Modeling the indoor tracking method based on particle water wave optimization

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Research

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Modeling the indoor tracking method based on particle water wave optimization

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Abstract: A new tracking algorithm is proposed based on particle filter and water wave optimization for the problem that indoor tracking accuracy is not high enough. In this algorithm, the observation equation of the node location is first given using the least squares estimation algorithm based on the node signal intensity. Meanwhile, the algorithm steps of indoor tracking are designed using the water wave optimization, and the particle filter is introduced to accelerate the convergence. Finally, the performance of the algorithm is simulated through simulation experiments. The results show that the algorithm can adapt well to indoor environment.

Key words: Indoor Tracking, Accuracy, Signal Intensity, Water Wave Optimization, Particle Filter

1 Introduction

With the development of IoT technology, the need for indoor tracking technology is increasing, so it has gradually become a hot spot and focus of the current research [1-5]. In order to achieve efficient management of available space and location service needs, the tracking of the services based on location information and the locations of indoor moving targets is generally considered as an indispensable key technology. Because of the complex attenuation caused by irregular reflection and scattering of wireless signals, NLOS and multipath transmission effects in indoor environment make it impossible to locate effectively as the wireless propagation delay is too small and radio frequency signals are blocked [6-9]. Therefore, indoor positioning and tracking are still difficult.

Currently, indoor positioning and tracking technology is mainly divided into sensor-based and WLAN-based technology. Sensor-based positioning and tracking

technology is divided into three steps: (1) relevant transmission networks and sensors are arranged in the positioning service area in advance. (2) The terminal system in the positioning area is sensed by sensor device. (3) The location of the terminal system is estimated. Compared with the sensor-based positioning method, WLAN-based positioning technology is more convenient, simple and has a wider coverage. It only needs to make full use of the existing WLAN resources for positioning analysis, so more and more attention has been paid to it. In recent years, many scholars have done a lot of research on indoor tracking methods. Wang et al [10] proposed an optimal target tracking algorithm exploiting the historical data of the target location information to help improve the accuracy, and tested the optimal target tracking based on dynamic fingerprint algorithm in a complex laboratory area with diverse target motion conditions and various obstacles. It indicated that this scheme successfully handled complex indoor structure. Jin et al [11] proposed an indoor pedestrian tracking system that comprises of a dead reckoning subsystem implemented on a mobile phone and a ranging subsystem with a sparse infrastructure, which a particle-filter-based fusion scheme is applied to bound the accumulated tracking error. Mendes et al [12] proposed an automatic people tracking system which allowed to map Wi-Fi networks in order to localize people indoor, and the final location is determined by combining information provided by wireless networks and Bayesian networks. Patricia et al [13] proposed a real-time two-step 3D Indoor Positioning System, and the results showed a mean location error of 1.24 cm for the three dimensions with an average process time of 18.2 ms per frame for four simultaneous targets correctly identified, at a distance of 2.00 m. Chen et al [14] proposed a grid partition method based on vertical projection distance and a trajectory frequent pattern mining algorithm based on vague grid sequence, which each grid was divided into explicit zones and vague zones according to vertical projection distance. The simulation results showed it is an effective and efficient algorithm in mining frequent patterns of indoor trajectories. Jae et al [15] presented a method that detects and tracks parking spaces in underground and indoor environments, and this proposed tracking method could enhance the previous method by considering pillar information.

On the basis of the above work, a new tracking algorithm is proposed based on water wave optimization and particle filter, and the location observation equation and the solution algorithm steps are also given in this paper. At the same time, simulation experiments are carried out to study the key factors affecting the algorithm.

2 Methods

In the indoor tracking and positioning algorithm, the positioning can be performed by observing the signal intensity received by each mobile node, and $Z_k=(z_1,z_2,\ldots,z_n)$ is set as the set of signal intensities received by mobile nodes. The measurement model between Z_k and X_k (mobile node location, etc.) is:

$$Z_k=h(X_k\ ,\mu_k) \tag{1}$$

Where, μ_k is the observation noise. However, this measurement model can not describe the relationship between signal intensity and mobile node location very well, so a new observation model will be proposed in this paper.

RSS values in indoor environment follow the lognormal distribution:

$$L(d)=L(d_0)+10n\log\frac{d}{d_0}+\xi \tag{2}$$

Where, L(d) is the distance from mobile node to AP, d_0 is the initial reference distance, n is the type of environment and building, and ζ is an obstacle factor and a normal random variable with variance σ.

Assuming that there are n APs in the room, and the set of signal intensities from different APs at the location (x_i,y_i) is $Z_k=(z_1,z_2,\ldots,z_n)$, in which z_i is the signal intensity from AP_i, and AP signals are independent of each other. Therefore, the joint probability density distribution of RSS at the location (x_i,y_i) is obtained from the marginal probability density, that is:

$$L(z_1,z_2,\ldots,z_n|(x_i,y_i))=L(z_1|(x_i,y_i))\cdot L(z_2|(x_i,y_i))\cdot\ldots L(z_n|(x_i,y_i)) \tag{3}$$

The location fingerprint based on probability distribution can be defined according to the above formula, that is, the fingerprint at the location (x_i,y_i) in the system is the sample mean at that location. Since RSS does not follow the lognormal distribution in most cases, the location estimation can be very inaccurate. In order to

reduce the estimation error, the marginal probability density is estimated in this paper using the maximum likelihood estimation method. Max and min represent the maximum and minimum values of the sample, and all samples of AP_i are in the interval [min, max]. The interval is divided into t sub-intervals, and t value will affect the error of probability density. Now the sample interval is divided into n sub-intervals of equal length, and the width of each sub-interval is w=(max-min)/t. If the total number of samples is N and the number of samples in the ith sub-interval is n, then the probability distribution function is:

$$P(z_i \in [\min+iw, \min+(i+1)w] | (x_i,y_i))=n/N \tag{4}$$

In this paper, the positioning is achieved using the least squares estimation algorithm in the range-based positioning to accurately describe the relationship between Z_k and X_k (mobile node location, etc.). If we can get the anchor point distance of three or more unknown nodes, then we can locate them using the trilateration or multilateration method. (x,y) is the coordinates of the unknown node A, (x_i,y_i) is the location coordinates of the ith anchor node, and $l_1,l_2,\ldots,l_i$ is the distance from each anchor node to the unknown node. The following equation set can be established using the least squares estimation method:

$$AX + N = b \tag{5}$$

Where, $A=-2x \begin{bmatrix} (x_1 - x_i)\ (y_1 - y_i) \\ (x_2 - x_i)(y_2 - y_i) \\ \cdot \quad \cdot \\ \cdot \quad \cdot \\ \cdot \quad \cdot \\ (x_{i-1} - x_i)(y_{i-1} - y_i) \end{bmatrix}$, $X = \begin{bmatrix} x \\ y \end{bmatrix}$, $b=\begin{bmatrix} l_1{}^2 - l_i{}^2 - x_1{}^2 + x_i{}^2 - y_1{}^2 + y_i{}^2 \\ l_2{}^2 - l_i{}^2 - x_2{}^2 + x_i{}^2 - y_2{}^2 + y_i{}^2 \\ \\ l_{i-1}{}^2 - l_i{}^2 - x_{i-1}{}^2 + x_i{}^2 - y_{i-1}{}^2 + y_i{}^2 \end{bmatrix}$.

And, N is the random error vector of the i-1 dimension, and N=b-AX should be minimized using the least squares method, and the vector X^* that $\| N \|_2^2$ is minimized is defined as the least squares solution, that is:

$$Q(x_1,x_2,\cdots,x_i)=\|AX^*-b\|_2^2 = \min_{\forall X \in R^n} \| AX - b \|_2^2 \tag{6}$$

$$Q(x_1,x_2,\cdots,x_i)=\sum_{i=1}^{m} N_i^2 = \sum_{i=1}^{m}(\sum_{j=1}^{n+1} a_{ij}\cdot x_{j-1}-b_i)^2 \tag{7}$$

In order to obtain the minimum value in the formula (4), it only needs to derive the formula (4) and set its derivative to 0 to get:

$$\sum_{i=1}^{m} a_{ik}(\sum_{j=1}^{n+1} a_{ij}\cdot x_j) = \sum_{i=1}^{m} a_{ik}b_i \tag{8}$$

The above formula is rewritten to matrix form:

$$A^TAX=A^Tb \tag{9}$$

Then, the least squares location of the unknown node is estimated as follows:

$$\hat{X} = (A^TA)^{-1}A^Tb \tag{10}$$

The coordinates of the ith anchor node at the moment t are $(x_i(n),y_i(n))$, and the distance from the unknown node to the ith anchor node is $l_i(n)$, and the range rate is $\rho_i(n)$, and the speed of the unknown node at the moment t is $(V_x(n),V_y(n))$. The observation noise of the tracking model is $\mu(n)$, and the mean value of $\mu(n)$ is 0, and the covariance matrix is R. The state equation of the location node at the moment t is as follows:

$$\underbrace{\begin{bmatrix} x(n) \\ y(n) \end{bmatrix}}_{Z(n)} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \underbrace{\begin{bmatrix} x(n) \\ y(n) \\ V_x(n) \\ V_y(n) \end{bmatrix}}_{X(n)} + \mu(n) \tag{11}$$

Then, the observation equation of the location node at the moment t is as follows:

$$\underbrace{\begin{bmatrix} l1(n) \\ \vdots \\ l\,i(n) \\ \\ \rho 1(n) \\ \vdots \\ \rho i(n) \end{bmatrix}}_{Z(n)} = \underbrace{\begin{bmatrix} \sqrt{(x(n)-x1)^2+(y(n)-y1)^2} \\ \vdots \\ \sqrt{(x(n)-xi)^2+(y(n)-yi)^2} \\ \\ \dfrac{x(n)-x1}{\rho 1}\cdot vx(n)+\dfrac{y(n)-y1}{\rho 1}\cdot vy(n) \\ \vdots \\ \dfrac{x(n)-xi}{\rho i}\cdot vx(n)+\dfrac{y(n)-yi}{\rho i}\cdot vy(n) \end{bmatrix}}_{h(X(n))} + \mu(n) \tag{12}$$

3 Solution Algorithm

WWO algorithm is a heuristic algorithm based on shallow water wave theory, which searches in high-dimensional space by simulating the propagation, refraction and breaking of water wave motion, etc. In this algorithm, each solution of the problem is analogized to a "water wave", and the search space of the problem is regarded as the seabed, in which the fitness of the water wave is inversely proportional to its vertical distance to the seabed, so that a better solution is searched in a smaller range, which thus promotes the evolution of the whole population to a better goal. Propagation, refraction and breaking are three specific evolutionary operations provided by WWO algorithm.

(1) Propagation process: in this paper, the nodes in space are regarded as water waves. Each water wave will be propagated during the loop execution of the algorithm, and the propagation operation is the moving operation of the target point. Each time the target point moves, a new location point is obtained. The new water wave obtained after the propagation of the water wave W is set to be W', and its location is updated as follows:

$$X_d' = X_d + rand(-1,1) \cdot \lambda L_d \tag{13}$$

Where, $1 \leq d \leq D$ (D represents the dimension of the problem), rand(-1,1) is a random number that randomly generates in [-1,1] and is uniformly distributed, and L_d is the search space length of the d-dimensional space. If the location of the new water wave is beyond the search scope, then a location coordinate within the search scope is randomly assigned to it again to get the location coordinates after the target point moves.

(2) Refraction process: after the completion of water wave propagation, the coordinates of the unknown node are calculated as per the formula (10), and the fitness values of new water wave W'(i.e. unknown node) and original water wave W (i.e. anchor node) are compared. The fitness function of the water wave is g. If $g(W') > g(W)$, then the original water wave is replaced with a new water wave, $h = h_{max}$. If $g(W) > g(W')$, then the new water wave W' is discarded, and the original water wave

W is reserved, h=h-1, which represents the loss of water wave energy. In the process of water wave propagation, the process of water wave optimization is the movement from the low-fitness location to the high-fitness location. Therefore, the wavelength of the water wave will be updated by the water wave optimization algorithm after each iteration. In this paper, the coordinate points will be updated, and specific updating formula is as follows:

$$\lambda=\lambda \cdot \alpha^{-(g(W)-gmin+\zeta)/(gmax-gmin+\zeta)} \quad (14)$$

Where, gmax and gmin are the maximum and minimum fitness values of the water wave group respectively, α is the wavelength attenuation factor of the water wave, and ζ is a random minuscule positive integer.

If a water wave has not been improved after several times of propagation, then the wave height of the water wave will gradually decrease to 0. For the water wave W (i.e. the number of anchor nodes is less than 3) that can not be improved, the refraction operation is carried out as per the following formula:

$$W_d'=Weibull((W_d^{best}+W_d)/2, W_d/2) \quad (15)$$

Where, W_d^{best} is the optimal water wave in the water wave group in d-dimensional space. Weibull(μ,θ) function is used to generate a Weibull random number with the mean μ and the variance θ, which makes the current water wave W learn from the current optimal solution W_d^{best}. Then, the wave height of the new water wave after refraction is h_{max}, and the wavelength is:

$$\lambda'=\lambda(g(W)/g(W')) \quad (16)$$

(3) Breaking process: as the water wave energy increases continuously, the wave crest will be steep until it breaks to form solitary waves. In this algorithm, we first randomly select the d-dimension (d is defined as the random number between (1, d_{max})), and then perform the breaking operation on the optimal solution W_d^{best} of each selected dimension. Specific updating formula is as follows:

$$W_d'=W_d+\beta L_d \text{ Weibull } (0,1) \quad (17)$$

Where, β is the breaking coefficient. d wavelets will be obtained by performing

the breaking operation each time, and the fitness value of d wavelets is compared with that of the original water wave. If the fitness value of all wavelets is less than that of original water wave, then the original water wave W is reserved or replaced with an optimal wavelet W'.

According to the above indoor tracking and positioning principle, the specific algorithm flow is given as follows in combination with WWO:

Step 1 The parameters are initialized, and the initial location of the target point and the location of each anchor node are entered, and the sampling period of anchor node is T, and the initial population size is NP_{max}, and the target fitness value of each solution is calculated to find the optimal solution W_{best}. If the population size at the end of the algorithm is NP_{min}, then the population size at the ith iteration is:

$$NP(t)= NP_{max}-(NP_{max}- NP_{min}) \cdot (i/N) \tag{18}$$

Step 2 After sampling, all samples are averaged to get the estimated location (x_i, y_i).

$$(sx_i, sy_i) = (\frac{1}{n}\sum_{t=1}^{n} x_i(s_t), \frac{1}{n}\sum_{t=1}^{n} y_i(s_t)) \tag{19}$$

Step 3 All the sampling points in Step 2 are taken as the initial population, and the fitness value of each sampling point is calculated to find the optimal individual. The fitness function is as follows:

$$\begin{cases} f(i,j) = [\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} - R_{ij}]^{-2} \\ f(i,j) = [\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} - R_{ij}]^{-2} \\ F_i = \sum \tau f(i,j) \end{cases} \tag{20}$$

The fitness value of each anchor node is estimated. If the termination conditions are satisfied, it will return to the current optimal solution and terminate the algorithm, or proceed to the next step.

Step 4 We can update the formula according to the location shown in the formula (18) and perform the propagation operation to generate a new unknown node W', and compare the fitness values of the original coordinate point W and the new coordinate point W'. If g(W')>g(W) and g(W')>g(W^{besr}), then the breaking operation is

performed as per the formula (17), and W^{best} is updated to W', and W in the population is replaced with W'. Otherwise, the wave height of W is reduced by 1. If W·h=0, then the refraction operation is performed as per the formulas (15) and (16), and the location of each coordinate point is continuously updated as per the formula (14).

Step 5 The global optimal solutions of all populations are updated to judge whether the current optimal solution satisfies the conditions. If so, jump to Step 6, or Step 2.

Step 6 The ends.

In order to further improve the convergence speed of the algorithm, Step 3 is improved and particle filter is introduced to speed up the search. Particle filter is based on Monte Carlo's Bayesian estimation method, which is suitable for any state space model. Step 3 is improved as follows:

Step 3.1 First, the particle swarm is initialized. The sample set $\{x_{i0},y_{i0}\}N_{si=1}$ is generated based on the probability density distribution function, and the weights of all particles are $1/N_S$.

Step 3.2 $z_i=(x_i, y_i)$. N_s new particles are extracted through the noise by the state transition probability density function $p(z_k,z_{i,k-1})$ from the particle sample set at the moment k.

Step 3.3 The prior state estimation $p(z_k|x_{1:k-1},y_{1:k-1})$ is corrected according to the current z_k, and the posterior probability distribution $p(z_k|x_{1:k},y_{1:k})$ at the current time point is calculated to get the weight of new particle. Specific calculation formula is as follows:

$$\sigma^i_k=\sigma^i_{k-1}[p(z_k|x_{1:k}, y_{1:k})\, p(z_k|x_{1:k-1}, y_{1:k-1})]/\, q(z_k|x_{1:k}, y_{1:k}|z_k) \tag{21}$$

$$\sigma^i_k=\sigma^i_k/(\sigma^1_k+\sigma^2_k+\ldots+\sigma^N_k) \tag{22}$$

Posterior distribution probability is as follows:

$$p(x_{1:k},y_{1:k} \mid z_{1:k}) \approx \sum_{i=1}^{N} \sigma_k^i \delta(z_k - z_k^i) \tag{23}$$

Where, $\delta(\cdot)$ is the Dirac function, and z_k^i is the newly sampled particle.

Step 3.4 Finally, the particle set is re-sampled. The weights of the new particles

sampled at the moment k are updated and the posterior probability density function is calculated as per the formula (23). According to the posterior probability distribution of the particle sample set, re-sampling is performed for N_S times according to certain principles, and the weights of all new particles are $1/N_S$.

Step 3.5 Estimated value of the state vector obtained from posterior probability distribution is as follows:

$$z_k = E(x, y) \cdot p(x_k, y_k \mid z_k) \tag{24}$$

New state estimation can be obtained from formulas (23) and (24):

$$z_k = \sum_{i=1}^{Ns} \sigma_k z_k^i = \frac{1}{Ns} \sum_{i=1}^{Ns} z_k^i \tag{25}$$

4 Results and discussions

The above algorithm is simulated mathematically in this paper to further verify its effectiveness. A 180*350 rectangular indoor space is constructed in the simulation environment, and anchor points and AP points are randomly distributed. Received signals follow the lognormal distribution, and 300 sample values are collected at each reference point. In this paper, the control variable method is employed to ensure the same sample set is used in all fingerprint databases. Assuming that the initial location of mobile node is (10,15), the initial velocity is (3,3), the initial reference distance is d0=5, the obstacle factor is ζ=7dB, the variance is σ=0.05, and the number of particles is 600. Optimal height of water wave=7, initial wavelength λ=0.5.

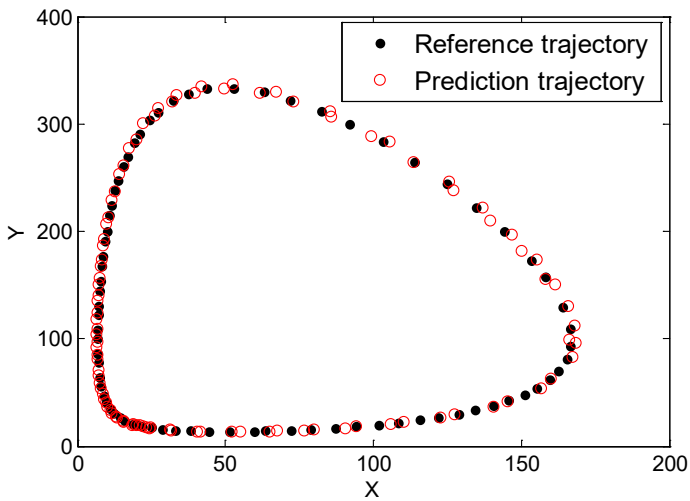

Fig. 1 Tracking Trajectory Diagram of WWO Algorithm

Fig. 1 shows the indoor tracking trajectory of the target node by our algorithm. As can be seen from Fig. 1, the trajectory of the model is almost close to the reference trajectory, which proves that the algorithm is more suitable for tracking in indoor environment. The algorithm can feed back the location and speed of particle motion in real time by constantly updating the location and speed in an iterative manner, which makes the tracking more convenient and fast.

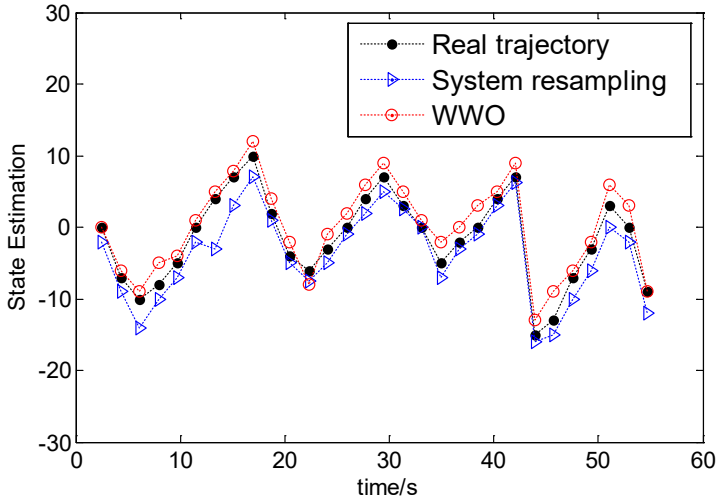

Fig. 2 State Estimation Curve

Secondly, Fig. 2 shows the comparison results between WWO algorithm and system re-sampling and real motion trajectory. As can be seen from Fig. 2, the state estimation values of the system always fluctuate from -20 to 20 with time. In addition, it can be seen from the figure that the system state estimate values of WWO algorithm are larger than that of system re-sampling and true trajectory, and the system state estimation values mentioned above are employed to describe the location and speed of the nodes. From this, it can be concluded that the proposed WWO algorithm can achieve tracking more accurately.

Meanwhile, Fig. 3 shows the error standard deviation curve of state estimation. As can be seen from Fig. 3, the error standard deviation of system state estimation is distributed in a certain range, which shows that our algorithm is relatively stable. In addition, our algorithm is better than the previous system re-sampling algorithm. This is because the proposed WWO algorithm filtrates and operates different particles

through propagation, refraction and breaking operations, etc. at the time of sampling, which avoids the elimination of low-weight potential particles, and further improves the filtering accuracy, and thus reduces the error standard deviation of state estimation and makes indoor tracking more accurate.

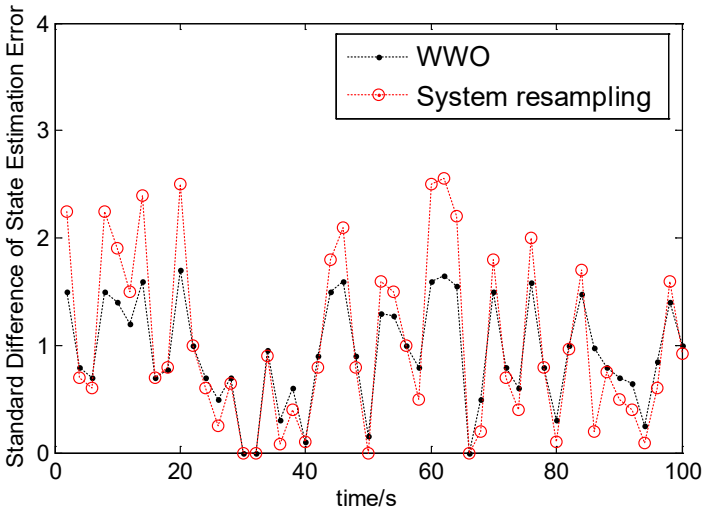

Fig. 3 Error Standard Deviation Curve of State Estimation

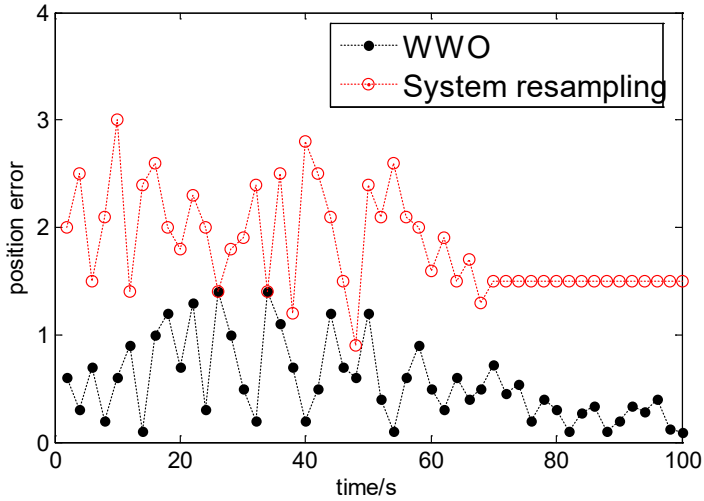

Fig. 4 Location Error Comparison

Finally, Fig. 4 and Fig. 5 show the estimation errors of the location and speed, respectively. The sampling period shown in the figure is T=1s, and there are 100 sampling periods. As can be seen from Fig. 4 and Fig. 5, the tracking progress of the proposed WWO algorithm is relatively superior, regardless of the speed or location error. Some particles with larger weight will be discarded when the new sampling is performed, while the particles with smaller weight will be retained. In the proposed

WWO algorithm, the particles are first propagated and different operations are selected according to the different attributes of the particles, which improves the diversity and tracking performance of the optimal particles.

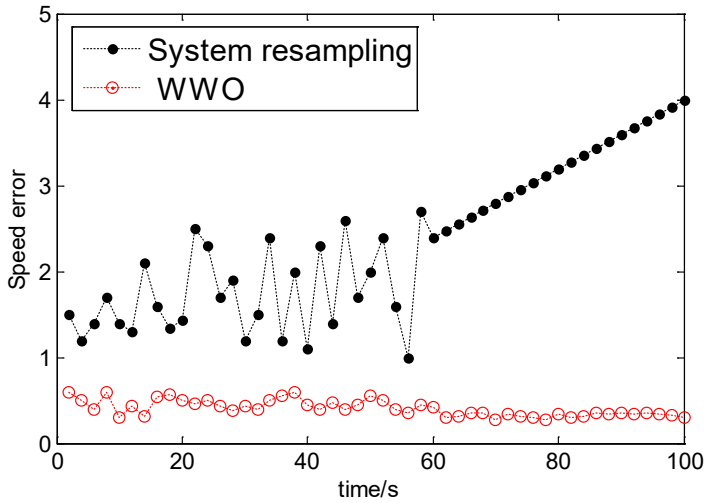

Fig. 5 Speed Error Comparison

5 Conclusions

A new tracking algorithm based on water wave optimization and particle filter is proposed in this paper to improve the accuracy of indoor tracking algorithm. In the tracking algorithm, the distance between anchor node and unknown node, observation equation and state information of node location are established based on RSS value in indoor environment and least squares estimation method. At the same time, the propagation, refraction and breaking processes of the nodes in indoor environment and the algorithm steps are designed using the WWO algorithm, and the particle filter is introduced to accelerate the convergence. Finally, we conduct an in-depth study on the performance of the tracking algorithm in a simulation environment, and especially give the curve trends of the target location and speed errors. The results show that the algorithm has good adaptability.

Abbreviations

IoT: Internet of Things; WLAN: Wireless Local Area Network; AP: Access Point; RSS: Received Signal Strength

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Authors' contributions

All authors take part in the discussion of the work described in this paper. These authors contributed equally to this work and should be considered co-first authors. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interest.

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Figures

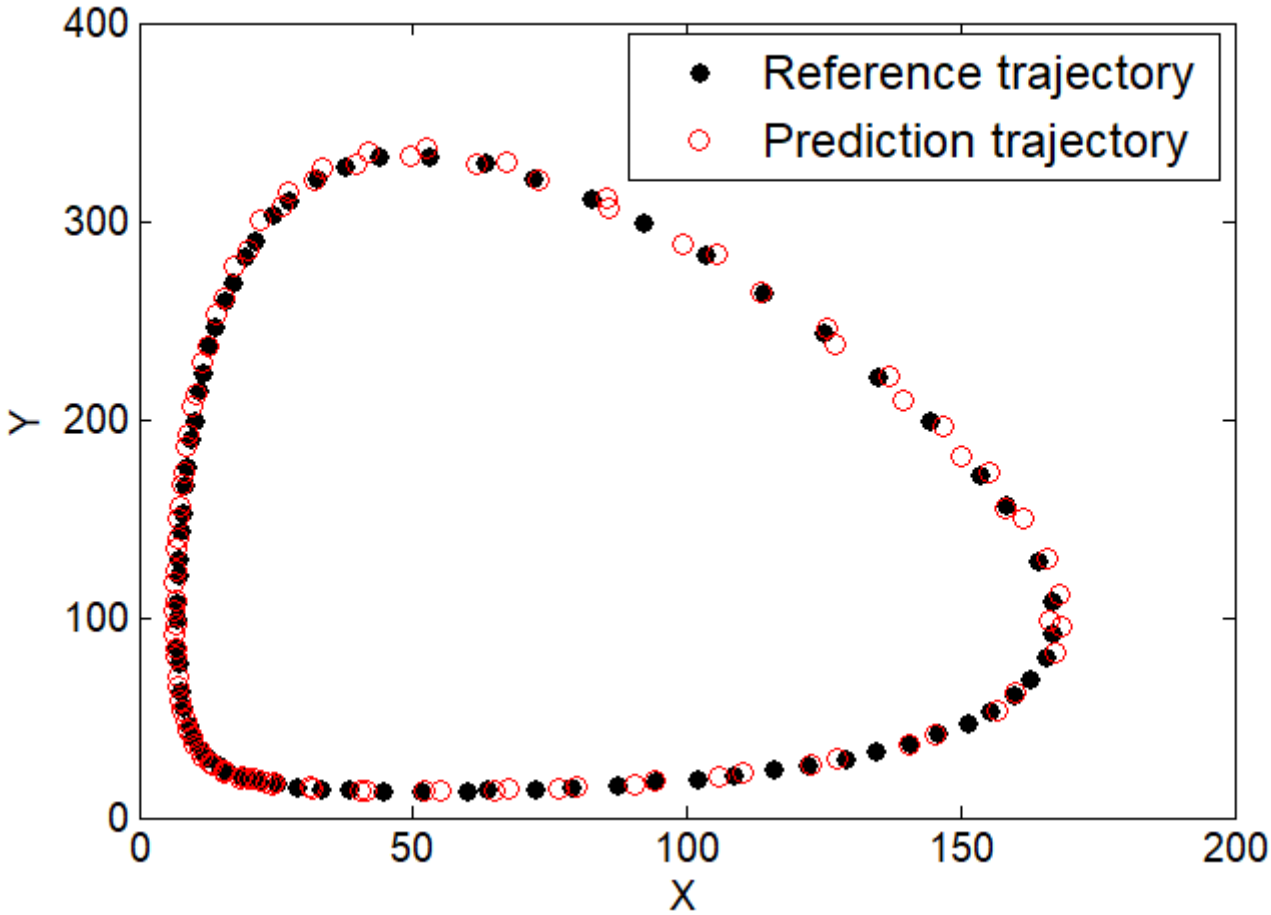

Figure 1

Tracking Trajectory Diagram of WWO Algorithm

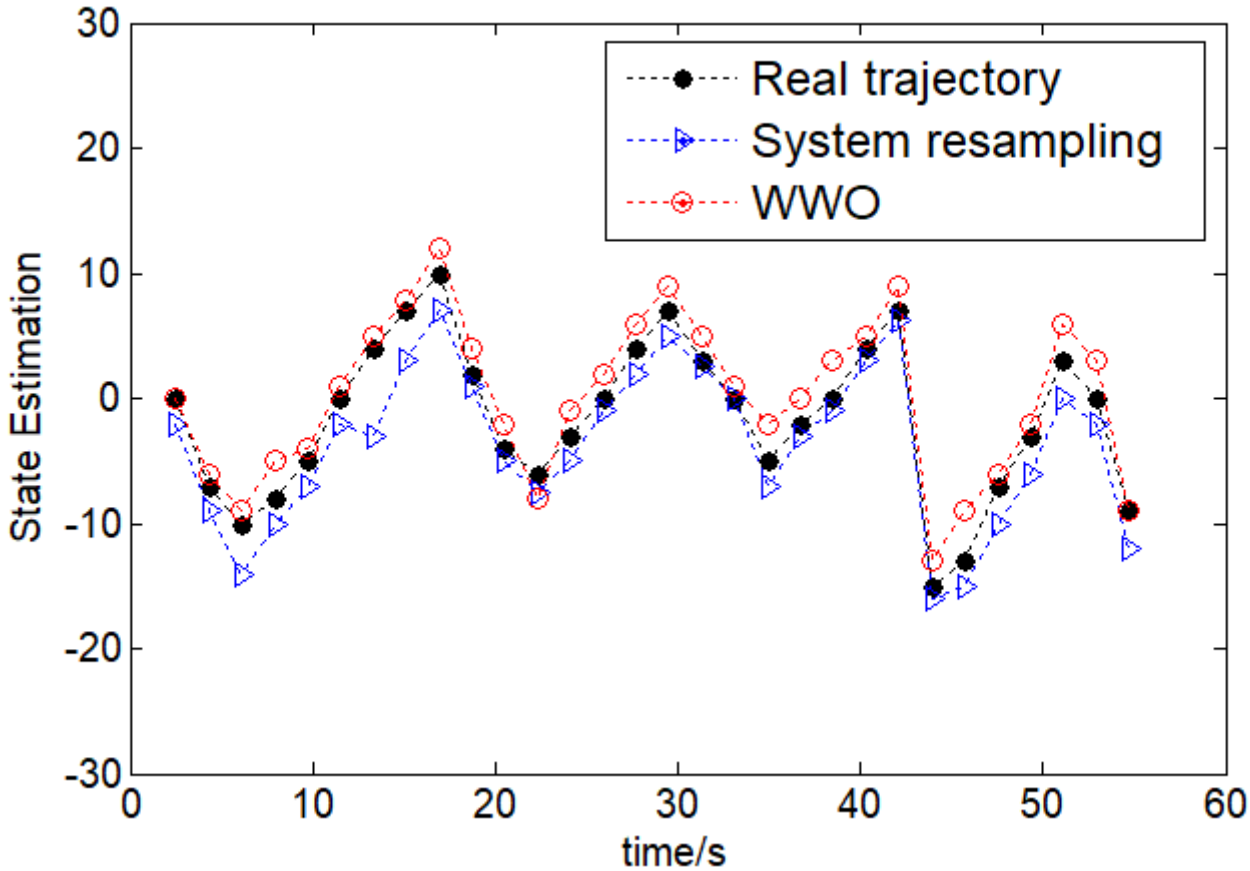

Figure 2

State Estimation Curve

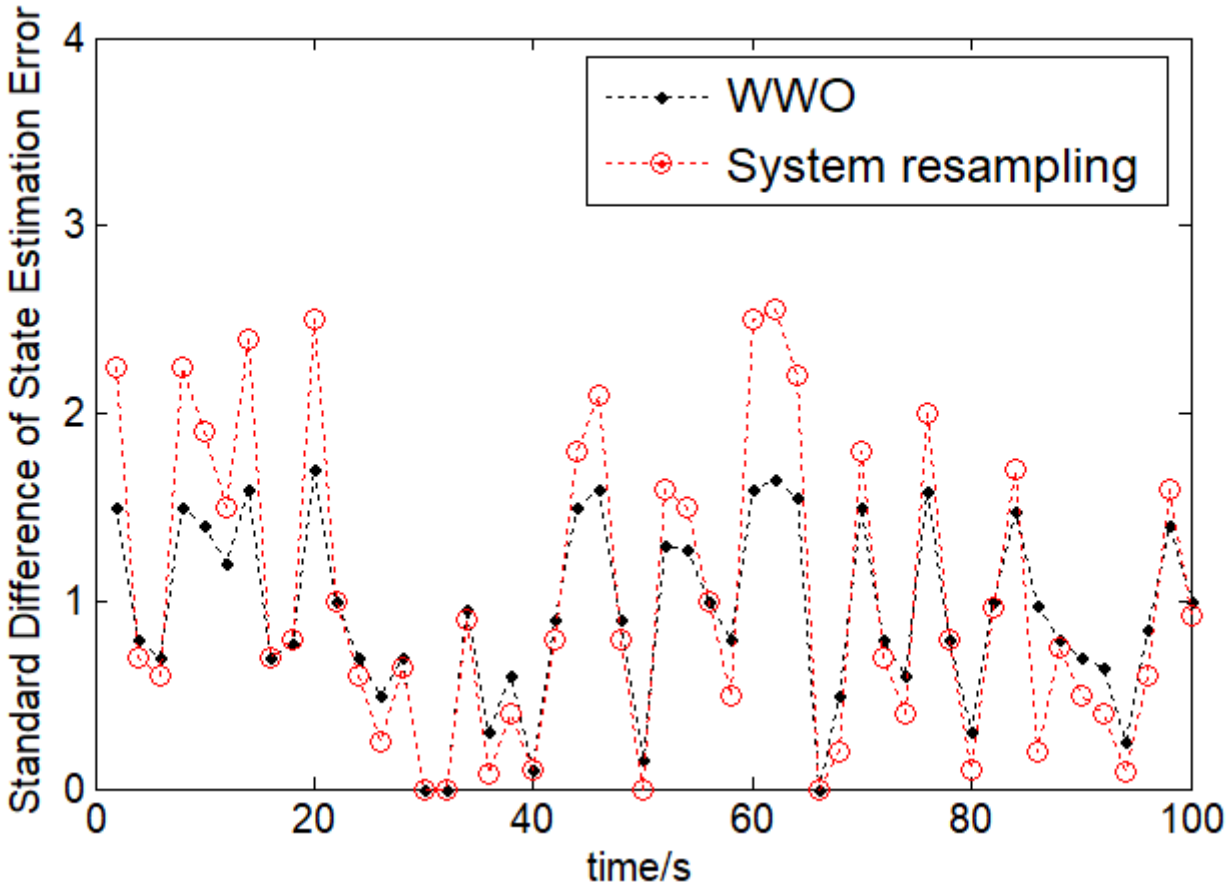

Figure 3

Error Standard Deviation Curve of State Estimation

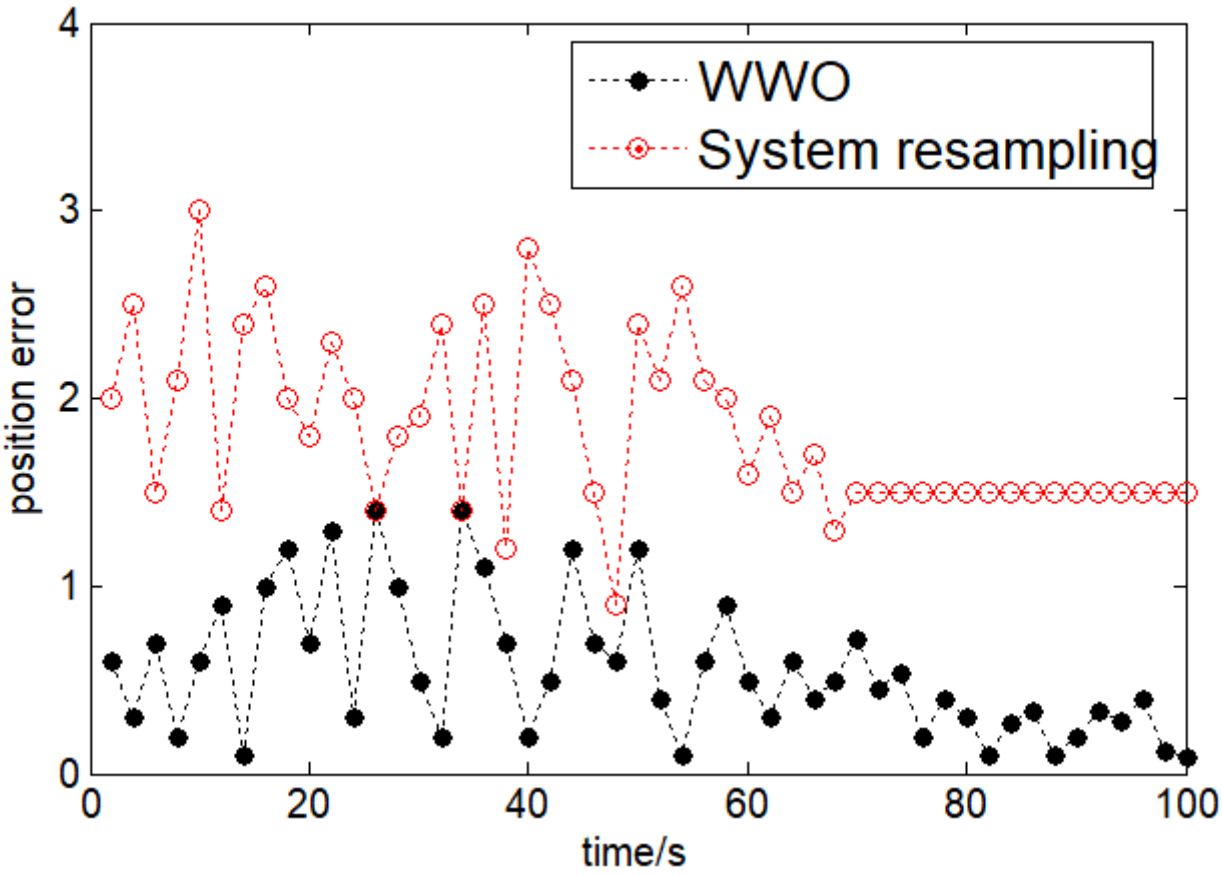

Figure 4

Location Error Comparison

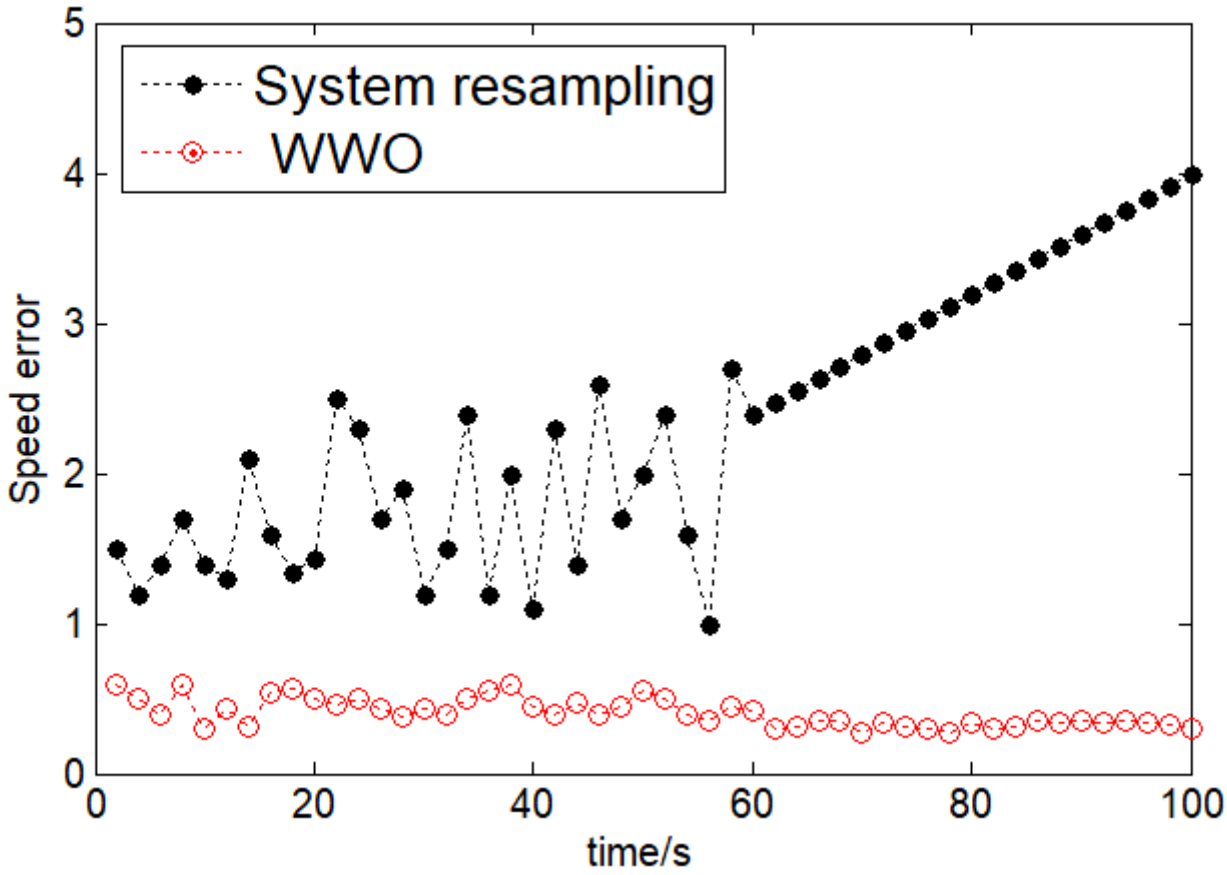

Figure 5

Speed Error Comparison