Application and Optimization of Centroid Algorithm in Indoor Positioning

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Abstract. Indoor mobile positioning is widely used in shopping malls, energy saving in buildings, medical care and emergency rescue. Range-free algorithms typically use the connectivity of a wireless sensor network system to estimate the location of target nodes, typically through Dv-hop, the prime method, approximate point-in-triangulation test, or APIT for short. -free algorithms can be obtained by changing the distribution density of reference nodes or by changing the blind node communication radius to obtain higher accuracy. Due to constraints such as complex indoor environments, current indoor positioning methods are often less accurate and more expensive. To address these issues, this paper improves on the traditional center-of-mass algorithm by using a six-point center-of-mass algorithm for indoor positioning to further improve the accuracy of the indoor positioning algorithm. To this end, the following work is accomplished in this paper: 1. introduced the algorithms currently used for indoor positioning and their shortcomings, laying the theoretical foundation for the improved approach proposed in the following paper. 2. introduced the basic working principle of the center-of-mass algorithm and proposed an improved system using the six-point center-of-mass algorithm. 3. established the best possible model through experiments, then input test data and evaluated it based on expert judgement. The experimental results show that the model proposed in this study has excellent accuracy in indoor wireless positioning.

Keywords: Indoor positioning · Wireless positioning · Multi technology integration · Multi-source information · The centre-of-mass algorithm

1 Introduction

Outdoor wireless positioning technology is a mature technology that has been integrated into all aspects of human life. For example, the global navigation satellite system (GNSS) provides accurate geographic positioning in outdoor scenarios. Global navigation satellite system (GNSS) can provide accurate geographical location, speed and other information in outdoor scenarios. In outdoor scenarios, for example, GNSS provides accurate information on geographical location, speed of traffic and other information, which makes people's daily lives much more convenient. However, in indoor conditions, GNSS cannot be used due to the obstruction of buildings. However, in indoor conditions, GNSS cannot provide accurate positioning and stable location information due to the obstruction of buildings.

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According to research, people spend on average only 10%–20% of their time outdoors, and most of their time is spent indoors. The demand for wireless positioning is increasing. The demand for indoor positioning of industrial IoT devices, personnel positioning and various types of robots has led to further research into indoor positioning technologies.There are currently two main types of indoor positioning algorithms: 1) range-based algorithms and 2) range-free algorithms. The measurement techniques commonly used in range-base based algorithms are received signal strength indicator (RSSI), time difference of arrival (TDOA), time of arrival (TOA). (TOA), angle of arrival (AOA), etc. Distance-based algorithms are very accurate and can reach centimeter-level accuracy with small errors in sensor acquisition data. The algorithms that do not require distance measurement usually use the connectivity of the wireless sensor network system to The typical algorithms are Dv-hop, prime algorithm, and distance-based algorithm.The typical algorithms are the Dv-hop, the prime algorithm, the approximate point-in-triangulation test (APIT), the Range-free based algorithms can be used to obtain higher accuracy by changing the reference node distribution density or changing the blind node communication radius The algorithm is based on the range-free. To address the problems affecting the accuracy of the center-of-mass algorithm, Huang et al. et al. proposed to classify the path loss coefficients and use the Euclidean distance to determine the actual RSSI value to select the corresponding path loss category. Triguero, D et al. [1] used the k-nearest neighbor algorithm to solve the problem. W. Luo et al. [2] proposed an improved center-of-mass localization algorithm when the reference nodes are not uniformly distributed. The larger the communication radius, the smaller the error. X. Feng et al. [3] pointed out that that one or more reference nodes can be added on top of the three reference nodes. The intersection of the two intersection points of the intersecting circles can then be used to solve for the blind node coordinates. The coordinates of the blind nodes can be solved by adding one or more reference nodes to the three reference nodes.

The traditional centroid location algorithm is a very simple and practical location algorithm, which is based on network connectivity. The basic principle of this algorithm is as follows: multiple reference nodes are arranged around the blind node in advance. Every certain time, the reference node will broadcast its ID and position coordinates to the neighbor node. After receiving the reference node ID and position coordinates sent by the blind node, the blind node will find several reference nodes with the highest signal intensity. Usually, there are 3–8 reference nodes, and the 3–8 nodes with the strongest signal intensity are the reference nodes closest to the blind nodes. It can be approximately considered that the blind nodes are located at the centroid of the polygon surrounded by these reference nodes. Therefore, the geometric centroid of the polygon surrounded by these reference nodes can be used as the position coordinates of the blind nodes. The traditional centroid algorithm is very low complexity, easy to implement, and the cost is small, besides the shortage of positioning accuracy is too low, in order to improve the positioning accuracy, it is necessary to improve the layout density of the reference node, that is, to increase the cost of hardware, and the reference node should be distributed as evenly as possible. In fact, the ultimate purpose of the high-density and uniform layout of reference nodes is to minimize the polygon used for the final determination of the centroid of blind nodes. The smaller the polygon area is, the more accurate the position coordinates of blind nodes will be obtained by the determination of their centroid. Because the traditional centroid algorithm either has low positioning accuracy or high hardware cost, it has great limitations in application.

To address the shortcomings of the traditional centre-of-mass algorithm, this paper proposes an improved six-point centre-of-mass algorithm based on it [4]. The BP neural network model has already been studied to fit the traditional distance loss model, which takes the received signal strength RSSI as input and the corresponding distance d as output, avoiding the need to find the parameters A and n in the signal propagation model. Once the distance d is obtained, the three nearest reference nodes to the node to be located are also obtained, and the six-point centre-of-mass algorithm proposed in this paper uses these three reference nodes as The six-point centre-of-mass algorithm proposed in this paper makes a circle with the measured distance of the blind node from these three reference nodes as the centre of the circle, and the six intersection points of these three circles as the radius of the circle. The polygon formed by the six intersections of these three circles is used as the new polygon for the position estimation of the blind node, and the centre of mass of this hexagon is used as the centre of mass for the position estimation of the blind node. Compared with the traditional center-of-mass localization algorithm, this improves the localization accuracy without increasing the hardware overhead and has a very high level of accuracy. Improves the localisation accuracy and has a very high practical value.

2 Method

2.1 Signal Transmission Model

The theoretical model commonly used in wireless signal transmission is the fading model [5].

$$p(d) = p(d_0) - 10n\,\lg\left(\frac{d}{d_0}\right) + X \tag{1}$$

where: d is the distance from the blind node to the reference node; p(d) denotes the signal strength received by the blind node when the distance from the reference node is d; p(d0) denotes the signal strength received by the blind node when the distance from the reference node is d0, where d0 is the reference distance; n is the path loss factor, the value changes with the complexity of the environment, generally the more obstacles, the larger the value of n, the normal range is from 2 to 6; X is a Gaussian random variable obeying normal distribution, the unit is dBm.

Simplified models are generally used in practical engineering applications,

$$p(d) = p(d_0) - 10nlg\left(\frac{d}{d_0}\right) \tag{2}$$

To simplify the calculation process, d0 is generally taken to be 1m and let p(d) be the received signal strength estimate, p(d0) = A. Thus we have

$$I_{RSS} = A - 10nlg(d) \tag{3}$$

A is the value of the signal strength received by the blind node when it is 1m away from the reference node.

2.2 Principle of the Center-of-Mass Algorithm

The basic principle of the center-of-mass algorithm is that a blind node detects a reference node that is connected to it. The basic principle of the placentric algorithm is that a blind node detects a reference node that is connected to it and estimates its own position based on the position information provided by the reference node. The process is as follows: the reference node periodically sends its position information around, and the blind node estimates its position based on the position information received from the different reference nodes. When the number of reference nodes received by the blind node or the signal strength reaches a certain threshold value, the blind node records the coordinates of the position of the reference nodes that meet the certain threshold value and uses the centre of mass of the polygon formed by these reference nodes as the self The blind node records the coordinates of the position of the reference node that meets a certain threshold, and uses the centre of mass of the polygon formed by these reference nodes as its own position, as shown in Fig. 1.

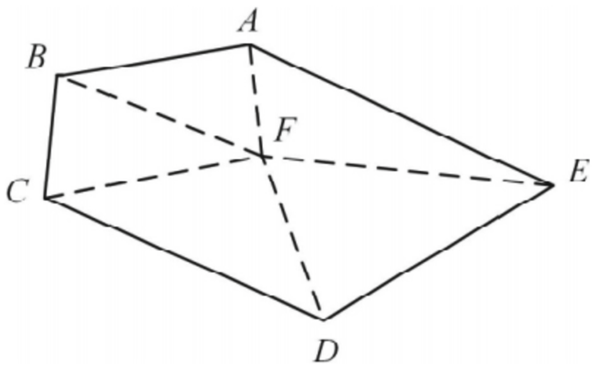

Fig. 1. Schematic diagram of the centre-of-mass positioning principle.

Suppose the blind node F (x, y) receives five reference node coordinates A to E, corresponding to the coordinate values (xi, yi), i = 1, 2, 3, 4, 5. Then the estimated coordinates of the blind node F is:

$$F(x, y) = \left(\frac{1}{5}\sum_{i=1}^{5} x_i, \frac{1}{5}\sum_{i=1}^{5} y_i\right) \tag{4}$$

2.3 The Proposed Six-Point Centre-of-Mass Algorithm

In an ideal case, [6] the blind node is at the intersection of three circles with the three reference nodes as the center of the circle and the distance between the blind node and the three reference nodes as the radius. Therefore, the intersection of the three circles can be calculated by calculating the distance between the blind node and the three reference nodes, and then the position coordinates of the blind node can be obtained [7]. However, in practice, due to the existence of errors, the three circles generally do not intersect at a point, but at an area. The position relationship between the typical three reference nodes and blind nodes is shown in Fig. 2 below:

$$F(x,y)=\left(\frac{1}{5}\sum_{i=1}^{5}x_i,\frac{1}{5}\sum_{i=1}^{5}y_i\right) \quad (4)$$

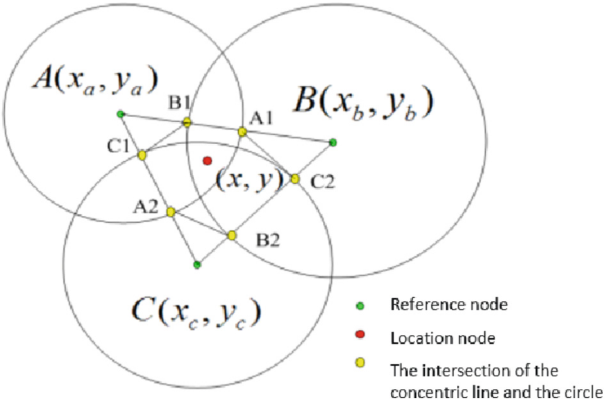

Fig. 2. Position Relation between Reference Nodes and Blind Node.

The traditional center-of-mass localization algorithm is to find the three reference nodes closest to the blind nodes [8] (i.e., the three nodes with the strongest RSSI sent to the blind nodes). (i.e., the three nodes with the strongest RSSI sent to the blind node), such as the three ABC points shown in Fig. 4-1, and then directly find the center of mass of these three reference nodes as the location estimate of the blind node. The center of mass of these three reference nodes is used as the position estimation of the blind node, but this method has too much error. In this paper, the traditional three-point In this paper, the traditional three-point center-of-mass algorithm is improved to a more accurate six-point center-of-mass algorithm, in which the received signal strength RSSI is firstly input to the trained The output is the distance d between the corresponding reference node and the blind node. The location of the blind node is on the circle with the reference node as the center and the distance d as the radius. The BP neural network is used to obtain three such distances, we can get three such circles, and the actual blind node is inside the polygon surrounded by these three circles. The actual blind nodes are inside the polygon formed by these three circles. Then we find the intersection of the three circles and the intersection of the two circles with the circle, a total of six points, and find the center of mass of these six points. The center of mass of these six points is used as the location estimate of the blind node [9].

According to the relationship between the reference nodes and the blind nodes in Fig. 2, the traditional center-of-mass algorithm is to find the center of mass of the three reference nodes ABC in Fig. 2, but the algorithm in this paper is to find the center of mass of the hexagon enclosed by the six yellow points A1, B1, C1, A2, B2, C2 in Fig. 2, so that the position of the localized nodes is precisely limited to the inside of the smaller hexagon, and the localization is more accurate. The six points of the six-point center of mass algorithm can be obtained from the position relationship between the two circles in Fig. 3 below. There are four types of position relations between two circles (tangent is divided into inner and outer tangent, and the intersection points are considered to be coincident, for one case) From Fig. 3, we can see that no matter how the position of the two circles changes, it is always possible to find the four points of intersection between the line connecting the two circles and the two circles, if we are the middle two points of these four points of intersection.

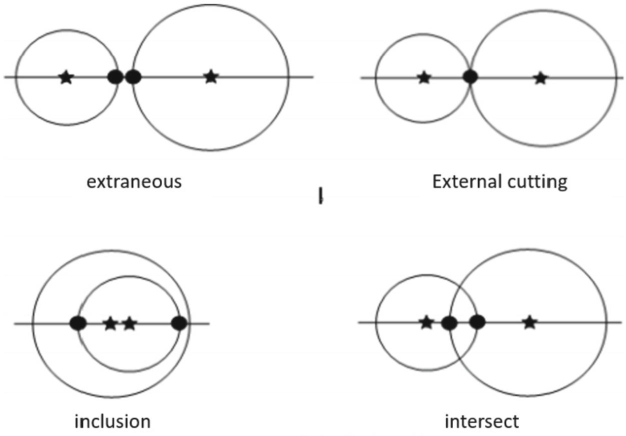

Fig. 3. Position Relation between Two Circles.

How to find the coordinates of these six points is the key to the six-point center of mass algorithm, [10] as shown in Fig. 4-1, for example. Let the signal strengths of the blind nodes received by the three reference nodes $A(x_A, y_A)$, $B(x_B, y_B)$, $C(x_C, y_C)$ are RA, RB, RC and input these three received signal strengths into the trained BP neural network to obtain the corresponding distance, , and The corresponding distances, , and RC d dB, d, so that three circles can be obtained.

$$Circle\,A : (x - x_A)^2 + (y - y_A)^2 = d_A^2 \tag{5}$$

$$Circle\,B : (x - x_B)^2 + (y - y_B)^2 = d_B^2 \tag{6}$$

$$Circle\,C : (x - x_C)^2 + (y - y_C)^2 = d_C^2 \tag{7}$$

Three straight lines:

$$LINE\,AB : \frac{y - y_A}{x - x_A} = \frac{y_A - y_B}{x_A - x_B} \tag{8}$$

$$LINE\,AC:\frac{y-y_A}{x-x_A}=\frac{y_A-y_C}{x_A-x_C} \tag{9}$$

$$LINE\,BC:\frac{y-y_B}{x-x_B}=\frac{y_B-y_C}{x_B-x_C} \tag{10}$$

First find the intersection of the line AB and the circle A. Combine (5) and (8) and solve the equations to obtain the solution as in Eqs. (10) and (11).

$$x=x_A\pm\frac{|(x_B-x_A)\times d_A|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}} \tag{11}$$

$$y=y_A\pm\frac{|(y_B-y_A)\times d_A|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}} \tag{12}$$

Two point can be made:
$\left(x_A+\frac{|(x_B-x_A)\times d_A|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}},y_A+\frac{|(y_B-y_A)\times d_A|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}}\right)$ and

$$\left(x_A-\frac{|(x_B-x_A)\times d_A|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}},y_A-\frac{|(y_B-y_A)\times d_A|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}}\right)$$

Similarly the solution to the two intersections of the line AB with the circle B can be solved by combining Eqs. (6) and (8) as in Eqs. (13) and (14).

$$x=x_B\pm\frac{|(x_B-x_A)\times d_B|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}} \tag{13}$$

$$y=y_B\pm\frac{|(y_B-y_A)\times d_B|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}} \tag{14}$$

Two point can be made:

$$\left(x_B+\frac{|(x_B-x_A)\times d_B|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}},y_B+\frac{|(y_B-y_A)\times d_B|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}}\right) \text{ and}$$
$$\left(x_B-\frac{|(x_B-x_A)\times d_B|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}},y_B-\frac{|(y_B-y_A)\times d_B|}{\sqrt{(x_B-x_A)^2-(y_B-y_A)^2}}\right)$$

The four points are ordered from smallest to largest (or from largest to smallest) by X-coordinate (or Y-coordinate), and then the two points corresponding to the X-coordinate (or Y-coordinate) of the middle size are the two points A1 and, and the coordinate values of the remaining four points can be obtained, assuming that the six intersections of the circle in Fig. 2 are:

$$A_1(x_{A1},y_{A1}),A_2(x_{A2},y_{A2}),B_1(x_{B1},y_{B1}),B_2(x_{B2},y_{B2}),$$
$$C_1(x_{C1},y_{C1}),C_2(x_{C2},y_{C2})$$

Then the loci of the blind node (x, y) can be estimated as shown in Eqs. (15) and (16) below.

$$x = \frac{(x_{A1} + x_{A2} + x_{B1} + x_{B2} + x_{C1} + x_{C2})}{6} \tag{15}$$

$$y = \frac{(y_{A1} + y_{A2} + y_{B1} + y_{B2} + y_{C1} + y_{C2})}{6} \tag{16}$$

This gives the coordinates of the estimated position of the blind node as:

$$\left(\frac{(x_{A1} + x_{A2} + x_{B1} + x_{B2} + x_{C1} + x_{C2})}{6}, \frac{(y_{A1} + y_{A2} + y_{B1} + y_{B2} + y_{C1} + y_{C2})}{6} \right)$$

3 Experiment Result

The blind nodes are randomly generated and to reduce the impact of this factor on the algorithm. To reduce the impact of this factor on the algorithm [11], 20 blind nodes were first generated randomly in a 130 m × 100 m area. The blind nodes were detected at a fixed distance (10 m to 70 m, with 5 m intervals, for a total of 13 different detection distances), and the detection distance was fixed by varying the distribution density of the reference nodes. The simulations were carried out with varying the distribution density of the reference nodes, and the results of each group were averaged to obtain Fig. 4.

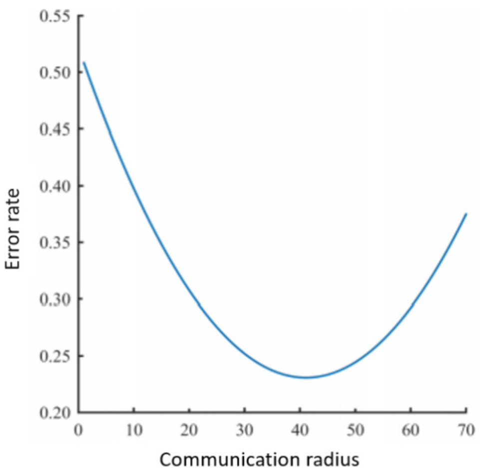

Fig. 4. The relationship between blind node communication radius and error rate.

As can be seen in Fig. 4, the error rate decreases and then increases with the communication radius. The simulation results fit a quadratic curve with a positioning error rate of approximately 0.2308 at the lowest point, which corresponds to a communication radius of 41 m, i.e. the optimum communication radius. On this basis, this point corresponds to a good positioning accuracy and the cost required under this condition is relatively low. The method used to achieve the optimum communication radius therefore gives a balance between cost and positioning error rate, which is the practical significance of finding the optimum communication radius.

A fixed monitoring area of $100 * 100\ m^2$ is simulated, and the radius of communication or the number of anchor nodes is varied to see how the improved center-of-mass localization algorithm changes with the change of index. (1) When the total number of nodes is 100, simulations are performed for beacon nodes 8, 14 and 20 respectively. The average error is 8.16 when the communication radius is a certain value and the beacon node n = 8, which is 1.56 and 2.26 higher than that of the beacon node 14 and 20, respectively, indicating that the localization error is smaller when the number of anchor nodes is higher and increases when the communication radius increases. (2) The total number of nodes is 100, and the simulation is carried out for the communication radius of 10 m, 30 m and 50 m respectively. The number of anchor nodes increases, and the error decreases and levels off. When the communication radius is 10 m, the average positioning error is 9.6 m, which is higher than the communication radius of 30 m and 50 m. The larger the radius, the higher the positioning accuracy depends on the increase in the number of anchor nodes.

The results of the Matlab simulation based on the six-point center of mass method are shown in Fig. 5. It can be seen that when the distance between the reference nodes is relatively close, its average error rate decreases significantly with increasing distance, and the error increases when the distance increases gradually.

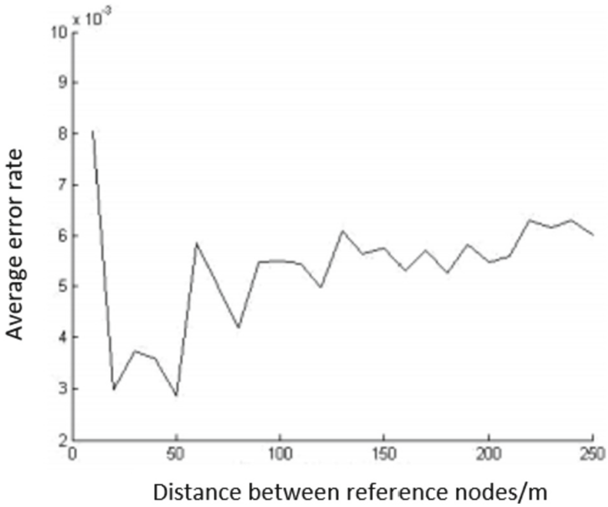

Fig. 5. Effect of varying distance on the mean error rate.

In addition, the traditional center-of-mass method and the improved algorithm are compared together, as shown in Fig. 6. It can be seen that both algorithms stabilise as the total number of beacon nodes increases to a certain value, due to the saturation of the system as the number of beacon nodes increases.

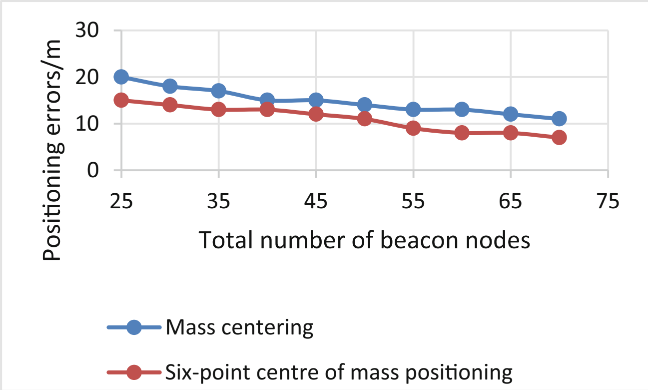

Fig. 6. Comparison of the traditional centre-of-mass method with the improved method.

Although the trends are roughly the same, the six-point placentric positioning algorithm achieves a significantly lower positioning error than the traditional placentric algorithm, proving that the proposed improved algorithm is indeed feasible.

4 Conclusion

To this end, the following work is accomplished in this paper: 1. introduced the algorithms currently used for indoor positioning and their shortcomings, laying the theoretical foundation for the improved approach proposed in the following paper. 2. introduced the basic working principle of the center-of-mass algorithm and proposed an improved system using the six-point center-of-mass algorithm. 3. established the best possible model through experiments, then input test data and evaluated it based on expert judgement. The experimental results show that the model proposed in this study has excellent accuracy in indoor wireless positioning.

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