, M., Jiang, F., & Pei, C. (2020). Review on positioning technology of wireless sensor networks. Wireless Personal Communications, 115(3), 2023-2046.
24. Ahmad, N. S. (2024). Recent Advances in WSN-based Indoor Localization: A Systematic review of emerging technologies, methods, challenges and trends. IEEE Access.
25. Najarro, L. A. C., Song, I., & Kim, K. (2022). Fundamental limitations and state-of-the-art solutions for target node localization in WSNs: a review. IEEE Sensors Journal, 22(24), 23661-23682.
26. Luomala, J., & Hakala, I. (2019). Analysis and evaluation of adaptive RSSI-based ranging in outdoor wireless sensor networks. Ad Hoc Networks, 87, 100-112.
27. Alkhatib, A. A., Elbes, M. W., & Abu Maria, E. M. (2020). Improving accuracy of wireless sensor networks localisation based on communication ranging. IET Communications, 14(18), 3184-3193.
28. Landolsi, M. A., Khan, H. R., Al-Ahmari, A. S., & Muqaibel, A. H. (2019). On the performance of wireless sensor network time difference of arrival localization under realistic interference and timing estimation errors. International Journal of Distributed Sensor Networks, 15(2), 1550147719832537.
29. Zou, Y., & Liu, H. (2020). TDOA localization with unknown signal propagation speed and sensor position errors. IEEE Communications Letters, 24(5), 1024-1027.
30. Wang, T., Xiong, H., Ding, H., & Zheng, L. (2020). TDOA-based joint synchronization and localization algorithm for asynchronous wireless sensor networks. IEEE transactions on communications, 68(5), 3107-3124.
31. Adeyelu, A. A., Onah, O. J., & Orban, I. J. (2020). An Enhanced-Time Difference of Arrival Technique for Estimating Mobile Station Position in Wireless Sensor Networks. International Journal of Computer Applications, 975, 8887.
32. Zheng, Y., Sheng, M., Liu, J., & Li, J. (2018). Exploiting AoA estimation accuracy for indoor localization: A weighted AoA-based approach. IEEE Wireless Communications Letters, 8(1), 65-68.
33. Arbula, D., & Ljubic, S. (2020). Indoor localization based on infrared angle of arrival sensor network. Sensors, 20(21), 6278.
34. Monfared, S., Nguyen, T. H., Van der Vorst, T., De Doncker, P., & Horlin, F. (2020). Iterative NDA positioning using angle-of-arrival measurements for IoT sensor networks. IEEE Transactions on Vehicular Technology, 69(10), 11369-11382.
35. Bianchi, V., Ciampolini, P., & De Munari, I. (2018). RSSI-based indoor localization and identification for ZigBee wireless sensor networks in smart homes. IEEE Transactions on Instrumentation and Measurement, 68(2), 566-575.
36. Dolha, S., Negirla, P., Alexa, F., & Silea, I. (2019). Considerations about the signal level measurement in wireless sensor networks for node position estimation. Sensors, 19(19), 4179.
37. Gautam, P. R., Kumar, S., & Kumar, A. (2023). An optimized sensor node localization approach for wireless sensor networks using RSSI. The journal of Supercomputing, 79(7), 7692-7716.
38. Zhang, L., Yang, Z., Zhang, S., & Yang, H. (2019). Three-dimensional localization algorithm of WSN nodes based on RSSI-TOA and single mobile anchor node. Journal of Electrical and Computer Engineering,

2019(1), 4043106.
39. Chen, H., Ballal, T., Saeed, N., Alouini, M. S., & Al-Naffouri, T. Y. (2020). A joint TDOA-PDOA localization approach using particle swarm optimization. IEEE Wireless Communications Letters, 9(8), 1240-1244.
40. Jiang, R., Wu, Q., & Xu, Y. (2018, October). An improved centroid localization algorithm based on virtual beacon nodes for WSNs. In 2018 IEEE 3rd International Conference on Cloud Computing and Internet of Things (CCIOT) (pp. 43-46). IEEE.
41. Fan, J., Hu, Y., Luan, T. H., & Dong, M. (2017). DisLoc: A convex partitioning based approach for distributed 3-D localization in wireless sensor networks. IEEE Sensors Journal, 17(24), 8412-8423.
42. Jain, S., Singh, A., Kaur, A., & Jain, S. (2017, September). Improved APIT localization algorithm in wireless sensor networks. In 2017 4th International Conference on Signal Processing, Computing and Control (ISPCC) (pp. 77-81). IEEE.
43. Liu, G., Qian, Z., & Wang, X. (2019). An improved DV-Hop localization algorithm based on hop distances correction. China Communications, 16(6), 200-214.
44. Sun, Y., Zhang, X., Wang, X., & Zhang, X. (2018). Device-Free Wireless Localization Using Artificial Neural Networks in Wireless Sensor Networks. Wireless Communications and Mobile Computing, 2018(1), 4201367.
45. Rama, P., & Murugan, S. (2020). Localization approach for tracking the mobile nodes using FA based ANN in subterranean wireless sensor networks. Neural Processing Letters, 51(2), 1145-1164.
46. Madagouda, B. K., & Sumathi, R. (2019, December). Analysis of localization using ANN models in wireless sensor networks. In 2019 IEEE Pune Section International Conference (PuneCon) (pp. 1-4). IEEE.
47. Annepu, V., Rajesh, A., & Bagadi, K. (2021). Radial basis function-based node localization for unmanned aerial vehicle-assisted 5G wireless sensor networks. Neural Computing and Applications, 33(19), 12333-12346.
48. Madagouda, B., & Sumathi, R. (2021). Artificial neural network approach using mobile agent for localization in wireless sensor networks. Advances in Science, Technology and Engineering Systems Journal, 6(1), 1137-1144.
49. Esheh, J., & Affes, S. (2024). Improving Localization in Wireless Sensor Networks for the Internet of Things Using Data Replication-Based Deep Neural Networks. Sensors, 24(19), 6314.
50. Dhouha El Houssaini, Zina Mohamed, Sabrine Khriji, Kamel Besbes & Olfa Kanoun. (2018). Distance measurement correction based on feedback filter for RSSI localisation technique in WSNs. Int. J. of Space-Based and Situated Computing, 8(3),160-168. https://doi.org/10.1504/IJSSC.2018.097293.
51. Ishii Kyoya, Shimono Keisuke, Suda Yoshihiro, Ando Takayuki, Nagao Tomohiko, Yamamoto Michiharu & Segawa Masaya. (2022). Vehicle Localization Using Magnetic Markers Incorporating EKF and Maximum Likelihood Estimation. IFAC PapersOnLine, 55(27),202-207. https://doi.org/10.1016/J.IFACOL.2022.10.512.
52. Hamed Sabahno & Davood Khodadad. (2025). A convolutional neural network-based joint detection and localization spatiotemporal scheme for process control through speckle pattern imaging. Computers & Industrial Engineering, 210,111538-111538. https://doi.org/10.1016/J.CIE.2025.111538.