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COAL MINE UNDERGROUND POSITIONING ALGORITHM BASED ON RSSI MODEL CORRECTION AND NODE COOPERATION

To address the issues of environmental complexity and low positioning accuracy faced by coal mine underground positioning systems, an improved localisation algorithm based on Received Signal Strength Indication (RSSI) model correction and node collaboration, namely, the RSSI-MCNC (RSSI Model Correction and Node Collaboration) algorithm, is proposed. First, this algorithm employs Kalman filter technology to optimise the collected RSSI values, improving signal stability and range model accuracy. Second, more precise ranging results are achieved by dynamically adjusting the RSSI model parameters to adapt to changes in mining environments. In the localisation stage, the localised unknown nodes are used as cooperative nodes to position other unknown nodes and solve the objective function through the improved weighted centroid algorithm and gradient descent method, precisely locating the unknown nodes. The simulation results indicate that the RSSI-MCNC algorithm can significantly improve the positioning coverage and accuracy of fixed anchor nodes and the random distribution of unknown nodes in mine roadways, especially in the case of limited anchor nodes. This is significant for improving the safety of mine personnel and equipment.

Keywords: Coal mine underground; model correction; node collaboration; Kalman filter; Objective function

1. Introduction

China has many coal mines and is developing smart mines. The controllability of safe production is directly related to the level of national industrial information and the secure development and utilisation of resources [1]. With technological advancements, coal mine underground

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positioning equipment is evolving towards higher accuracy and lower power consumption. Coal mine underground positioning technology is primarily applied in personnel tracking, material tracking, emergency rescue, and more. Through precise positioning, real-time monitoring and management of personnel and materials underground can be achieved, improving the safety and efficiency of coal mine production. Currently, several coal mines have successfully implemented underground positioning systems, which have achieved favourable results in practical applications, providing robust support for safe coal mine production [2]. For instance, the combination of Ultra-Wideband (UWB) technology and machine vision technology enables transmission rates of up to hundreds of Mbps, improving equipment accuracy.

Furthermore, the integration of technologies such as artificial intelligence will further propel the development of underground coal mine positioning technology [3]. RFID positioning technology is a regional positioning technology that achieves regional positioning of targets by setting up RFID positioning substations at mine entrances, roadway exits, and more. ZigBee-based positioning technology realizes target positioning by constructing a communication network and using the RSSI ranging principle. Inertial navigation technology is an autonomous navigation technology that continuously determines the position, attitude, and speed of the carrier in real time. In addition to the above mainstream positioning technologies, several other positioning technologies are also being applied in coal mine underground positioning, such as laser scanning positioning, ultrasonic positioning, and infrared positioning. Each of these positioning technologies has its advantages and disadvantages, suitable for different application scenarios and requirements [4]. However, the underground environment of coal mines in China is complex, and the acquisition of personnel, equipment, and location information still needs to be improved in the absence of reliable and stable deployment of full-coverage nodes in the existing positioning system. Therefore, it is important to build a new type of mine sensor node collaborative positioning algorithm with high precision and coverage for mine information collection, safety production, post-disaster search and rescue, and personnel flow information acquisition.

The particularity of mining environments is mainly manifested in the narrow space, significant multipath effect, high density of coal dust, high-power mechanical and electrical equipment, and distribution of various gases, making it extremely difficult to build a transmission loss model that conforms to the mining environment [5]. The improvement in the accuracy of underground target positioning mainly depends on optimising the algorithm process or combining other methods on the ground. Range-based algorithms are mainly used for underground target locations, including those based on RSSI [6], signal angle of arrival (AOA) [7], time of arrival (TOA) [8], and time difference of arrival (TDOA) [9], etc. These algorithms are influenced by various factors in the mine, which decreases positioning accuracy. The RSSI positioning method is widely popular because it does not require additional hardware and has a low power consumption [10]. Due to the uniqueness of coal mine environments, the underground signal attenuation model is different from that of the ground, resulting in the low accuracy of the range-based RSSI positioning algorithm. An algorithm based on the signal's angle of arrival requires high-precision angle measurements. If the angle measurement is inaccurate, the positioning result may differ from the actual coordinates. The algorithm based on the TDOA requires the cooperation of a high-precision time synchronisation algorithm, and the impact of the measurement time error on the positioning result can be described as thousands of miles [11].

Based on the special environment of underground coal mines, scholars have proposed various improved algorithms to improve positioning accuracy. Zhang [12] proposed an RSSI-based

Gaussian filtering weighted centroid positioning algorithm, which uses the reciprocal distance product between two circles as the weight coefficient to weigh the nodes to improve localisation accuracy. Gao et al. [13] proposed a node cooperation underground precise positioning algorithm, providing a weighted non-convex positioning model from unknown nodes to reference nodes, and using the Canonical Duality algorithm to find the global optimal solution. This algorithm can only improve the accuracy in the positioning stage, but not improve the RSSI ranging model when the mining environment changes. Zhao et al. [14] proposed a node auxiliary localisation algorithm for interval-segmented sight distance in coal mines. This algorithm uses the segmented threshold to select the interval for unknown nodes and treats the located unknown nodes as virtual reference nodes for other unknown nodes to improve localisation accuracy. However, the located unknown nodes are treated as reference nodes for auxiliary localisation, causing an accumulation of errors. Combined with the whale optimisation algorithm and the Taylor series, Li et al. [15] introduced the underground TDOA positioning algorithm. They use TDOA to establish the fitness function to obtain initial positioning and then use the positioning result as the initial value of the Taylor series algorithm for further iterative refinement to achieve higher positioning accuracy. However, the TDOA localisation algorithm requires signals received by the nodes to follow strict time synchronisation, which requires high hardware. Jin et al. [16] introduced the concept of a minimum condition outlier node, selecting three anchor nodes nearest to the unknown node for localisation. It can improve the localisation accuracy compared to the trilateral localisation method. However, when the environment changes, the accuracy of the RSSI ranging model is affected, and the node information is not fully used for positioning.

The algorithm proposed can improve the localisation accuracy from the following five aspects: Kalman filtering, RSSI ranging model parameter correction, improved weighted centroid localisation algorithm, cooperative node participation in localisation, and gradient descent method refinement. It can improve the localisation coverage and accuracy of mining roadways without increasing additional hardware overhead.

2. Proposed methods

2.1. RSSI Ranging Model

In a complex underground coal mining environment, the principle of RSSI ranging is to use a logarithmic path loss model to convert the loss into distance, and then calculate the position coordinates of the tested node based on this distance [17-19].

The RSSI propagation model is calculated as follows:

$$RSSI(d) = RSSI(d_0) - 10n\lg\left(\frac{d}{d_0}\right) + \xi_n \tag{1}$$

where $RSSI(d)$ represents the $RSSI$ value when the transmitted and received signals travel through the distance of d; $RSSI(d_0)$ represents the RSSI value when the transmitted and received signal travel through a distance of d_0, usually taken as $d_0 = 1m$; n is the Path loss factor, and ξ_n is the Gaussian random noise.

The actual mining environment is complex. To further cope with environmental interference in mines, the RSSI ranging model usually adopts the simplified log-normal distribution model:

$$RSSI(d) = RSSI(d_0) - 10n\lg\left(\frac{d}{d_0}\right) \tag{2}$$

Assuming d_0 = 1m, $RSSI(d_0)$ uses a constant A express; $RSSI(d)$ stands for the Received Signal Strength Indicator, and $\overline{RSSI}$ expression. Formula (2) can be simplified as follows:

$$\overline{RSSI} = A - 10n\lg d \tag{3}$$

Further refinement of the available estimated distances is as follows:

$$d = 10^{\frac{A-\overline{RSSI}}{10n}} \tag{4}$$

The main factors affecting the accuracy of the *RSSI* ranging model are A and n. My laneway is a typical dense multipath frequency-selective fading channel, and the propagation loss in the lane is significantly affected by these two parameters. The environment of a coal mine has its particularity: once the environment changes, even if the distance is the same, the path loss will be different in different environments, leading to a change in the two parameters A and n. Therefore, if the fixed *RSSI* model parameters are used to describe the entire coal mine underground environment, a certain deviation will affect the accuracy of the ranging model. To improve the positioning accuracy, the parameters of the *RSSI* model must be modified dynamically to adapt to changes in the underground environment.

2.2. Kalman filtering and *RSSI* ranging model improvement

The complexity of the underground coal mine environment poses a significant challenge to the transmission of radio signals, which is mainly manifested in the diffraction, attenuation, multipath effect, and scattering of signals. These complex transmission characteristics make the traditional *RSSI* ranging model inaccurate, affecting the positioning results. To enhance the accuracy of the localization results, we focused on optimizing and correcting two key parameters, A and n, in the *RSSI* model.

2.2.1. *RSSI* signal preprocessing

The accuracy of the RSSI ranging model is significantly affected by the variability of the underground environment in coal mines. In this environment, even unknown nodes at the same location can receive fluctuating RSSI signal values at different times. The instability of this signal is mainly caused by noise and interference from environmental factors. To improve the accuracy of results, the *RSSI* signal must be filtered to eliminate the influence of these abnormal signals. Kalman filtering [20-21] stands out for its excellent performance among the various filtering techniques. It can extract useful signals from noisy data and predict future states. The stability of the *RSSI* system can be significantly improved by applying the Kalman filter algorithm to preprocess the *RSSI* signal and optimise the *RSSI* ranging model.

The preprocessing steps using the Kalman filter algorithm include initialising the state estimation and covariance and then extracting the true trend of the signal step-by-step through a continuous time update and measurement update process. This process improves the accuracy of a single measurement and enhances the robustness of the entire *RSSI* ranging model in the face of environmental change. A discrete mathematical positioning system model was established based on positioning information.

State equation is as follows:

$$x(k) = Ax(k-1) + Bu(k) + w(k) \tag{5}$$

Observation equation is as follows:

$$z(k) = Hx(k) + v(k) \tag{6}$$

The state matrix $x(k)$ represents the filtered *RSSI* value; $u(k)$ is the control matrix; $z(k)$ is the observation matrix; A and B are system matrices; H represents the observation matrix; $w(k)$ and $v(k)$ are the process noise and measurement noise at time k; the covariance matrices Q represents process noise, and R represents measurement noise.

Time Update:

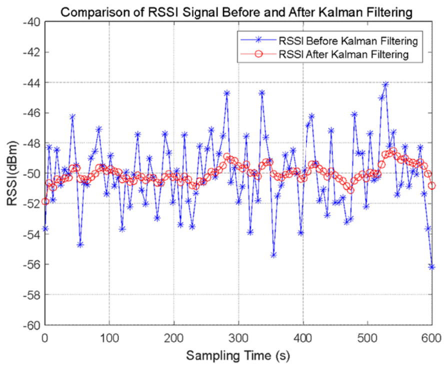
$$\begin{cases} x(k \mid k-1) = Ax(k-1 \mid k-1) + Bu\left(k\right) \\ P(k \mid k-1) = AP(k-1 \mid k-1)A^T + Q \end{cases} \tag{7}$$

Status Update:

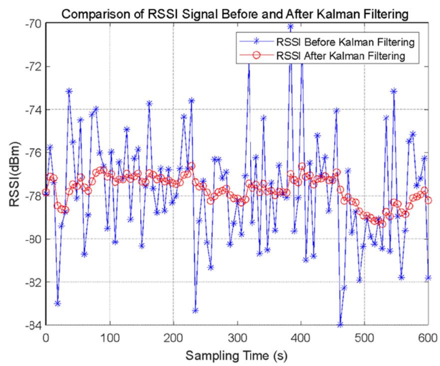
$$\begin{cases} x(k \mid k) = x(k \mid k-1) + K_g(k)(z(k) - Hx(k \mid k-1)) \\ K_g(k) = \dfrac{P(k \mid k-1)H^T}{HP(k \mid k-1)H^T + R} \\ P(k \mid k) = (I - K_g(K)H)P(k \mid k-1) \end{cases} \tag{8}$$

$P(k \mid k-1)$ is the covariance of $x(k \mid k-1)$, and $P(k-1 \mid k-1)$ is the covariance of $x(k-1 \mid k-1)$. K_g represents the Kalman gain; Kalman filtering updates the model parameters in two steps: time update and state update. From the above formulas, the optimal estimate of the previous moment plus the external control variable prediction can obtain a new optimal state estimate $x(k \mid k)$ for the current moment. This can be iterated continuously with the new $P(k \mid k)$ at a subsequent time, and measurement updates can be made for the next moment.

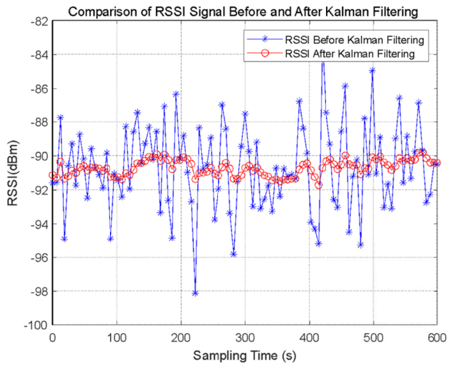
Based on the above theory, the Kalman filter algorithm is used to process *RSSI* data. Assuming that the mine environment is harsh; the path loss factor n is 4, and the signal strength (A) at $1m$ from the transmitting node is –50 dBm. There is a Gaussian random noise with a variance of 7 and a mean of 0, and the unknown node starts the positioning process by sending a data packet to the anchor node. The unknown node is placed one meter away from the anchor node and receives data packets from the anchor node every 6 s for 10 min. The mean of *RSSI* is used as the initial state estimation, and the variance of *RSSI* is used as the initial estimation error covariance. The process noise covariance is 0.1, and the measurement noise covariance is the variance of *RSSI*. As shown in Fig. 1, the original *RSSI* signal is highly affected by environmental interference, with an error of up to 14.54% at $1m$. After applying Kalman filtering, the maximum error is reduced to 2.93%, significantly reducing the interference of environmental factors. From Fig. 1, Kalman filtering cannot only improve the performance when $d = 1$ meter, but also mitigate the interference in the positioning environment when $d = 5$ meters, $d = 10$ meters, and $d = 20$ meters.



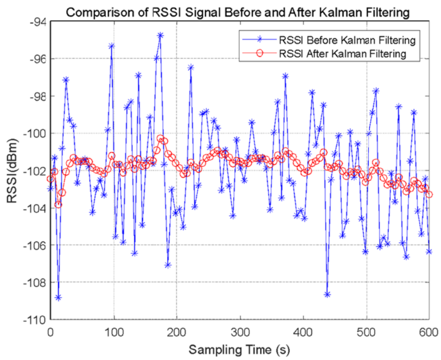
$d = 1$ m



$d = 5$ m



$d = 10$ m



$d = 20$ m

Fig. 1. Comparison of *RSSI* Signal before and After Kalman Filtering

2.2.2. Parameter Optimization of *RSSI* Ranging Model

To ensure that the ranging model accurately reflects the wireless signal propagation characteristics of the mining environment, the *RSSI* value processed by the Kalman filter is used to optimise the key parameters A and n of the ranging model. This optimisation helps to reduce the interference of environmental factors on the ranging results. It is assumed that within a certain area, unknown nodes periodically transmit data signal packets to nearby anchor nodes. After receiving the broadcast signal, the anchor nodes simultaneously provide feedback on the estimated distance information between themselves and the unknown node, as well as the *RSSI* value processed by the Kalman filter algorithm. Given that the *RSSI* measurements are significantly influenced by the distance factors, a shorter distance between an anchor node and an unknown node implies less interference and higher measurement accuracy. Selecting the three anchor nodes closest to the unknown node as reference benchmarks during the positioning process is recommended. The three reference nodes directly participate in subsequent positioning calculations using their spatial location information. The parameters A and n can be determined using formula (3).

Assuming that the three closest anchor nodes within the communication range of the unknown node P are labeled as $O_1(x_1, y_1)$, $O_2(x_2, y_2)$, and $O_3(x_3, y_3)$, the anchor node O_1 can receive the largest *RSSI* from *P*. The distances between the anchor node O_1 and the other anchor nodes can be calculated using Eq. (9).

$$\begin{cases} r_{1,2} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \\ r_{1,3} = \sqrt{(x_1 - x_3)^2 + (y_1 - y_3)^2} \end{cases} \tag{9}$$

Through setting the *RSSI* values from the anchor node O_1 to other anchor nodes as $\left(\overline{RSSI_{1,2}}, \overline{RSSI_{1,3}}\right)$, *A* and *n* within this region can be solved by establishing a system of Eq. (10):

$$\begin{cases} \overline{RSSI}_{1,2} = A - 10n \lg d_{1,2} \\ \overline{RSSI}_{1,3} = A - 10n \lg d_{1,3} \end{cases} \tag{10}$$

Finally, to solve the system of equations in Eq. (10), we obtain the values of $\hat{A}$ and $\hat{n}$ within this region. The values of $\hat{A}$ and $\hat{n}$ are then used as optimised model parameters to correct the ranging model. Substituting these into Eq. (4), we obtain:

$$d = 10^{\frac{\hat{A} - \overline{RSSI}}{10\hat{n}}} \tag{11}$$

2.3. Construction of cooperative localisation model based on improved weighted centroid

2.3.1. Cooperative Nodes Participate in the Localisation Process

In this special environment, the traditional positioning method may not meet the accuracy requirements due to the limited number of positioning base stations. Therefore, fully utilising unknown nodes is the key to improving positioning accuracy. An adaptive node cooperative localisation method is proposed: traversing the whole network, obtaining the *RSSI* between all unknown nodes and anchor nodes, set an *RSSI* threshold value, randomly select the unknown nodes that receive more than three anchor nodes and have signal strength exceeds the *RSSI* threshold as candidate nodes, and determine the position of unknown nodes. Then, the unknown node is substituted into the positioning process to be an auxiliary positioning anchor node. The mean value of the position estimation error of the anchor node is recorded as the error of the unknown node, and the positioning range is continuously expanded. In this manner, every node in the network may participate in the localisation process to provide more localisation information, enhance the robustness of the localisation system, and improve the overall localisation accuracy.

Assuming *N* unknown nodes and *M* anchor nodes in the sensor network deployed in the underground tunnel, with the received signal strength indicator threshold as $RSSI_T$, let the coordinates of the anchor node *i* be $O_i(x_i, y_i)$ and the coordinates of the unknown node *j* be $P_j(x_j, y_j)$. The selection of an unknown node for priority localisation must satisfy:

$$\begin{cases} \{RSSI\_PO_1 \quad RSSI\_PO_2 \quad \cdots \quad RSSI\_PO_m\} \quad m \geq 3 \\ RSSI\_PO_k \geq RSSI_T \quad k = 1 \cdots m \end{cases} \tag{12}$$

According to Eq. (12), the unknown nodes to be localised are prioritised and selected, and the coordinates of these unknown nodes can be obtained by calculation. However, deploying underground anchor nodes is rare, and when the received signal indication strength threshold is set, some unknown nodes may not be located. Although the located unknown nodes can be regarded as anchor nodes through node cooperation, the location results of the unknown nodes have errors. If they are used directly as anchor nodes without selection in subsequent localisation, it will lead to error accumulation and reduce the localis ation accuracy of the overall network. A positioned unknown node cannot be directly used as an anchor node. Therefore, it is crucial to select unknown nodes located as anchor nodes.

Assuming an unknown node P localizes its estimated coordinates (x, y) based on the three nearest anchor nodes $O_1(x_1, y_1)$, $O_2(x_2, y_2)$, and $O_3(x_3, y_3)$. Now taking the node P as a known node, one of the anchor nodes O_1, O_2, O_3 is selected as an unknown node, for example, taking anchor node O_1 as the unknown node. P_1, O_2, O_3 are used as the anchor nodes to estimate the coordinates of O_1 and obtain an estimated coordinate $O_1(\hat{x}_1, \hat{y}_1)$ for node O_1. The true coordinates (x_1, y_1) of node O_1 are compared with the estimated coordinate $(\hat{x}_1, y_1)$ to determine the positional approximation error. The approximation error is denoted for anchor node O_1 as $\tilde{\mu}_1 = (x_1 - \hat{x}_1)^2 + (y_1 - \hat{y}_1)^2$. Similarly, the positional approximation errors can be calculated for the other two anchor nodes, that is O_2, O_3. If there are M anchor nodes, the average of positional approximation errors of the anchor node represents the approximation error of the unknown node P.

$$\tilde{\mu} = \sum_{i=1}^{M} \left[\left(x_i - \hat{x}_i \right)^2 + \left(y_i - \hat{y}_i \right)^2 \right] / M \tag{13}$$

According to Eq. (13), a smaller approximation error $\tilde{\mu}$ indicates a higher positioning accuracy for an unknown node.

Cooperative localisation involves considering a localised unknown node as a cooperative node to participate in the localisation process. As shown in Fig. 2, OP_i is a collaborative node with IDi, whose position is determined by the anchor nodes. Under a communication radius of R, the unknown node P can only receive information from two anchor nodes, O_3 and O_4, which cannot complete localisation. Assuming that after traversing the network within the communication radius R of the unknown node P, there are three cooperative nodes O_{P1}, O_{P2}, and O_{P3}. Their approximation errors are calculated by formula (13), and then arranged from small to large. Assuming that $\tilde{\mu}_{O_{P1}} < \tilde{\mu}_{O_{P2}} < \tilde{\mu}_{O_{P3}}$, The cooperative node with the minimum approximation error is adaptively selected according to the size of the approximation error of the cooperative node O_{P1} as a location-unknown node P anchor node.

During the positioning process, the localisation condition can be satisfied by using the position data of two anchor nodes (O_1, O_3, and O_4) and one cooperative node, and the positioning system can obtain the coordinates of the unknown node. Similarly, if only one anchor node is found within the communication radius of an unknown node after traversing the network, when traversing the underground wireless sensor network and detecting that the unknown node has only one anchor node within a specific communication radius, two cooperative nodes with relatively small approximation errors can be selected to make the positioning system satisfy the positioning conditions. Three cooperative nodes in the communication radius are selected if there is no anchor node around the unknown nodes. When the anchor and cooperative nodes around the unknown node are smaller than three, the unknown node cannot be positioned.

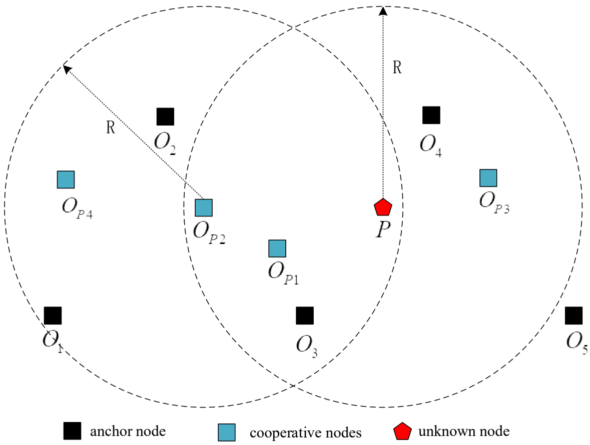


Fig. 2. Collaborative nodes participating in positioning

Assuming that M anchor nodes are distributed within the communication radius of the unknown node P during the localization process, N cooperative nodes are utilised. Let the coordinates of the unknown node i be (x_1, y_1), and the coordinates of the j^{th} assisting localisation node be (x_j, y_j). The distance between P and assisting localisation node j is d_{pj}, and the distance between P and the anchor node $k(x_k, y_k)$ is denoted as d_{pk}. A positioning model is established using the unknown nodes to solve the minimum objective function of the positioning model:

$$f(x_i, y_i) = \min \begin{pmatrix} \sum_{k=1}^{M} \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 - d_{pk}^2} \\ + \sum_{j=1}^{N} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 - d_{pj}^2} \end{pmatrix} \tag{14}$$

In Eq. (14), if the anchor nodes are greater than 3, the objective function will become an overdetermined equation set. Therefore, in the position coordinate estimation stage, when the total number of anchor nodes and cooperative nodes required for the localisation of a target node is 3, the improved weighted centroid positioning algorithm will be used to solve the problem and enhance localisation efficiency quickly when anchor nodes are greater than 3. We use the improved weighted centroid localisation algorithm as the initial value of the localisation result and then solve the optimal solution of the objective function through the gradient descent method.

2.3.2. Improved weighted centroid localisation algorithm

Due to the special environment in the coal mine, there is a deviation between the *RSSI* value and the true value received by the signal, resulting in a circle with the distance from the unknown node to the anchor node of the received signal as the radius. The circle cannot intersect at one point but forms a region. A common strategy to solve this problem is to calculate the centroid of the overlapping area and consider it the estimated location of an unknown node [22]. To further enhance the positioning accuracy, the influence of anchor nodes during the positioning process is dynamically adjusted through weighting. That is, the smaller the distance, the greater the weight. In Fig. 3, the distances from the three anchor nodes O_1, O_2, O_3 to the unknown node $P(x, y)$ are d_1, d_2, d_3, respectively. $A(x_1, y_1)$, $B(x_2, y_2)$, $C(x_3, y_3)$, is the intersection area of the three circles, and the coordinates of point A can be calculated using Eq. (15).

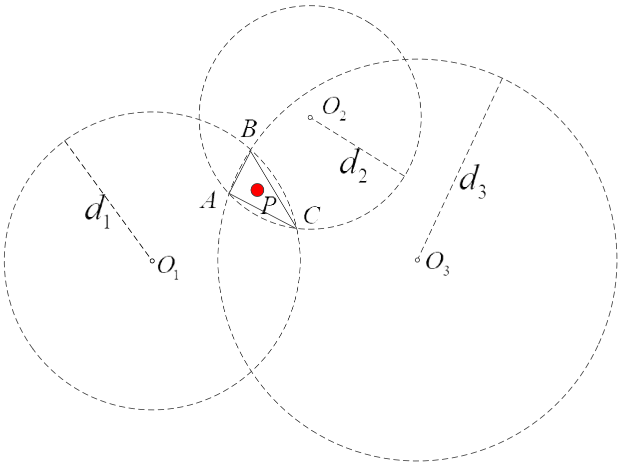


Fig. 3. Centroid localisation algorithm

$$\begin{cases} \sqrt{(x-x_1)^2+(y-y_1)^2} \le d_1 \\ \sqrt{(x-x_2)^2+(y-y_2)^2} = d_2 \\ \sqrt{(x-x_3)^2+(y-y_3)^2} = d_3 \end{cases} \tag{15}$$

Similarly, the coordinates of points B and C can also be calculated. To improve the positioning accuracy, a weight coefficient w is introduced to weight the corresponding anchor nodes. The greater the weight, the smaller the distance d. Therefore, an improved weighted centroid algorithm used to describe the weight is as follows:

$$\begin{cases} w_1 = \dfrac{1}{\dfrac{d_1}{d_2}+\dfrac{d_1}{d_3}} \\ w_2 = \dfrac{1}{\dfrac{d_2}{d_1}+\dfrac{d_2}{d_3}} \\ w_3 = \dfrac{1}{\dfrac{d_3}{d_1}+\dfrac{d_3}{d_2}} \end{cases} \tag{16}$$

Then, the coordinates of unknown node $P(x, y)$ are as follows:

$$\begin{cases} x = \dfrac{w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3}{w_1 + w_2 + w_3} \\ y = \dfrac{w_1 \cdot y_1 + w_2 \cdot y_2 + w_3 \cdot y_3}{w_1 + w_2 + w_3} \end{cases} \tag{17}$$

2.3.3. Solution by gradient descent method

Gradient descent [23], as a classic optimisation technique, revolves around the core strategy of iteratively adjusting parameter values by moving in the opposite direction to the gradient of the objective function, aiming to gradually approach and reach the minimum point. To improve the positioning efficiency, when the number of anchor nodes required for the localisation of unknown nodes exceeds three, the weighted centroid localisation result is used as the initial parameter for the gradient descent method to iteratively solve the coordinates of the unknown nodes. The solution steps are as follows:

(1) Initialise the parameters $\theta(\hat{x}, y)$ (parameter θ is the result of the weighted centroid localisation);
(2) Calculate the gradient of the current parameter $\nabla f(\theta)$ $\left(\nabla f(\theta) = [\partial f/x_1, \partial f/x_2, ..., \partial f/x_n]\right)$;
(3) Update the parameters $\theta = \theta - \alpha * \nabla f(\theta)$, where θ is the parameter vector and α is the learning rate;
(4) Steps 2 and 3 are repeated until the convergence criteria are met.

2.4. Algorithm implementation

The process of the proposed algorithm includes several aspects: In the initial stage, the unknown nodes actively capture and collect signal information emitted by the surrounding anchor nodes, particularly by recording the *RSSI* value each time they receive a signal. This process is continuously repeated *N* times to ensure the adequacy and stability of the data. After traversing the entire network, the Kalman Filter algorithm is applied to filter the collected *RSSI* value sequences. The goal is to eliminate noise interference and enhance the reliability of *RSSI* values. In the ranging phase, the area is dynamically divided based on the information received from the anchor nodes by the unknown nodes. By estimating the *RSSI* ranging model parameters *A* and *n*, we can obtain a regional signal transmission model that is closer to the actual mining environment. In the positioning stage, first, under the condition of setting the *RSSI* threshold, when it is determined that there are more than three anchor nodes, the coordinates of unknown nodes that can receive information from three or more anchor nodes can be obtained using an improved weighted centroid positioning algorithm. After that, iterative refinement is performed through a gradient descent method. If an unknown node can only receive signals from fewer than three anchor nodes, the located unknown nodes are considered cooperative nodes during the positioning process to ensure that there are at least three positioning reference points. Subsequently, an improved and optimised weighted centroid localisation algorithm is used to accurately calculate the coordinate position of the unknown nodes. The flowchart of the entire algorithm is shown in Fig. 4.

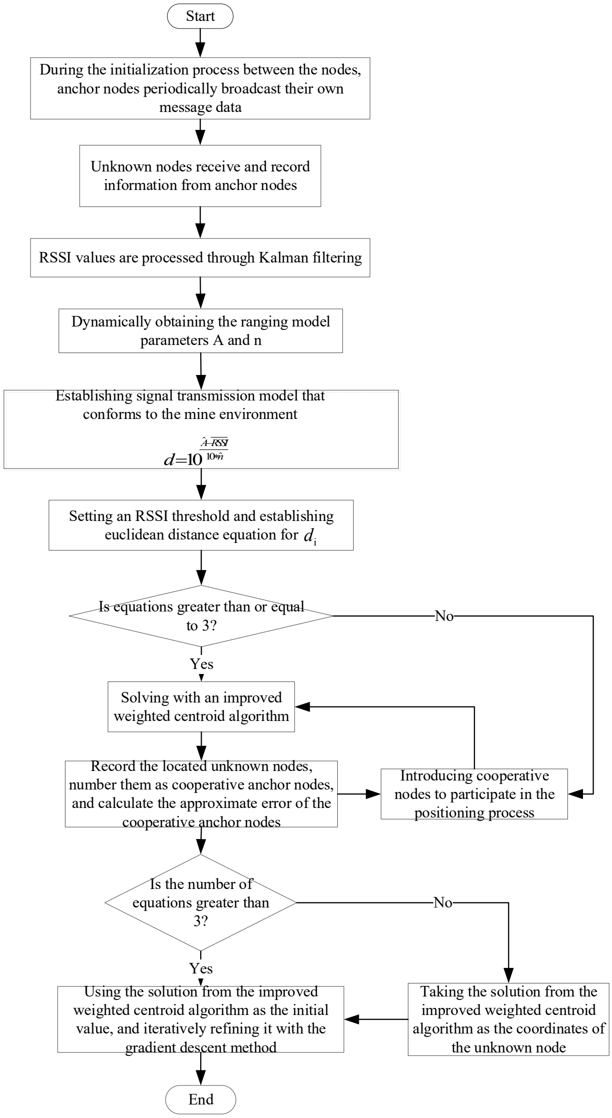


Fig. 4. Flowchart for the implementation of the positioning algorithm

3. Results and Analysis

3.1. Simulation environment

To validate the positioning performance of the proposed algorithm (*RSSI*-MCNC), MATLAB software is used to establish a simulation experimental platform, and compared with [12] and [13]. Assuming the roadway is 100 m long and 5 m wide, the number of deployed anchor nodes is 6, and the unknown nodes are 20, each with a communication range of 30 m. The *RSSI* threshold is –110 dBm; the path loss factor n is 4; the signal strength A 1 m away from the transmitting node is –50 dBm, and the Gaussian noise variance of the channel is between 6 and 8. In the set, the positions of anchor nodes are fixed and unchanged. On the contrary, the unknown nodes are randomly distributed throughout the entire network area, forming a network topology, as shown in Fig. 5.

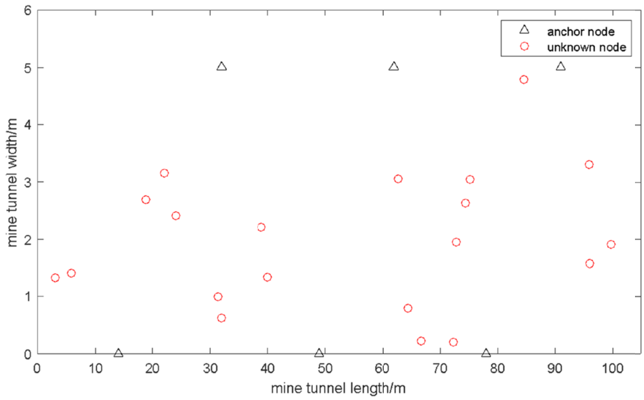


Fig. 5. Diagram of underground mine tunnel network topology

The simulation time N is set as 100; the communication radius is R, and the localisation coverage [24] and the average localisation error [25] are selected as the positioning accuracy indicators. This is defined as follows:

1) Localisation Coverage (LC) is a key metric that measures the correlation between the number of anchor nodes and proportion of unknown nodes that are successfully localised. This directly reflects the degree to which the deployment density of nodes influences the localisation capability of the overall network.

$$LC = \frac{Number\ of\ Successfully\ Localised\ Nodes}{Total\ Number\ of\ Nodes} \times 100\% \tag{18}$$

2) The actual position of node p is C_p, while its estimated position $\hat{C}_p$. We define the positioning error *err* and its average value *ave_e* as follows:

$$err = \frac{\sum_{k=1}^{N} \left| C_p - \hat{C}_p \right|}{N} \tag{19}$$

$$ave\_e = \frac{\sum_{k=1}^{N} \sum_{p=1}^{M} \left| C_p - \hat{C}_p \right|}{MN} \tag{20}$$

In the formula, the total count of unknown nodes is M.

3.2. Simulation results

To analyse the influence of each optimisation on the localisation accuracy of the *RSSI*-MCNC algorithm, it is assumed that all unknown nodes can be located. Ten anchor nodes are deployed in the lane. The original *RSSI* centroid localisation algorithm is marked as RSSI; the Kalman filter is marked as K-RSSI; the improved ranging model is marked as MK-*RSSI*; the improved weighted centroid localisation algorithm is marked as WMK-*RSSI*, and DWMK-*RSSI* refers to the gradient descent method. As shown in Fig. 6, the algorithm optimisation strategies at each stage can improve the positioning accuracy of the algorithmic framework.

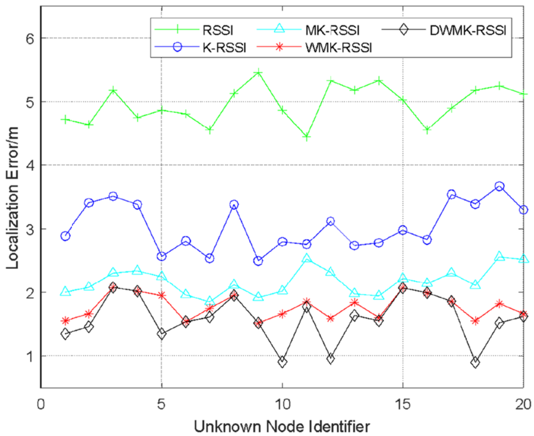


Fig. 6. Comparison of Location Errors for Various Optimis ation Contents in the *RSSI*-MCNC Algorithm

In the underground roadway, the more anchor nodes, the higher the localisation coverage rate, as shown in Fig. 7. Compared with Ref. [12], the localisation coverage rate of the algorithm can

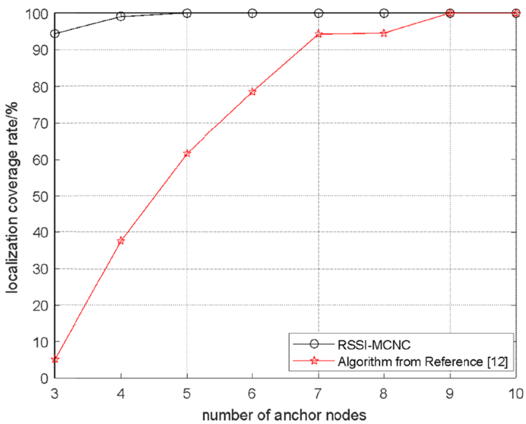


Fig. 7. Relationship between localisation coverage and the number of anchor nodes

reach 100% when six anchor nodes are deployed at the same location. The localisation coverage rate of Ref. [12] only reached 78.5%.

As shown in Fig. 8, six anchor nodes are used on the roadway. In the first round, the algorithm traverses the network and calculates the coordinates of the 15 unknown nodes that do not require cooperative nodes. In the second round, the coordinates of the remaining five unknown nodes are calculated with the assistance of the cooperative nodes. According to the experimental results, the average positioning error for the first round is 2.6727 m, whereas that for the second round increases to 3.3715 m.

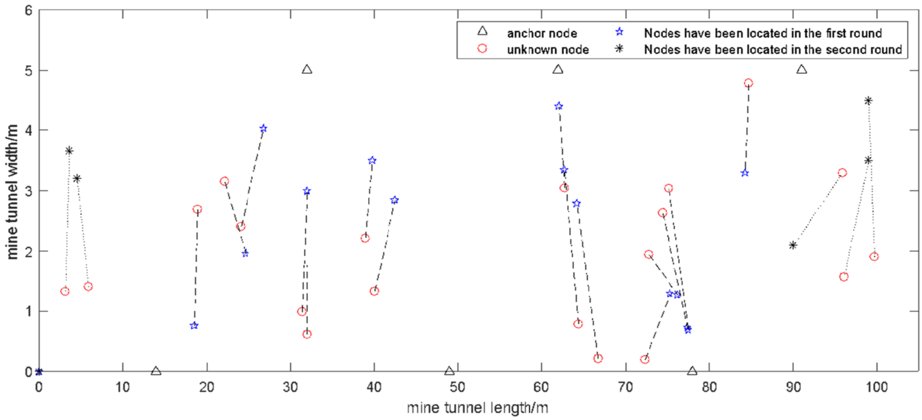


Fig. 8. Localisation Results of the *RSSI*-MCNC Algorithm

A comparative analysis is conducted based on the average positioning errors from the two rounds. It can be observed that when cooperative nodes are introduced into the localisation, the average localisation error of the system increases. In Fig. 9, one of the critical determinants of

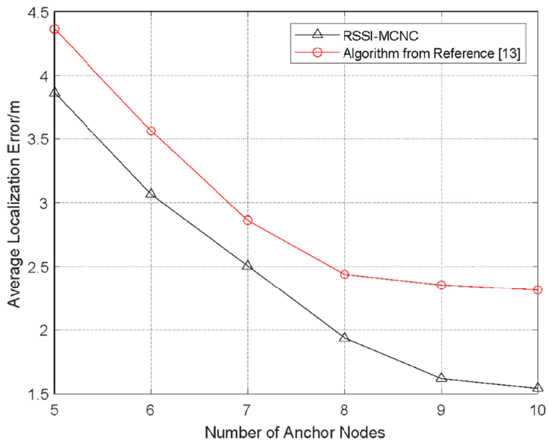


Fig. 9. Relationship between average localisation error and the number of anchor nodes

positioning accuracy is the number of anchor nodes. The average error in location estimation rises significantly as the number of anchor nodes progressively diminishes. This is because when the cooperative nodes participate in positioning, their positioning errors accumulate. Compared with the algorithm in Ref. [13], the *RSSI*-MCNC algorithm has a strong positioning accuracy when anchor nodes are scarce, and the mean error in location determination is diminished to 1.55 meters. Further addition of anchor nodes results in a reduced effect on the improvement of the positioning accuracy.

To further verify the positioning accuracy, it is compared with Refs. [12] and [13]. To ensure that the localisation coverage of Ref. [12] reaches 100%, it is assumed that nine anchor nodes are placed in the roadway, and other simulation parameters remain unchanged. As shown in Fig. 10, the positioning accuracy of the *RSSI*-MCNC algorithm is improved by 28.98% compared with Ref. [12] and 31.81% compared with Ref. [13].

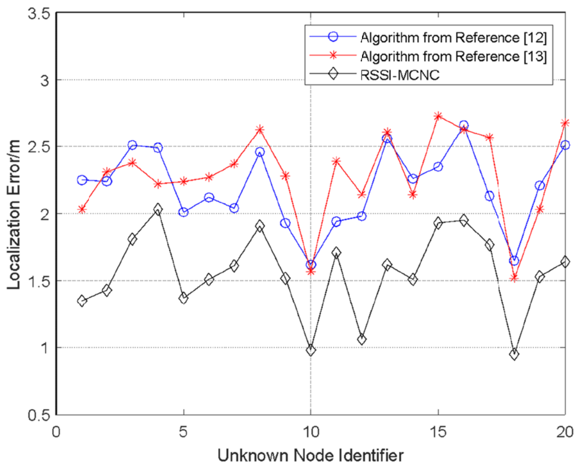


Fig. 10. Comparison of Localisation Errors

4. Conclusion

A coal mine underground positioning algorithm based on *RSSI* model modification and node cooperation (*RSSI*-MCNC) is proposed, aiming to improve the positioning accuracy and expand coverage in the demanding environments in underground operations of coal mines. By introducing Kalman filtering to optimise the RSSI values and dynamically adjust the model parameters, it is adapted to the environmental changes and improves the accuracy of the ranging model. In addition, using the localised nodes as cooperative nodes and combining the improved weighted centroid algorithm and gradient descent method, the algorithm can more precisely estimate the positions of unknown nodes during localisation. The experimental results demonstrate that compared with other algorithms, the *RSSI*-MCNC algorithm can significantly improve positioning coverage and accuracy in the case of fixed anchor nodes and random distribution of unknown nodes in the mining roadway. This algorithm can still leverage its powerful positioning capability, especially when anchor node resources are relatively scarce, demonstrating its unique accuracy advantage.

Therefore, this algorithm has crucial practical application value and promotion potential for improving the positioning and monitoring capabilities of mining personnel and equipment and ensuring safe production in mines.

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Author Contribution Statement

Xin Qiao, as the primary contributor to the article, was responsible for determining the research topic, constructing the article's framework, and coordinating the writing of each section. Fei Chang primarily designed and implemented the research methods for the article, including the experimental procedures, data collection, and analysis, ensuring the scientific rigour and precision of the study. Jing Wang was mainly in charge of data collection, processing, and analysis. Xiuying Wang focused on the compilation of the discussion and conclusion sections, summarizing the research findings. Yun Jiang was primarily responsible for meticulously proofreading and revising the entire article, ensuring its logical clarity and linguistic fluency. All five authors conducted multiple reviews and discussions of the article, collectively ensuring its quality and academic value.

References

[1] Y.F. Ni, Z.G. Wang, J. Wang, P. Guo, Improvement of Underground Personnel Location Algorithm Based on RSSI. Radio Engineering **53** (03), 663-668 (2023).

[2] J. Geng, X. Yu, C. Wu, G. Zhang, Research on pedestrian in-door positioning based on two-step robust adaptive cubature kalman filter with smartphone MEMS sensors. Micromachines **14** (6), 1252 (2023). DOI: https://doi.org/10.3390/mi14061252

[3] M. Zare, R. Battulwar, J. Seamons, J. Sattarvand, Applications of wireless indoor positioning systems and technologies in underground mining: A review. Mining, Metallurgy & Exploration **38**, 2307-2322 (2021). DOI: https://doi.org/10.1007/s42461-021-00476-x

[4] X. Qiao, H. S. Yang, Z. C. Wang, Iterative L-M algorithm in WSN-Utilizing modifying average hopping distances. International Journal of Online Engineering **10** (13), 4-20 (2017). DOI: https://doi.org/10.3991/ijoe.v13i10.7006

[5] X. Qiao, F. Chang, Underground location algorithm based on random forest and environmental factor compensation. International Journal of Coal Science & Technology **8** (5), 1108-1117 (2021). DOI: https://doi.org/10.1007/s40789-021-00418-4

[6] A. Booranawong, N. Jindapetch, H. Saito, Adaptive filtering methods for RSSI signals in a device-free human detection and tracking system. IEEE Systems Journal **13** (3), 2998-3009 (2019). DOI: https://doi.org/10.1109/jsyst.2019.2919642

[7] S. Kumar, S. Kumar, N. Batra, Optimized Distance Range Free Localization Algorithm for WSN. Wireless Personal Communications **117**, 1879-1907 (2021). DOI: https://doi.org/10.1007/s11277-020-07950-7

[8] P. Zuo, H. Zhang, C. Wang, H. Jiang, B. Pan, Directional target localization in NLOS environments using RSS-TOA combined measurements. IEEE Wireless Communications Letters **10** (11), 2602-2606 (2021). DOI: https://doi.org/10.1109/LWC.2021.3109787

[9] Y. Zhu, B. Deng, A. Jiang, X. Liu, Y. Tang, X. Yao, ADMM-based TDOA estimation. IEEE Communications Letters **22** (7), 1406-1409 (2018). DOI: https://doi.org/10.1109/LCOMM.2018.2833546

[10] K.Q. Ren, C.M. Pan, Collaborative localization algorithm based on dynamic correction of RSSI model parameters. Journal of Huazhong University of Science and Technology (Natural Science Edition) **48** (02), 97-102 (2020). DOI: https://doi.org/10.13245/j.hust.200217

[11] V. Bianchi, P. Ciampolini, I. De Munari, RSSI basedindoor localization and identification for ZigBee wireless sensor networks in smart homes. IEEE Transactions on Instrumentation and Measurement **68** (2), 566-575 (2019). DOI: https://doi.org/10.1109/TIM.2018.2851675

[12] N. Zhang, Mine weighted centroid positioning algorithm based on improved Gaussian mixture filter. Journal of Mine Automation **45** (11), 24-30 (2019). DOI: https://doi.org/10.13272/j.issn.1671-251x.17420

[13] L. Gao, Y.J. Hu, L. Zhang, T. Zhao, Wireless accurate location algorithm based on node cooperation in underground coal mine. Journal of Mine Automation **44** (08), 39-45 (2018). DOI: https://doi.org/10.13272/j.issn.1671-251x.2018030086

[14] T. Zhao, X.S. Li, L. Zhang, E.J. Ding, Y.J. Hu, Algorithm for cooperational localization of the sectional interval and LOS node in a coal mine. Journal of Xidian University **46** (01), 166-173 (2019). DOI: https://doi.org/10.19665/j.issn1001-2400.2019.01.026

[15] J.M. Li, J.H. Zhang, X.H. Wang, S.P. Wang, M. Zhao, X.Z. Chen, Downhole TDOA positioning method with improved whale optimization algorithm and Taylor series. Experimental Technology and Management **39** (12), 30-36+54 (2022). DOI: https://doi.org/10.16791/j.cnki.sjg.2022.12.005

[16] R. Jin, Z. Che, H. Xu, Z. Wang, L. Wang, An RSSI-based localization algorithm for outliers suppression in wireless sensor networks. Wireless Networks **21** (8), 2561-2569 (2015). DOI: https://doi.org/10.1007/s11276-015-0936-x

[17] X. Qiao, J. Wang, H. Shen, F. Chang, An Improved Received Signal Strength Indication Location Algorithm Based on Gaussian Filter and Quasi-Newton Method. International Journal of Network Security **26** (3), 501-509 (2024). DOI: https://doi.org/10.6633/IJNS.202405_26(3).17

[18] C. Gao, J. Yan, X. Yang, X. Luo, X. Guan, An attack-resistant target localization in underwater based on consensus fusion. Computer Communications **218**, 131-147 (2024). DOI: https://doi.org/10.1016/j.comcom.2024.02.011

[19] Z. Piao, J. Wang, L. Tang, B. Zhao, W. Wang, AccLoc: Anchor-Free and two-stage detector for accurate object localization. Pattern Recognition **126**, 108523 (2022). DOI: https://doi.org/10.1016/j.patcog.2022.108523

[20] R. Jiang, Y. Yu, Y.Y. Xu, X.M. Wang, D.P. Li, Improved Kalman filter indoor positioning algorithm based on CHAN. Journal on Communications **44** (02), 136-147 (2023). DOI: https://doi.org/10.11959/j.issn.1000-436x.2023006

[21] L. Sun, B. Li, D. Gao, B. Fan, Adaptive multi-object tracking algorithm based on split trajectory. The Journal of Supercomputing **80** (15), 22287-22314 (2024). DOI: https://doi.org/10.1007/s11227-024-06285-5

[22] X. W. Yu, L. P. Huang, Y. Liu, H. Yu, Y. Li, Convex Localization Algorithm based on Time Difference of Arrival for WSN in Uranium Tailings Radioactive Contamination. Wireless Personal Communications **118** (2), 999-1015 (2021). DOI: https://doi.org/10.1007/s11277-020-08055-x

[23] Q.Y. Li, W. Li, W. Sun, J.P. Wang, J. Li, Wi-Fi indoor localization algorithm based on RSSI and assistant nodes collaboration. Journal of Electronic Measurement and Instrumentation **30** (05), 794-802 (2016). DOI: https://doi.org/10.13382/j.jemi.2016.05.017

[24] D. Yan, C. Shi, T. Li, An improved PDR system with accurate heading and step length estimation using handheld smartphone. The Journal of Navigation **75** (1), 141-159 (2022). DOI: https://doi.org/10.1017/S0373463321000631

[25] C. Jiang, Y. Chen, C. Chen, J. Jia, H. Sun, T. Wang, J. Hyyppä, Smartphone PDR/GNSS integration via factor graph optimization for pedestrian navigation. IEEE Transactions on Instrumentation and Measurement **71**, 1-12 (2022). DOI: https://doi.org/10.1109/TIM.2022.3186082