Mobile self-organising network positioning algorithm based on node clustering

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Abstract: Traditional mobile self-organising network (MSON) positioning algorithms cannot correct position node's space and lead to low positioning accuracy. Node clustering is optimised DV-hop algorithm, and applied to node location of MSON. Narrative principle of MSON is completed by building RSSI ranging model. Strength of MSON transmission signal and propagation loss of MSON signal are calculated by combined RSSI technology in three-dimensional MSON model structure. Then, transmission loss is converted into node propagation distance, and node position of MSON is calculated. DV-hop algorithm is used for positioning by distance between nodes and position of anchor point. Positioning accuracy is improved and positioning range is expanded without increasing hardware overhead of mobile ad hoc network space node. Simulation experiment results show that node coverage of DV-hop positioning algorithm is higher than traditional algorithm. Besides, spatial localisation of MSON nodes expands network space node coverage rate, thereby improve the positioning accuracy.

Keywords: node clustering; mobile self-organising network; spatial location; algorithm; internet manufacturing; internet services.

Reference to this paper should be made as follows: Cui, J. and Fu, W. (2020) 'Mobile self-organising network positioning algorithm based on node clustering', *Int. J. Internet Manufacturing and Services*, Vol. 7, Nos. 1/2, pp.20–35.

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1 Introduction

Radiolocation was usually a technique for determining the position of an object on the Earth's surface in a reference coordinate system by measuring certain characteristic parameters of a radio signal. Radio positioning was originally used in navigation and positioning systems. The user receiver calculated its own position by a specific method based on changes in parameters such as the frequency, phase, and time of a series of radio navigation stations received. With the development of the mobile communication industry, people put forward more and higher requirements for mobile communication system services, and the majority of mobile phone users can be gotten voice (Liu et al., 2013b; Raj et al., 2016). At the same time as data and multimedia business services, they also hoped that mobile communications brought them more conveniences and services. Wireless location service referred to the cooperation of wireless terminals and wireless networks, and determined the latitude and longitude coordinate data of the actual location information of mobile users, thereby providing the user with the required location and orientation-related services. For example, mobile phones query each other, emergency rescue positioning and other services.

The optimisation of the mobile self-organising network positioning system became the main problem to be solved, plaguing the relevant scholars and experts. At present, the design method of mobile self-organising network positioning system adopted six-axis MEMS sensors. It used the 3-axis MEMS gyroscope, 3-axis MEMS acceleration calculation space location research, and the SimpliciTI protocol to transmit information, thereby improving the positioning accuracy of the mobile self-organising network. It can also be applied in the positioning field with high precision requirements. This was an effective way to solve the above problems (Hudaib et al., 2016; Liu et al., 2013a).

Zeng et al. (2017) used ultra-wideband UWB technology for mobile self-organising network positioning, but the actual positioning process needed to synchronise the time between nodes and obtained a higher range value. This method made the network node need to use the battery to provide energy, and its energy was greatly limited, and it was easy for the node to enter the state of necrosis prematurely. Based on the geometric relationship between nodes, the TDOA ranging method was used to achieve a more accurate positioning of network space nodes on the Mica system by Prabhu et al. (2017). However, it did not have a corresponding infrastructure in the cyberspace area and cannot meet the self-organising characteristics of the positioning algorithm. Yan et al. (2016) proposed a localisation algorithm that can check network nodes based on the centroid algorithm. However, the working environment of the network space was complex and changeable, and the node configuration in the network was not high, so some nodes may fail due to some special circumstances or energy exhaustion during work.

To solve the above problems, on the basis of improving the DV-hop positioning method, the spatial node positioning of the mobile ad hoc network was proposed. First, the distance between the nodes and the position of the anchor node were obtained, and the position obtained by the node clustering correction was adopted. Without increasing the hardware overhead of the mobile ad hoc network space node, the positioning accuracy was improved and the positioning range was expanded. Simulation experiments showed that the node coverage of the DV-hop positioning algorithm was higher than the traditional algorithm. The proposed spatial positioning of mobile self-organising network nodes was conducive to expanding the coverage of network space nodes and effectively improving the positioning accuracy. The hop distance obtained by the proposed method was closer to the actual situation and the positioning accuracy was higher in the case of more anchor points. It was good to the development of computer positioning system. Therefore, it was significant in daily application.

2 Mobile self-organising network cluster positioning method

2.1 RSSI ranging model construction

RSSI calculated the actual distance between nodes by measuring the attenuation of the signal from the transmitter to the receiver. In wireless communication, the commonly used propagation models include the free space propagation model, the logarithmic distance path loss model, the Hatta model, and the log-normal distribution model. This paper used the Shadowing theoretical model (Ding et al., 2017; Yang and Liu, 2014).

$$P = P_o + 10n \lg \frac{d}{d_o} + \sigma \tag{1}$$

In equation (1), d_o is the near-ground reference distance; P_o is the received signal strength when the distance is d_o; d is the real distance from the transmitter; P is the received signal strength when the distance is d; ξ is the shadowing factor in units of dB; n is the path loss index, the size of which depends on the propagation environment of the wireless signal, as shown in Table 1. Since in the actual environment ξ is a normal random variable with a mean value of 0 and a standard deviation of σ and the effect of ξ is ignored, the model in equation (2) is used.

Table 1 Typical values of path loss index

	Environment	*n*
Outdoor	Free space	2.0
	Shaded urban space	2.7–5.0
Indoor	Line of sight	1.6–1.8
	Blocked obstacle space	4.0–6.0

$$RSSI = -(10n \lg d + A) \tag{2}$$

In equation (2), parameter A is the average received signal strength at a distance of 1 m from the transmitting node represented by *dBm*; RSSI is the received signal strength at the transmitting node *d*. Model parameters A and n of the radio propagation path loss directly affect the accuracy of RSSI ranging.

2.2 Self-organising network description

Ad hoc network has the characteristics of mobile communication and computer network at the same time, it is a kind of special communication network. The research on ad hoc network technology is also one of the hotspots in current wireless communication technology research. Compared with other traditional communication networks, ad hoc, the network has the following remarkable features (Mittal Kumar, 2017; Rastegarnia et al., 2016; Xu et al., 2016; Wang and Jiang, 2018).

- No centre and self-organisation: there is no absolute control centre in the ad hoc network. All nodes are equal in status, and nodes in the network coordinate their behaviour with each other through distributed algorithms. Without manual intervention and any other pre-configured network facilities, they can be rapidly deployed and automatically networked at any time. Due to the distributed nature of the network, the redundancy of the nodes, and the absence of single points of failure, the network is robust and resistant to destruction.
- Dynamically changing network topology: in ad hoc networks, mobile terminals can move in the network at any speed and in any manner, and can turn off the radio at any time. In addition, the wireless transmission apparatus has various types of antennas, changes in transmission power, mutual interference among wireless channels, terrain, weather, and the like. The network topology formed between mobile terminals through wireless channels may change at any time, and the manner and speed of change are difficult to predict.
- Multi-hop routing: the node's coverage is limited due to the limited transmit power of the node. When it wants to communicate with nodes outside its coverage, it needs the forwarding of intermediate nodes. In addition, ad hoc, the multi-hop mountain in the network is completed by common nodes instead of dedicated routing devices such as routers.
- Special channel sharing method: The traditional shared broadcast channel is shared by one hop. In ad hoc networks, broadcast channels are shared by multiple hops. A node's transmission, only its one-hop neighbouring node can hear.
- Limitations of mobile terminals: in ad hoc networks, mobile terminals have the advantages of convenience of portability, lightweight, and smartness, but they also have inherent drawbacks such as limited energy, small memory, and low performance. However, it brings certain difficulties to application design and development, which is not conducive to the development of more complex functions.

Since the ad hoc network is a wireless network without a central self-organisation, it does not rely on any of its own fixed facilities to build a temporary network to complete a task anytime, anywhere. Therefore, in some places where it is impossible or inconvenient to lay out network facilities in advance, special occasions for rapid and automatic networking are required. Self-organising network wireless positioning technology has important applications. Such as the determination of the location of the wounded in the rescue after the disaster, the mutual arrangement and cooperation among the teammates in the military operations, the distance relationship among the vehicles in the intelligent transportation system, etc. These occasions involve the location of each mobile node. It is of great practical significance to use the self-organising network wireless positioning technology to obtain its exact location. In summary, the research on the location technology and parameter estimation methods of mobile stations in wireless ad hoc networks has important theoretical and practical values.

2.3 Network node clustering principle

Because RSSI is easily affected by the environment, in order to improve the reliability of positioning in a complex environment and reduce the impact of environmental differences on the positioning accuracy, this paper uses a K-means algorithm to cluster all the nodes to be located in the location space. All the nodes to be located (the number is N) are composed of a data set containing N objects, and each node is corresponded to an object in the data set (Sun et al., 2017; Yu et al., 2016). RSSI can reflect the degree of similarity of the environment around the node to a certain extent, that is, the nodes in the signal space are similar, and the environment is basically similar. Therefore, the RSSI vector received by the node is used as an attribute of the object. K objects are randomly selected first, and each object represents the average or centre of a cluster. Each of the remaining objects is assigned to the nearest cluster according to its proximity function value with each cluster centre. Then recalculate the average value of each cluster and repeat until the objective function is at its minimum or reaches the specified number of iterations. The proximity function and the objective function in this algorithm respectively use the Euclidean distance and the sum of the squares of the Euclidean distances of the minimised object to its cluster centre. Let any two objects A and B in the wireless sensor network receive the RSSI vector to the same M reference nodes as 1, then the proximity function 2 and the objective function are defined by equations (3)–(4).

$$dist(A, B) = \sqrt{\left[\sum_{i=1}^{m}\left(R_{Ai} - R_{Bi}\right)^2\right]} \tag{3}$$

$$\min\left\{SSE = \sum_{i=1}^{K}\sum_{A\in Ci} dist\left(c_i, A\right)^2\right\} \tag{4}$$

In equations (3)–(4), R_{Ai}, R_{Bi} denotes the RSSI value of A and B to the i^{th} reference point respectively, C_i denotes the i^{th} cluster, and c_i denotes the centre of C_i. The specific algorithm is described as follows.

Input: Number of datasets and clusters containing N objects K

Output: K clusters initialise each cluster centre $m_1, m_2, \ldots, m_k$, Assign each object to the cluster with the closest centre and recalculate the new cluster.

In equations (3)–(4), R_{Ai}, R_{Bi} represent the RSSI value of A and B to the i^{th} reference node respectively, C_i represents the i^{th} cluster, and C_i represents the centre of cluster C_i.

The specific algorithm is described as follows.

Input: Number of datasets and clusters containing N objects K

Output: K clusters initialise each cluster centre m_1, m_2, …, m_k,

Repeat assigns each object to the cluster with the closest centre and recalculates the new cluster until the convergence condition is reached. After the nodes to be located are clustered into clusters, the model parameters of each cluster are calculated separately, and the node positioning within the cluster is achieved. When solving the model parameters and node coordinates of each cluster, this paper uses the optimisation method to improve the second stage of the joint solution method. Taking cluster C_i as an example, the node positioning stage first uses the empirical values of the model parameters and the maximum likelihood method to roughly locate all nodes to be located (number t) in the cluster C_i. Then the model parameters A_i and n_i corresponding to cluster C_i and the coordinates of all nodes in the cluster are used as unknown parameters (Bodyanskiy et al. 2017; Tabatabaei et al., 2017). The objective function V is set, and the empirical value of the model parameter and the rough value of the node are taken as the initial value of the unknown parameter, and the solution of the unknown parameter is obtained by using the descending gradient method in equation (5).

$$\min\left\{V\left(\left(x_j, y_j\right), A_i, n_i\right) = \sum_{a=1}^{t}\sum_{b=1}^{M}\left(R_{ab} - R_{ab}^{RSS}\right)^2\right\} \tag{5}$$

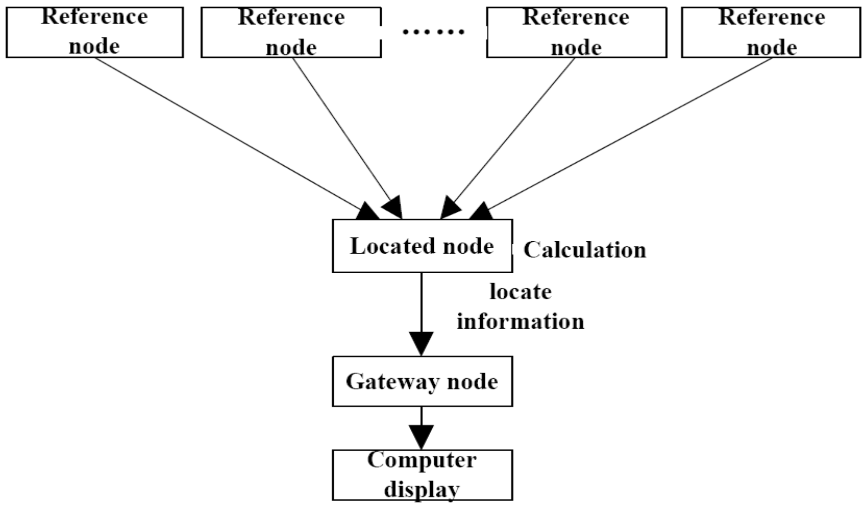
In equation (5), $i = 1, 2, \ldots, t$; (x_j, y_j) represents the position coordinate of the j^{th} node to be positioned; R_{ab} is the measured signal strength value of the a^{th} reference node received by the b^{th} position-to-be-positioned node; R_{ab}^{RSS} is the intensity value calculated by the signal attenuation model.

3 Mobile self-organising network positioning system design

3.1 Creating a location environment

In this paper, RSSI algorithm is used to create a three-dimensional space model to prepare for positioning work. The three-dimensional space has three-dimensionality, three-directions, respectively, X, Y, Z three-way, constitute a spatial three-dimensional, three-dimensional infinite extension established. The design of the model is shown in Figure 1. By calculating the transmitted signal strength of the mobile ad hoc network (Ramos et al., 2017; Nakamura and Hasegawa, 2016), the propagation loss of the mobile ad hoc network signal is calculated. With the prior knowledge and experience model, the transmission loss is converted into the node propagation distance, and the node position of the mobile self-organising network is calculated. The spatial coordinates are determined according to the RSSI algorithm and the position information of the reference node, and the coordinates are sent to the gateway. Through the gateway, the node's position information and other environmental information are sent to the host, and the host's provisioning commands are sent back to the system, thereby completing the creation of a three-dimensional space model and creating an environment for positioning.

Figure 1 Model design schematic



The RSSI technology calculates the propagation loss of the signal by receiving the node signal and using the transmitted signal strength of the known transmitting node. The transmission losses are then converted into distances based on theoretical and empirical models. Then use the RSSI algorithm to calculate the position of the node to complete the positioning. In the process of converting signal strength into distance, there are three kinds of signal attenuation models, including free space model, logarithmic distance path loss model, and log-normal distribution model, which is defined as equation (6).

$$P_L(d) = 32.44 + 10K_P(d) + 10n\lg(f) \tag{6}$$

In equation (6), $P_L(d)$ represents the path loss of the distance d, f is the signal frequency of the system, n is the attenuation coefficient of the signal

$$P_L(d) = P_L(d_0) + 10K_P \lg\left(\frac{d}{d_0}\right) + X_\sigma \tag{7}$$

where X_σ mean is equal to 0, σ represents a Gaussian variable.

$$P(d) = P(d_0) - 10K_P \lg\left(\frac{d}{d_0}\right) + X_\sigma \tag{8}$$

where d_0 represents the reference distance, K_P represents the attenuation index of the signal, X_σ represents a Gaussian variable with a mean of 0 and a variance of σ, and $P(d)$ and $P(d_0)$ represent the signal strengths at distances of d and d_0, respectively. However, due to the problems of the traditional RSSI positioning technology being affected by the environment, the error correction is still needed in practical applications. By correcting the known position, the error can be minimised. Using the actual distance between the anchor points and the calculated distance in the network space, the positioning error is obtained. Finally, the mean error is cut off the correction error, thereby reducing the spatial positioning system error (Liu et al., 2016; Jia et al., 2014). Its expression is as shown in equations (9)–(11).

$$d_{i,j} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{9}$$

$$e_{i,j} = d_{i,j} - \tilde{d}_{i,j} \tag{10}$$

$$e_i = \frac{\sum_{j=1}^{n} e_{i,j}}{n} \tag{11}$$

where d_{ij} and $\tilde{d}_{i,j}$ represent the actual distance between the anchors i, j and the predicted distance, respectively. e_{ij} represents the difference between the actual distance and the predicted distance. n represents the number of other anchors in the communication range. After the error is corrected, the distance between the anchor point and the cyberspace node is defined as equation (12).

$$d = \tilde{d} + e \tag{12}$$

Through the interference signal filtering in the Gaussian filter network, the probability density function is constructed by using the mean and variance of the received n RSSI values to find the confidence interval; and averaged by its internal RSSI value. The process is expressed as a function expression as equations (13)–(16).

$$\mu = \frac{1}{n}\sum_{i=1}^{n} RSSI \tag{13}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(RSSI_i - \mu\right)^2} \tag{14}$$

$$f(RSSI) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(RSSI-\mu)^2}{2\sigma^2}} \tag{15}$$

$$RSSI_p = \frac{\sum_{i=1}^{n} RSSI_i}{m} \tag{16}$$

Through the above method, the RSSI algorithm is optimised, and a three-dimensional space model of the mobile self-organising network space is created to prepare for positioning.

3.2 DV-hop positioning algorithm to achieve positioning

The DV-hop positioning algorithm is also called the distance vector hop segment algorithm. There are three stages in this algorithm. Firstly, distance vector exchange protocol is used to get the number of hops between anchor points for all nodes in the mobile ad hoc network. Then it uses the obtained hop count to calculate the minimum hop count and the average hop distance. Based on this, it uses the minimum hop count times the average hop distance to calculate the estimated distance between the node and the anchor point. Finally, the maximum likelihood estimation method is used to accurately locate.

The maximum likelihood algorithm is to make a lot of information owned by a node into a system. Assume that this system is composed of multiple equations, and the solution of this equation is unique. This is the maximum likelihood algorithm.

Assuming that in the mobile ad hoc network space, n known coordinate anchors are (x_1, y_1), (x_2, y_2), …,(x_n, y_n), the node D coordinate is (x, y), and the known coordinate anchor distance is d_1, d_2, …, d_n then the relational expression can be established by equation (17).

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = d_1^2 \\ \vdots \\ (x_n - x)^2 + (y_n - y)^2 = d_n^2 \end{cases} \tag{17}$$

Suppose you subtract the nth formula from the i^{th} $(1 \le i \le n - 1)$ formula, equation (18) can be obtained.

$$\begin{cases} x_1^2 - x_n^2 - 2(x_1 - x_n)x + y_1^2 - y_n^2 - 2(y_1 - y_n)y = d_1^2 - d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 - 2(x_{n-1} - x_n)x + y_{n-1}^2 - y_n^2 - 2(y_{n-1} - y_n)y = d_{n-1}^2 - d_n^2 \end{cases} \tag{18}$$

When the above expression is represented by the linear expression 1, equations (19)–(21) can be obtained.

$$A = \begin{bmatrix} 2(x_1 - x_n), 2(y_1 - y_n) \\ \vdots \\ 2(x_{n-1} - x_n), 2(y_{n-1} - y_n) \end{bmatrix} \tag{19}$$

$$b = \begin{cases} x_1^2 - x_n^2 + y_1^2 - y_n^2 - d_1^2 + d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 - d_{n-1}^2 + d_n^2 \end{cases} \tag{20}$$

$$X = \begin{bmatrix} x \\ y \end{bmatrix} \tag{21}$$

For node D, the function relation is defined in equation (22) using the least mean square error estimation method.

$$\hat{X} = (A^T A)^{-1} A^T b \tag{22}$$

Since the system is used in network space positioning, the anchor sends information packets, and the nodes only send untransmitted packets, so each network node sends 2A data packets on average, and the communication overhead of the DV-hop algorithm is 2▪A▪N. The node computational overhead of the algorithm includes distance calculation and least squares algorithm. Assuming there are anchor points to estimate the nodes, the distance between the nodes and the anchor points can be calculated. Position estimation is performed by least squares operation to complete positioning. The computational cost per node is calculated by equation (23).

$$k + 2(k-1) + 5(k-1) + 6(k-1) + 2^2(k-i) + 2^3/3 = 18k - 17 + 2^3/3 \tag{23}$$

In summary, the total energy consumption of the algorithm is shown in Table 2.

Table 2 Energy consumption of the DV-hop algorithm

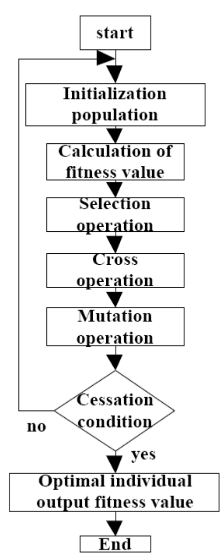
Algorithm	*Communication costs*	*Calculation cost*
DV-Hop	$2 \cdot A \cdot N$	$18k - 17\ 2^3/3$

Through the above arguments, we can see that the DV-hop algorithm achieves a simple positioning method, and the communication and computational overhead of nodes in space are moderate, but the error may be large. Therefore, the position of the mobile self-organising network node needs to be refined through node clustering to complete the design of the mobile self-organising network positioning system.

3.3 Node clustering accurate positioning

The application of node clustering can optimise the deployment of network space positioning nodes. Node clustering is a search method originated from biological evolution theory. The chromosome is used to optimise the problem. By grouping the solutions of the problem together, a population is formed, and the operators in the chromosome algorithm are applied to this group of chromosomes. The main genetic operations are selective, crossover, and mutation. Through this method, the accuracy of network positioning is improved. The process is shown in Figure 2.

Figure 2 Node clustering process



By setting the qubits to represent the minimum information, the state of the qubit can be expressed as:

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \tag{24}$$

Among them, α and β are a pair of affiliates and they need to satisfy $|\alpha|^2 + |\beta|^2 = 1$, which is represented by a probability of magnitude, and its formula is expressed as $[\alpha\ \beta]T$.

In the node clustering, the chromosome population defining the t^{th} generation can be expressed as $Q(t) = [q_1^t, q_2^t \cdots q_n^t]$, of which represents the chromosome, and are expressed as follows:

$q_i^t = \begin{bmatrix} \cos t_1 & \cos t_2 & \cdots & \cos t_m \\ \sin t_1 & \sin t_2 & \cdots & \sin t_m \end{bmatrix}$ among them $t_1 = 2\pi r$, $r = random[0, 1]$, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, m$. Among them, m represents the length of the chromosome, n represents the size of the population, and represents the evolutionary number.

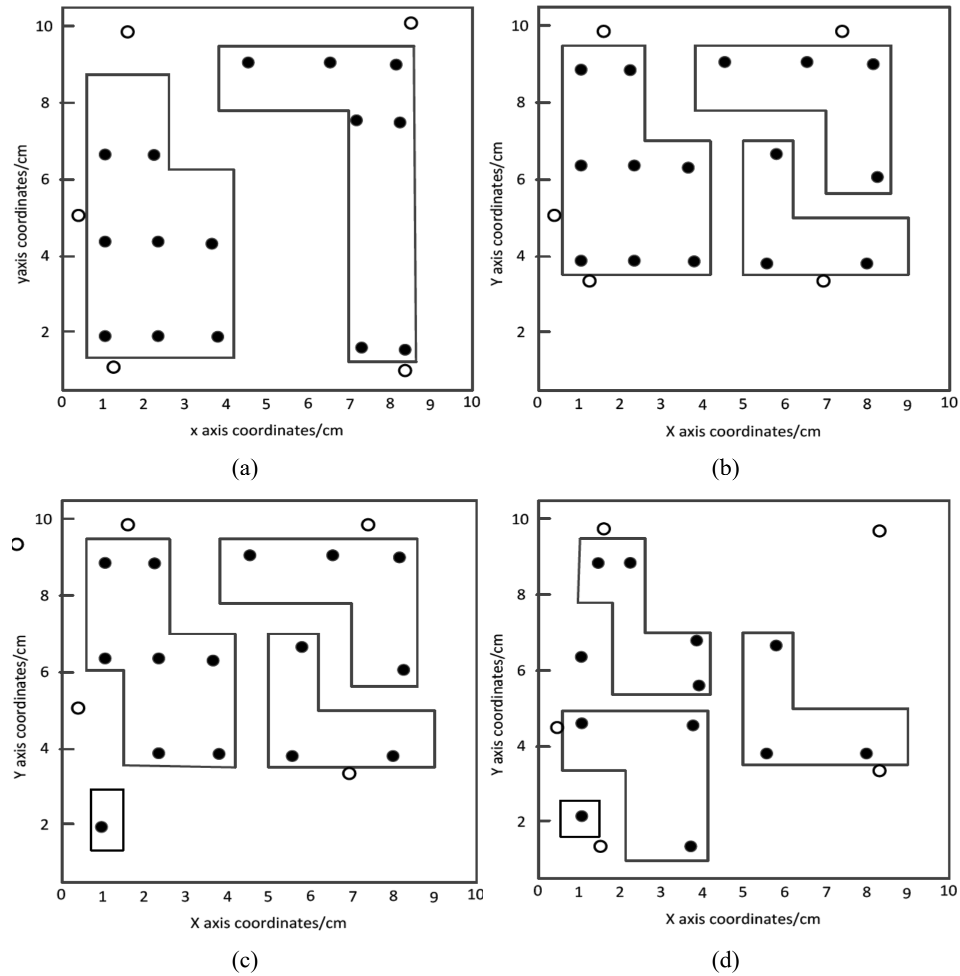
4 Experimental results and analysis

In this paper, we use the Zigbee-based wireless sensor network indoor positioning platform to verify the cluster positioning method in the actual scene. The implementation of the positioning system uses the I-RIS sensor node, and the internal program of the node is written in C language. In the experiment, the launch energy of the node was set to 8 dBm. The experimental scene was an indoor laboratory of the college building, and the size was 9 m × 7 m. There were five reference nodes and 15 nodes to be located. The five reference nodes send information every two seconds. Ten measurements were performed on each node to be located and averaged for calculation. In order to verify the similarity of the environment, all the nodes to be located in the positioning area are clustered and clustered when K is 2, 3, 4, and 5, as shown in Figure 3.

Table 3 Model parameter calculation values for each cluster

K	*1*	*2*	*3*	*4*	*5*
A	–57.599	–57.623	–57.685	–57.214	–57.272
	1.781	1.696	1.696	1.719	1.718
		–57.752	–57.700	–57.852	–57.952
		1.8415	1.9542	1.6359	1.6201
			–57.801	–57.402	–57.208
n			1.7152	1.9546	1.5403
				–57.852	–57.102
				1.7512	1.9263
					–57.265
					1.7021

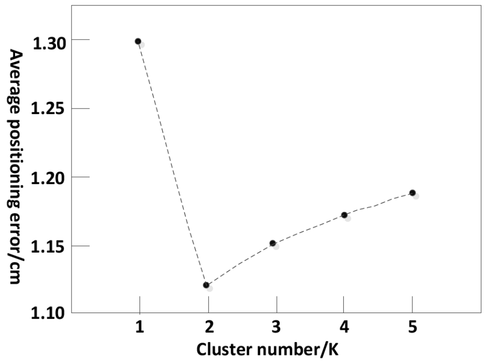
Figure 3 Cluster clustering



As can be seen from Figure 3, the surrounding environment of the node to be located in the positioning area has a certain degree of similarity and difference. In this paper, the average positioning error of the nodes is calculated for each of the four clustering conditions and the non-clustered condition (1), as shown in Figure 2. Among them, the model parameters A and n of each cluster calculated according to the positioning stage method are shown in Table 2. The results show that the clustering accuracy is significantly improved compared to the cluster-free situation. Among them, the improvement in positioning accuracy is most pronounced when K = 2. Therefore, the number of clusters under this scenario is set to 2.

Finally, through the measured data, the clustering method was compared with the curve fitting method proposed by Raj et al. (2016), the linearisation method proposed by Hudaib et al. (2016), and the joint solution method proposed by Liu et al. (2013b). The cumulative distribution of the average positioning error for the four algorithms is shown in Figure 3. The results show that the clustering location method has a probability of less than 1.2 cm with a probability of 70%, which is superior to other algorithms.

Figure 4 Comparison of average positioning error at different K values



In order to prove the comprehensive effectiveness of the proposed design method of mobile self-organising network positioning system based on improved DV-hop, a simulation experiment is needed. The simulation laboratory used a comparison method to compare the DV-hop positioning algorithm with the traditional positioning algorithm to obtain experimental results.

Figure 3 shows the comparison of the network node coverage (m2) between the DV-hop positioning algorithm and the traditional positioning algorithm. It can be seen from Figure 3 that the coverage degree of the DV-hop positioning algorithm is high.

Figure 5 Comparison of node coverage of DV-hop positioning algorithm and traditional algorithm

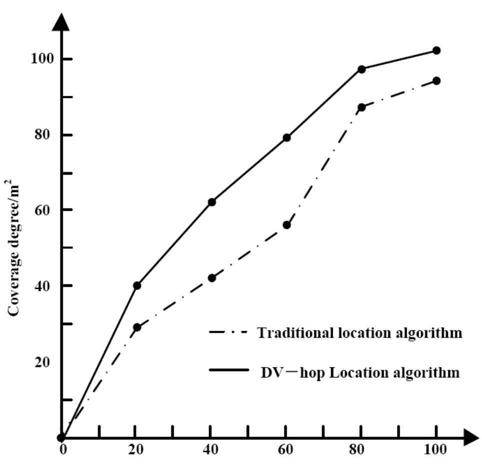


Figure 5 is an analysis graph of positioning coverage (%) based on a DV-hop positioning algorithm and a conventional positioning algorithm. As can be seen from the figure, when the node based on the DV-hop algorithm is located at the anchor point rate less than

20%, the location coverage rate reaches 90%. However, the traditional algorithm has not reached the anchor node ratio of 20%. This shows that the proposed method has a significant increase in the coverage rate.

Figure 6 Analysis of location coverage based on DV-hop positioning algorithm and traditional algorithm

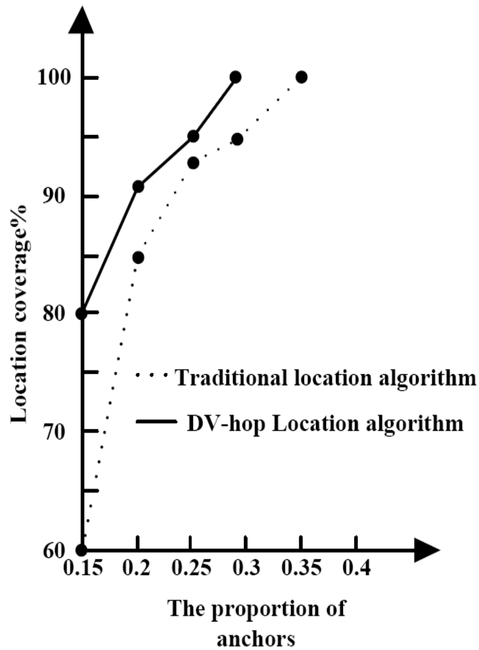


Figure 7 The relationship between the change of anchor ratio and positioning error

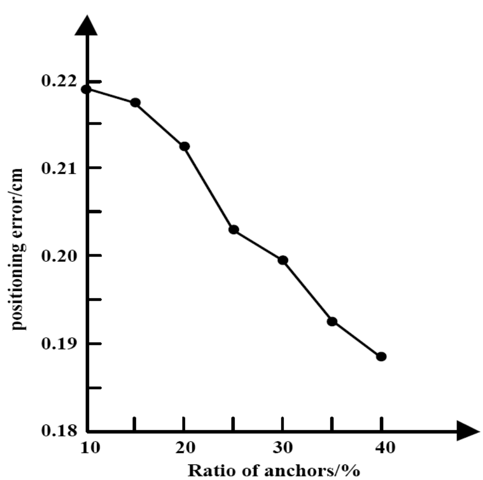


Figure 6 is a diagram showing the relationship between the change of the anchor ratio and the positioning error (cm). As can be seen from the figure, as the proportion of anchor points increases, the positioning error decreases. When the anchor points are distributed evenly and regularly, the transmission path of the signal is almost a straight line, and the positioning algorithm has less error. In the average hop distance, because the anchor points are more, the hop distance obtained is closer to the actual situation, so the positioning accuracy is higher.

5 Conclusions

Positioning the mobile ad hoc network is conducive to the stable operation of the network. On the basis of improving the DV-hop algorithm, node clustering is used to optimise the DV-hop algorithm, which is applied to the spatial localisation of mobile self-organising network nodes. Then the positioning range is expanded, the positioning accuracy is improved. It plays a positive role in the development of the computer industry.

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