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A chaos particle swarm optimization ranging correction location in complex environment

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Abstract

In complex environment, issues such as reflection, multipath propagation, non-line of sight and antenna gain, etc. would result in significant propagation losses as for the same distance. In order to effectively reduce ranging error and location error caused by received signal strength indication (RSSI) measurement distance, a location algorithm based on chaos particle swarm optimization ranging (CPSOR) is proposed for indoor location and navigation applications. By setting reference beacon nodes within location region, the relationship between distance and RSSI which is measured from target node to each beacon node is automatically corrected, and RSSI ranging error is effectively reduced, thus the objective of improving location accuracy is achieved. Numerical results show that the processing time of CPSOR location algorithm is reduced by 62% and the location accuracy of CPSOR is improved by 72% in contrast that of back propagation (BP) neural network location algorithm. Besides, practicality experiment results show that when the distance between beacon nodes is 50 m, the average location error of CPSOR location algorithm is 1.21 m and the location error of BP location algorithm is 3.36 m, thus the location accuracy is improved by 63%.

Keywords location, RSSI, particle swarm, chaos, neural network

1 Introduction

Wireless sensor networks (WSN) will change how human beings interact with the world. Through deployment of a large number of sensor nodes to target area, complex monitoring and tracking tasks can be accomplished in a wide range of application areas. However, for most applications, sensor data without the knowledge of sensor location is meaningless [1–2].

Due to the complexity of indoor environment, signal propagation is often interrupted by obstacles such as wall, partition and ceiling, etc., which results in signal reflection, refraction and diffraction. Transmit signals reach receiving terminals through different paths at different time, i.e., multipath propogation, which results in time delay spreading and frequency domain spreading, etc. What's more, indoor items and personnel moving, will have influence on signal strength, and therefore the location accuracy of system will be greatly influenced. In addition, signal strength varies with time, and will be influenced by different temperature and humidities [3–5].

RSSI ranging is usually seen as a kind of rough ranging technology, and it is a meaningful question on how to improve RSSI-based location accuracy. On the basis of comparing all kinds of location algorithms, and by analyzing the radio propagation path loss model, In this paper we proposed an RSSI-based CPSOR location algorithm, which has low communication cost, low hardware requirement, high location accuracy, and is suitable for sensor node processing.

2 CPSOR location optimization model

Due to the super global search characteristics of particle swarm optimization algorithm and the rapid local search capability of BP algorithm, the weight of neural network will be optimized if these two algorithms can be

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effectively integrated into two hybrid algorithms. Because of the characteristics of the chaos system such as randomness, ergodicity and regularity, and because of the strong local search ability of chaos search in a small space, the effectiveness of its locally meticulous search, the swarm variety can be enriched and the effectiveness of algorithms can be further improved if the concept of chaos can be introduced into these hybrid algorithms [6]. A location optimization model based on chaos particle swarm theory was shown in Fig. 1.

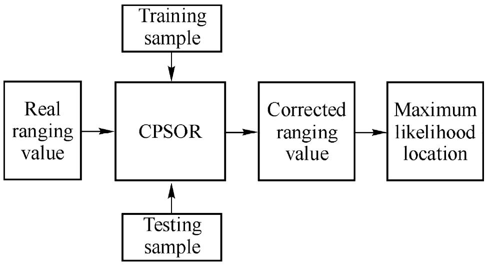


Fig. 1 CPSOR location optimization algorithm model

Mathematical description of particle swarm optimization algorithm is as follows: suppose in an n-dimensional target search space, a swarm $\boldsymbol{x}=(x_1,x_2,...,x_m)^{\mathrm{T}}$ is composed of m particles. Location $\boldsymbol{x}_i=(x_{i,1},x_{i,2},...,x_{i,m})^{\mathrm{T}}$ at which each particle located denotes a solution of the search. Particle searched for new solution by continuously adjusting its own location. Each particle can record the optimum search solution as $\boldsymbol{p}_{id}=\{p_{i,1},p_{i,2},...,p_{i,m})^{\mathrm{T}}$ and optimum location through which the whole particle swarm experienced, i.e, the current optimum search solution is expressed as $\boldsymbol{p}_{gd}=\{p_{g,1},p_{g,2},...,p_{g,m})^{\mathrm{T}}$. Moreover, velocity of each particle is expressed as $\boldsymbol{v}_i=\{v_{i,1},v_{i,2},...,v_{i,m})^{\mathrm{T}}$. After two optimum solutions are identified, each particle updates its velocity according to Eqs. (1–2).

$$v_{i,d}^{k+1}=v_{i,d}^{k}+c_1\mathrm{rand}(\ \ )(p_{i,d}^{k}-x_{i,d}^{k})+c_2\mathrm{rand}(\ \ )(p_{g,d}^{k}-x_{i,d}^{k}) \tag{1}$$

$$x_{i,d}^{k+1}=x_{i,d}^{k}+v_{i,d}^{k+1} \tag{2}$$

Where, c_1 and c_2 are learning factors or acceleration constants. rand( ) is a random value between (0,1). $v_{i,d}^k$ and $x_{i,d}^k$ are d-dimensional velocity and location of particle i for the kth iteration, respectively. $p_{i,d}^k$ is an individual extreme location of particle i in d-dimensional space, $p_{g,d}^k$ is a global extreme location of swarm in d-dimensional space [7].

The random state of motion which is obtained by definite equations is generally called as chaos. The variables with chaos state are called as chaos variables. Chaos in a non-linear system is a common phenomenon. In a certain range, chaos variables change with the characteristics of randomness, ergodicity and regularity. The search is refined by these characteristics and therefore the search can jump out of local optima. The classical logistic equation is utilized in this paper to realize the evolution of chaos variables, as shown in Eq. (3).

$$cx_i^{k+1}=4cx_i^k(1-cx_i^k);\quad k=1,2,...,K \tag{3}$$

where cx_i denotes a chaos variable, cx_i^k denotes the value of cx_i after k iterations, k denotes the number of iterations of chaos mapping. If $cx_i^1\in(0,\ 1.0)$ and $cx_i^1\notin(0.25,\ 0.5,\ 0.75)$, the system will be in a complete chaos state, and cx_i will be ergodic within $(0,\ 1.0)$. By integrating the particle swarm optimization algorithm and the BP algorithm, making full use of the advantages of the two algorithms, i.e., the global search characteristics of particle swarm optimization algorithm and the local search capabilities of BP algorithm, two different kinds of hybrid algorithms are proposed [8].

3 CPSOR location algorithm

In indoor complex environment, issues such as reflection, multipath propagation, non line of sight and antenna gain, etc., would result in significant propagation losses as for the same distance. In order to effectively reduce ranging error and location error caused by RSSI measurement distance, a location algorithm based on CPSOR is proposed for indoor location and navigation applications. Suppose that the coordinates of beacon nodes are $B_1(x_1,y_1)$, $B_2(x_2,y_2)$,…, $B_n(x_n,y_n)$, the coordinates of nodes to be determined is $O(x,y)$, the distances from the node to be determined to the beacon nodes are d_1, d_2,…, d_n, respectively. A group of non-linear equations can be obtained according to the calculation formula for distance in a two-dimensional space, as shown in Eq. (4) [9].

$$\begin{cases}(x-x_1)^2+(y-y_1)^2=d_1^2\\(x-x_2)^2+(y-y_2)^2=d_2^2\\\quad\vdots\\(x-x_n)^2+(y-y_n)^2=d_n^2\end{cases} \tag{4}$$

Starting from the first equation, the last equation is substracted from other equations in turn, then we have

$$\left.\begin{array}{l} x_1^2 - x_n^2 - 2(x_1 - x_n)x + y_1^2 - y_n^2 - 2(y_1 - y_n)y = d_1^2 - d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 - 2(x_{n-1} - x_n)x + y_{n-1}^2 - y_n^2 - 2(y_{n-1} - y_n)y = \\ d_{n-1}^2 - d_n^2 \end{array}\right\} \quad (5)$$

The linear equation in Eq. (5) is expressed as $\boldsymbol{AX} = \boldsymbol{b}$, where

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

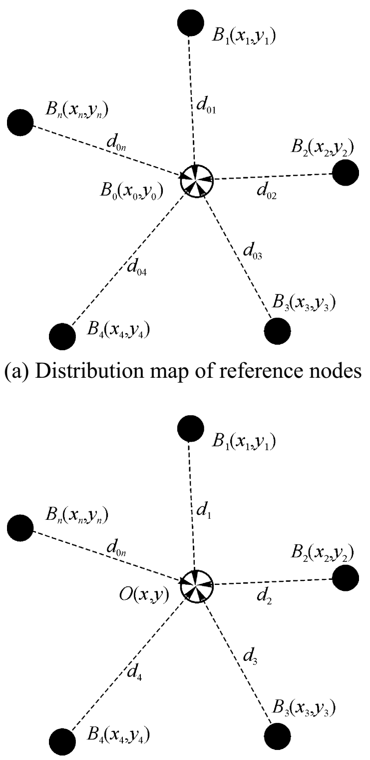
$$\boldsymbol{b} = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 - d_1^2 + d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 - d_{n-1}^2 + d_n^2 \end{bmatrix},$$

$$\boldsymbol{X} = \begin{bmatrix} x \\ y \end{bmatrix}$$

Using the standard minimum mean square error estimation method, the coordinate of node O can be derived as:

$$\hat{\boldsymbol{X}} = (\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A})^{-1}\boldsymbol{A}^{\mathrm{T}}\boldsymbol{b} \quad (6)$$

As shown in Fig. 2, the beacon nodes are $B_0(x_0, y_0)$, $B_1(x_1, y_1)$, $B_2(x_2, y_2)$,…, $B_n(x_n, y_n)$, the target node is $O(x, y)$. B_0 is the beacon node within the moving region of target node O for ranging correction, which is called correction reference node. The distance from reference node B_0 to beacon nodes $B_1, B_2, \ldots, B_n$ are d_{01}, d_{02},…, d_{0n}, respectively; when target node O and correction reference node B_0 are in the same location, the measured distances from target node O to beacon nodes B_1, B_2,…, B_n will be $d_1, d_2, \ldots, d_n$, respectively.



(a) Distribution map of reference nodes

(b) Overlapped location of target nodes with reference nodes

Fig. 2 Schematic graph of location algorithm

Because the RSSI is used for distance measurement, errors must exist. The essence of the locating algorithm is to minimize errors, and the location of adjusted node is given by Eq. (7).

$$f_i(\hat{x}, \hat{y}) = d_i - \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (7)$$

As shown in Fig. 2, since the distance from the reference node to the beacon nodes is known, when the target node and the reference node are in the same location, the distances from the target node to each beacon node which are in communicating is known, they are denoted as $d_{01}, d_{02}, \ldots, d_{0n}$, respectively. Then the measured distance of overlapped location between target node O and correction reference node B_0 is viewed as an input of chaos particle swarm neural network, the distance of d_{01}, d_{02},…, d_{0n} is viewed as an output of chaos particle swarm neural network for training. Therefore, the mapping from a real distance to a corrected distance is obtained, and the distance d_1', d_2',…, d_n' which is from the corrected target node to beacon node is obtained. Taking d_1', d_2',…, d_n' into Eq. (4), we can have the coordinate of target node (x, y).

Eqs. (1–2) are used to update location and velocity of each particle. The fitness function in Eq. (8) is used to evaluate the fitness value of the particles. The algorithm is terminated when the number of iterations reaches a certain value. The optimum solution of the algorithm is used as the final estimated location of unknown nodes.

$$\mathrm{fitness}(\hat{x}, \hat{y}) = \sum_{i=1}^{n} \frac{1}{h_i^2} f_i^2(\hat{x}, \hat{y}) \quad (8)$$

where h_i is the real distance from the number i beacon node to the target node, the distance is obtained when the target node overlaps with the reference node [10].

4 Experiment results

4.1 Simulation experiments

To demonstrate the effectiveness of maximum likelihood estimation location algorithm, BP neural network location algorithm and CPSOR location algorithm, simulations were carried out with Matlab. In order to simulate the actual state of node communication, the communication distance of WSN nodes was set to 120 m and the nodes were distributed within a square area of 400 m×400 m, the beacon nodes were uniformly distributed within the sensing area, the beacon node spacing was 50 m, and there were totally 81 beacon nodes. 50 out of the total 81 beacon nodes were selected as training reference nodes while 10 out of the total 81 beacon nodes were selected as testing reference node. The node distribution in the sensing area was shown in Fig. 3.

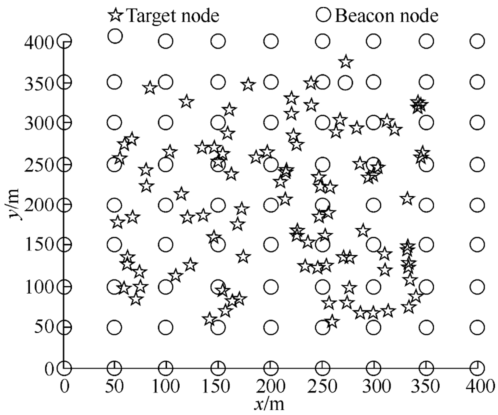


Fig. 3 Graph of node distribution

Training algorithm swarm scale of CPSOR algorithm $n = 40$. Initial inertia weight $\omega(0) = 0.8$ and linearly decreased to 0.3 with iteration number. $c_1 = c_2 = 1.2$. Connection weight varies in the range of $[-1, 1]$. Node number $n_h = 8$ for hidden layer of neural network was determined by empirical formula. Training iteration number of algorithm was 400 (1 000 for BP location algorithm).

It was known from Eqs. (4–6) that the more beacon nodes are involved in the locating, the more helpful it is to improve location accuracy. Suppose that RSSI-based ranging was observation noise in accordance with Gaussian distribution and standard deviation of observation noise was determined as 5 m, the number of beacon nodes involved was 4–8. Simulation results of the locations for 100 randomly distributed target nodes were shown in Fig. 4. Average location accuracy for two location algorithms with different number of beacon nodes involved was given in Fig. 4. It was not difficult to identify from simulation result of Fig. 4 that no matter what location algorithm was used, the more beacon nodes were involved in locating, the higher location accuracy would be obtained. The numerical results showed that the location accuracy of CPSOR location algorithm was significantly higher than that of the other two locating algorithms.

Location error and processing time corresponding to likelihood, BP and CPSOR algorithms for different number of beacon nodes were shown in Table 1. The processing time of CPSOR location algorithm is 20.15 s and the location error of CPSOR location algorithm is 3.36 m, and in contrast, the processing time of BP neural network location algorithm is 53.56 s and the location error of BP location algorithm is 0.61 m, thus the computing time is reduced by 62% and the location error is reduced by 72%.

Table 1 Performance comparison of location algorithms

Location beacon number	Likelihood		BP		CPSOR	
	Location error/m	Processing time/s	Location error/m	Processing time/s	Location error/m	Processing time/s
4	8.41	7.20	5.35	30.23	3.34	12.78
5	6.22	8.32	3.42	35.56	2.65	14.53
6	5.14	9.78	2.95	41.21	2.47	16.13
7	4.51	11.35	2.36	47.45	2.35	18.32
8	4.36	13.76	2.25	53.56	2.11	20.15

4.2 Practicality experiments

Rectangular testing region had an area of 100 m×100 m, eight beacon nodes involved in locating and a few persons walked within the testing region. When the target nodes reached the location of reference beacon nodes, automatic recognition through radio frequency identification tag was carried out. RSSI ranging compensation correction was conducted after recognition through CPSOR algorithm proposed in this paper. 81 locations in total were tested. The maximum of location error for maximum likelihood estimation location algorithm was 6.12 m, the minimum was 1.62 m with the average 3.36 m. The maximum of location error for CPSOR location algorithm was 3.73 m and minimum was 0.72 m with the average of 1.21 m when the distance between beacon nodes is 50 m. The location error of BP location algorithm is 3.36 m, thus the location accuracy is improved by 63%.

The distribution effect of location error was shown in Fig. 5. The coordinate unit is meter. Circular symbol denoted the real location of the nodes. Square symbol denoted the location result of CPSOR location algorithm. Triangle symbol denoted the location result of likelihood estimation location algorithm. A line segment between circular symbol, square symbol and triangle symbol denoted location error for different algorithms.

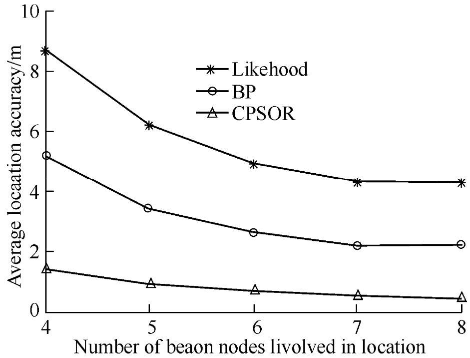


Fig. 4 Average location accuracy with different quantity of beacon nodes

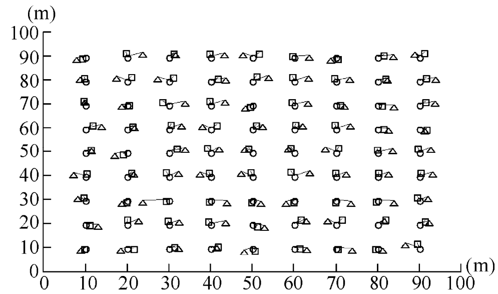


Fig. 5 Effect illustration of location error distribution

5 Conclusions

The factors of reflection, multipath propagation, non line of sight, antenna gain, etc., result in significant change of propagation loss and ± 50% ranging error may occur. If the RSSI measurement values are not well processed, it will be difficult to obtain good locating result regardless of what location algorithm is used. Aiming to the characteristic of RSSI in strong randomness with environmental change, a ranging correction location algorithm is proposed with the use of advantage of chaos particle swarm theory in dealing with uncertain issues. Issues such as relatively large ranging error and difficult location in complex environment are effectively solved. Effectiveness of the algorithm is verified through simulation and experiment, thus providing a new solution to accurate location in complex indoor environment.

Acknowledgments

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