A DW-SAPSO Localization Method based on Correctional RSSI Ranging Model

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Abstract. Aiming at the problem of low localization accuracy caused by the ranging error generated by the RSSI ranging model with empirical parameters in different indoor scenarios, a simulated annealing-based particle swarm optimization localization algorithm with decreasing inertia weight (DW-SAPSO) is proposed. In the RSSI ranging phase, the parameters of ranging model are estimated and corrected by the difference between different reference points. In the localization phase, the nonlinear cost function is constructed according to the measurable quantity. Simultaneously the simulated annealing and decreasing inertia weight mechanism are introduced to the standard particle swarm optimization (PSO) localization algorithm, which effectively improves the algorithm's global optimization ability and local search accuracy. Experimental results show that compared with an existing method and the PSO localization algorithm, the modified DW-SAPSO localization algorithm has better convergence performance and can improve the average localization accuracy of the latter by about 32.7%, which has some practical value.

1 Introduction
Since GPS has not been able to meet people's indoor localization needs, more and more indoor wireless localization methods have been researched and proposed to make up for this. According to different measurement targets in localization, wireless localization algorithms are generally divided into two categories: non-ranging localization algorithms and ranging localization algorithms. The APIT algorithm, multi-dimensional calibration method and DV-Hop algorithm are common non-ranging localization algorithms [1], which belong to coarse-grained localization method and are hard to meet the requirements of high-precision localization. Ranging localization algorithm [2] can achieve higher precision, such as TOA, TDOA, AOA, RSSI and so on. Considering hardware requirements, cost and accuracy, RSSI is widely used due to its high environmental adaptability and low facility deployment overhead [3].

Among the research of indoor localization of RSSI ranging model, Li X [4] use the least squares method to obtain the ranging model parameters by using the first-order Taylor expansion, but the complexity of its computation is too high to be practical. The Bayesian probability model optimizes the RSSI measurement value, which improves the accuracy of the RSSI measurement in [5]. But choosing the empirical parameters of ranging model actually does no help in real experimental scenarios. Ouyang et al. [6] propose a node localization algorithm based on constrained particle swarm optimization algorithm, but the particle swarm optimization algorithm is easy to fall into local optimum in the search process and its premature convergence and local optimization ability in the late evolutionary stage, which make it an obstacle to improving the localization accuracy of test points. A self-localization method based on improved particle swarm optimization is proposed in [7], which set the learning factor to linear decrement mode and use the component variation method to jump out of
the local optimum when the search is stagnant. Although the localization performance of this method is improved, the computational complexity is significantly increased. Yingyu et al. [8] propose a Newton localization algorithm based on artificial neural network for RSSI ranging, which to estimate the position of node by least squares method and then the position is modified by Newton's localization algorithm. But its neighborhood-based search strategy makes the localization accuracy is not ideal.

In view of the existing problems of above methods, this paper proposes DW-SAPSO, a modified method of simulated annealing-based particle swarm optimization localization algorithm with decreasing inertia weight, which to achieve higher localization accuracy in certain experimental scenario. The parameters estimation and correction of the RSSI ranging model are carried out for the real experimental scenario of this paper. Then the nonlinear cost function is constructed according to the measurable quantity. Finally, this modified method performs global search optimization in the process of solving the minimum nonlinear cost function value, and then finds the positions of the unknown test points, thus achieving a higher localization accuracy estimation in the experimental scenario of this paper.

2 Parameter Estimation of RSSI Ranging Model

2.1 RSSI Ranging Model
Considering that indoor scenarios usually exist human flow and obstacles instead of open space in real life, the electromagnetic wave propagation path is blocked. The log-normal shadowing model (LNSM) simulates the received signal strength indication (RSSI) that varies logarithmically with distance in this case [9]. And compared with the MK model [10], the Ericsson multiple breakpoint model and the inversion propagation model [11], LNSM has the characteristics of less model parameters and simple practical application. A large number of experimental results indicate that LNSM can approximate the propagation of electromagnetic waves indoors as follows:

\[ P_d = P_{d_0} - 10n \log_{10} \left( \frac{d}{d_0} \right) + X_\sigma \]  

(1)

Where: \( P_d \) represents the received signal strength indication in dBm at distance \( d \); \( P_{d_0} \) represents the received signal strength indication in dBm at reference distance \( d_0 \), refer to as the reference RSSI, which generally assume that \( d_0 \) equals 1 meter for simplicity; \( n \) is the path loss exponent (PLE), which represents the rate at which the path loss increases with distance; \( X_\sigma \) is the random variable due to the shadowing effects that follows a zero-mean normal distribution:

\[ X_\sigma \sim \mathcal{N}(0, \sigma^2) \]  

(2)

2.2 Parameter Estimation of LNSM
Since the localization method based on RSSI ranging is often affected by environmental factors, if the propagation model parameters are still set according to the empirical values given in [12] in different indoor scenarios, the ranging error will be brought into the localization stage. Therefore, in the experimental scenario of this paper, the RSSIs from the \( L \) routers which placed at the reference points are measured at \( m \) known-coordinate measurement points, and the measurable quantity \( P_d \) in the formula (1) is set to \( Y \), and the known amount \(-10 \log_{10}(d)\) is set to \( X \). The propagation model parameters \( P_{d_0} \) and \( n \) to be estimated are set to \( a \) and \( b \) respectively (3). Parameter estimation of LNSM is based on the principle of minimizing the sum of squares of errors of least squares method according to formula (4-6):

\[ Y = a + bX + X_\sigma \]  

(3)

\[ R = \sum_{i=1}^{m} (X_\sigma)_i^2 = \sum_{i=1}^{m} [Y_i - a - bX_i]^2 \]  

(4)
3 Location Algorithms based on Particle Swarm

3.1 Description of the Problem

According to the LNSM parameter estimation, the RSSI ranging model in the experimental scenario is confirmed, and the coordinates of \( L \) reference points are set to \((x_1, y_1), (x_2, y_2), \ldots, (x_L, y_L)\) respectively. In an unknown-coordinate test point \( A(x, y) \), the measurable value of RSSI is simplified to:

\[
\log_{10}(d_l) = P_{d_0} - P_{d_0} = -10n \log_{10}(d_l) + X_{\sigma,l}
\]

Where \( l = 1, 2, \ldots, L \)

Its vector is expressed as:

\[
r = f(x) + X_\sigma, x = [x, y]^T
\]

Where:

\[
r = [r_1, r_2, \ldots, r_L]^T
\]

\[
X_\sigma = [X_{\sigma,1}, X_{\sigma,2}, \ldots, X_{\sigma,L}]^T
\]

\[
f(x) = -10n
\]

\[
\left[ \begin{array}{c}
\log_{10}\left(\sqrt{(x-x_1)^2 + (y-y_1)^2}\right) \\
\log_{10}\left(\sqrt{(x-x_2)^2 + (y-y_2)^2}\right) \\
\vdots \\
\log_{10}\left(\sqrt{(x-x_L)^2 + (y-y_L)^2}\right)
\end{array} \right]
\]

The nonlinear least square is introduced into the localization algorithm based on RSSI ranging, and the cost function is as following:
Then the nonlinear least squares localization estimation problem can be expressed as the following formula (14):

\[
\hat{x}, \hat{y} = \arg \min J_{NLS}(\hat{x})
\]

To solve the nonlinear estimation problem described in formula (14), the traditional localization method such as Gauss-Newton algorithm, Steepest Descent algorithm and Newton algorithm [13] are based on an initial guess position and the regular iteration to search in the neighborhood of the initial guess position, thus only a locally optimal position estimate can be obtained. The purpose of this paper is to make use of the idea of swarm intelligence. And the simulated annealing-based particle swarm optimization localization algorithm with decreasing inertia weight (DW-SAPSO) can efficiently and globally search the target space and converge to the global optimal, and solve the global optimal position estimation.

3.2 Location Algorithm based on Standard Particle Swarm Optimization (PSO)

The coordinate of an unknown test point that need to be estimated is abstracted into one position in the 2-dimensional target search space, and then a group of random particles are initialized in the target search space [14]. That is to set the population consisting of \( M \) particles be \( X = (X_1, X_2, X_i, \ldots, X_M) \), where the i-th particle is represented as a 2-dimensional vector \( X_i = (X_{i1}, X_{i2})^T \), representing a potential solution in the target search space, whose velocity is \( V_i = (V_{i1}, V_{i2})^T \).

\( J_{NLS}(\hat{x}) \) in formula (14) is represented as \( J(x) \) and is set as the objective function. The iterative process of particle swarm optimization algorithm aims to minimize the objective function value. In the k-th iteration process, \( X_i \) is substituted into \( J(x) \) to calculate its objective function value. According to formula (15), the i-th particle tracks its optimal position searched so far \( P_i = (P_{i1}, P_{i2})^T \) and the optimal position searched by the entire particle swarm \( P_g = (P_{g1}, P_{g2})^T \) to update its speed formula (16) and position formula (17) until the k+1-th iteration.

\[
\begin{align*}
\hat{x}, \hat{y} & = \arg \min J_{NLS}(\hat{x}) \\
\end{align*}
\]

Where: \( w \) is the inertia weight, controlling the influence of the previous speed on the current speed; \( c_1 \) and \( c_2 \) are the learning factors of the control step; \( r_1 \) and \( r_2 \) are independent pseudo-random numbers, obeying the uniform distribution on \([0,1]\).

3.3 Simulated Annealing-based Particle Swarm Optimization Localization Algorithm with Decreasing Inertia Weight (DW-SAPSO)

Because of the standard particle swarm optimization algorithm is a forward feedback process, when the local information is too good, it is easy to generate a large number of particle aggregation, which leads to the problem of early convergence and falls into the local optimal solution. Therefore, the idea of simulated annealing is introduced to improve the convergence performance of the algorithm.
addition, the inertia weight $w$ is generally set to a constant in the standard particle swarm optimization algorithm, which causes the oscillation near the global optimal solution in the later stage, so linearly varying inertia weights are used to solve this problem.

The idea of simulated annealing algorithm is derived from the simulation of the solid annealing cooling process. In practical applications, the internal energy can be simulated as the objective function value $J(X_i)$, the temperature is simulated as the control parameter $T$. It follows the Metropolis acceptance criteria and is improved on the basis of standard particle swarm optimization algorithms [15].

After obtaining the RSSI ranging model by parameter estimation of the measurable quantity of known-coordinate points, based on the RSSI ranging principle, $J_{NLS}(\hat{x})$ is the objective function of both localization algorithms, which to estimate the global optimal position coordinates of the unknown test points by minimizing the nonlinear objective function $J_{NLS}(\hat{x})$. The localization error of a single test point is defined as: $error_{one} = \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2}$, and the average localization error of $\beta$ test points is defined as formula (18) to evaluate the localization algorithms.

$$error_{average} = \frac{\sum_{i=1}^{\beta} \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{\beta}$$ (18)

The algorithm flow of DW-SAPSO in this paper is shown in Table 1.

**Table 1. DW-SAPSO localization algorithm flow**

| Set parameters: $c_1, c_2, w_{max}, w_{min}, N, M, d, V_{max}, \lambda, P_r$ |
| Input: $r_l, J(x)$ |
| Output: $\hat{x}, \hat{y}, error_{one}$ |
| Initialize the location and velocity of group: for $i=1,2,..,M$ |
| $X_i = rand(1,d); V_i = rand(1,d)$ |
| Calculate the value of the target function: $fitness_i = J(X_i)$ |
| Set the initial annealing temperature: $T_0 = \frac{|fitness_{max} - fitness_{min}|}{lnP_r}$ |
| **The iterative optimization:** |
| for $k=1,2,..,N$ |
| for $i=1,2,..,M$ |
| $w_k = w_{max} - \frac{k(w_{max} - w_{min})}{N}$ |
| Calculate formula (16) and (17) |
| end |
| for $i=1,2,..,M$ |
| **Annealing operation:** generate $X_i'$ around $X_i$ and calculate: $\Delta J = J(X_i') - J(X_i)$ |
| if $\Delta J < 0$ or $exp(-\Delta J/T_k) > random[0,1]$ |
| $X_i = X_i', T_{k+1} = \lambda T_k$ |
| else retain $X_i$ |
| According to formula (15), the individual optimal and the whole optimal are updated |
| end |
| end |
In the DW-SAPSO localization algorithm, the annealing temperature T controls the direction of optimization of the solution process to the optimal value, and at the same time, the inferior solution is accepted with a probability \( \exp\left(-\frac{\Delta J}{T_k}\right) \) in each iterative process, so it can be more effective. The local extreme point is jumped out, and as the temperature gradually decreases, the probability of accepting the inferior solution is gradually reduced, thereby improving the convergence performance of the algorithm. In addition, the decreasing mechanism of the inertia weight makes it leap out the local minimum point in the early iteration to facilitate the global search; in the later stage of the iteration, the smaller inertia weight is beneficial to the accurate local search of the current search area to facilitate the algorithm convergence. Therefore, the DW-SAPSO localization algorithm has stronger convergence performance than the PSO localization algorithm.

4 Simulation and Result Analysis

4.1 Experimental Environment

The experimental scenario is corridor hall on the first floor of the Information Department, Yunnan University. During the experiment, 4 reference points, 40 known-coordinate measurable points and 20 unknown-coordinate test points were arranged in a rectangular area of 12*8 meters. The test points were irregularly distributed in the proposed coordinate system. The signal transmitting end are routers on 4 reference points respectively, transmitting 2.4GHz Wi-Fi signal. The signal receiving end is a vivo mobile phone, equipping with the self-programmed Android-based Wi-Fi RSSI measurement software. One person holds the mobile phone to collect the RSSI value from each of the four reference points at each test point, and then using MATLAB to do further processes of the data. Figure 1 is a distribution diagram of reference points and unknown-coordinate test points.

![Figure 1. Distribution of reference points and test points](image)

4.2 Establishment of RSSI Ranging Model

Considering the difference between each reference point, the RSSI values are collected at 40 known-coordinate measurable points, and the propagation model parameters are estimated for 4 reference points respectively. Then the model parameters are corrected according to formula (7) as the LNSM ranging model of the experimental scenario in this paper. Fig 2 is a graph showing the fitting result of the RSSI value of known-coordinate measurable point and distance of the modified propagation model.

In the experimental scenario of this paper, the RSSI ranging model parameter \( P_{d_0} \) takes -37.02 and \( n \) takes 2.04. If the scenario changes, the parameter values need to be recalibrated.
4.3 Simulation Performance Analysis

Table 2. Selection of algorithm parameters

| Parameter | PSO | DW-SAPSO |
|-----------|-----|----------|
| $M$       | 50  | 50       |
| $N$       | 30  | 30       |
| $d$       | 2   | 2        |
| $c_1, c_2$| 1.4962 | 1.4962 |
| $w$       | 0.7298 | $w_{\text{max}}=0.9$ |
| $w_{\text{min}}=0.4$ |
| $V_{\text{max}}$ | 1.2 | 1.2 |
| $\lambda$ | 0.6 | 0.6 |
| $P_r$     | 0.8 | 0.8 |

Based on the requirements of the global exploration and balance of the local improvement ability, as well as the suitable control of the calculation time, the parameters of the PSO localization algorithm and the DW-SAPSO localization algorithm in the experimental scenario are shown in Table 2.

4.3.1 Comparison of Iteration Times. Figure 3 (a), (b) are the comparison of the test points $(7.5, 6)$’s coordinate estimates of the PSO and the DW-SAPSO with iteration respectively. It can be seen from the figure that the PSO localization algorithm converges to the global optimum when the iteration reaches the 18th time, and the DW-SAPSO localization algorithm iterates to the 4th time to estimate the coordinates $(\hat{x}, \hat{y})$ can converge to global optimality, indicating that the DW-SAPSO is affected by the annealing mechanism and the decreasing inertia weight in the search strategy. The acceptance probability reduces with the decrease of temperature, which avoids the search process falling into the local optimal solution. Thus, the convergence performance is improved.
4.3.2 Comparison of Localization Error at 20 test Points. 

Figure 4 is a localization error distribution of 20 test points. Comparing with the Newton localization algorithm based on least squares estimation (N-LS) that proposed in [8]. It can be seen from the figure that at most of the test points, the DW-SAPSO has higher localization accuracy than the PSO and N-LS, but the localization performance of DW-SAPSO at some test points is inferior to PSO. The reason is that the simulated annealing algorithm has randomness of the acceptance probability in the annealing process, so that in some cases, the better solution will be eliminated, resulting in the inferior situation of the optimal solution.

4.3.3 Comparison of Cumulative Distribution Functions of Localization Error.

Figure 5 shows the cumulative distribution function of the test points’ localization error. It can be known from the results of position estimation of 20 test points. Compared with the average error 1.10m of N-LS, the PSO’s performance is 0.774m thus the average localization accuracy is improved by 30.3%. Compared with the PSO, the average localization accuracy of the DW-SAPSO is improved by 32.7%. And 85% of the test points’ localization error is below 1 meter when DW-SAPSO works, which is 10% and 45% higher than that of PSO and NLS respectively, and the control effect on the maximum error is better means it has stronger anti-interference ability, which can meet the demand of position service with certain precision.
Conclusion
Based on the RSSI-based ranging model, the nonlinear cost function is constructed according to the measurable quantity and combined with the particle swarm optimization algorithm to estimate the position of the test points globally. Two optimization strategies are adopted to improve the localization accuracy: one is to estimate and correct the RSSI ranging model considering the difference between the routers placed on reference points; the other is to introduce the idea of simulated annealing and the decreasing inertia weight into the standard particle swarm localization algorithm, which enhances the performance of the algorithm. After analyzing simulation experiment, the DW-SAPSO localization algorithm is better than the PSO localization algorithm in terms of convergence speed and localization accuracy, which is a better solution for location services that require a certain precision.

6 References
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