TDOA Location Based on Improved Particle Swarm Optimization

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Abstract

Aiming at the problem that the performance in non-line-of-sight environment in TDOA location estimation will be greatly affected, an improved particle swarm optimization algorithm is proposed. The first half of the particles with the lowest fitness in the PSO algorithm are directly entered into the next generation, and the latter half of the particles are mutated using the optimal particle position and the optimal velocity of each iteration of the PSO algorithm, and then a new particle group is determined according to the fitness function. The simulation results show that the particle swarm algorithm can find the solution which is close to the global optimum, and the accuracy of the traditional algorithm is higher and the convergence speed is faster.

Keywords

Particle Swarm Optimization algorithm; Time Difference of Arrival; Positioning Technology; Error correction.

1. Introduction

In the existing wireless positioning system, the TDOA (time differences of arrival) method has the advantages of good concealment, strong anti-interference ability, high positioning speed, and high positioning accuracy, and there is no strict time synchronization between the mobile station and the base station. The problem, therefore, is widely used. The positioning system obtains the distance difference between the mobile station and the two positioning base stations through the acquired TDOA measurement values. The multiple TDOA measurement values form a set of hyperbolic equations about the position of the mobile station, and then the nonlinear equation is solved. The group can get the estimated position of the mobile station [1].

Literature [2] based on TDOA-UWB indoor positioning technology, put forward differential UWB positioning algorithm. At the same time, combined with the weighted moving average method, the differential UWB indoor positioning system based on TDOA algorithm is studied and proposed. Due to the introduction of the squared term of the measurement parameter, when the measurement error is large, the quadratic term of the noise cannot be ignored and its performance deteriorates. Due to the introduction of the squared term of the measurement parameter, when the measurement error is large, the quadratic term of the noise cannot be ignored and its performance deteriorates. In [3], the accuracy of TDOA positioning technology is closely related to the accuracy of ranging. The Kalman filtering technology is used to optimize the distance between the terminal and each base station.

The swarm intelligence algorithm is a new type of bionic evolutionary algorithm, which has strong robustness, adopts distributed computer system, and is easy to implement. It is often used to solve the Traveling Salesman Problem (TSP) problem, continuous optimization problem, constrained optimization problem and the positioning problem in this paper. Therefore, this paper proposes an improved particle swarm optimization algorithm to correct the non-line-of-sight error of multiple base station TDOA measurements to make it close to the value in the line-of-sight environment, and then directly enters the next generation through the first half of the particles with the lowest fitness. Half of the particles use the PSO algorithm to obtain the optimal particle position and the optimal velocity for the each iteration to perform the mutation. Then the variant particle is used to determine whether to replace the particle before mutation or not, so as to generate a new particle group and accelerate the convergence rate.

2. TDOA Hyperbolic Mathematical Model

TDOA is a multi-site positioning system. Therefore, at least three monitoring stations must perform simultaneous measurements to locate the signal. The composition of each monitoring station is relatively simple, including receivers, antennas, and time synchronization modules. In theory, an existing monitoring station can be upgraded to a TDOA monitoring station as long as it has a time synchronization module, without the need for complicated technological transformation.

As shown in Fig. 1, suppose the M receivers are randomly distributed on the two-dimensional plane, and the distance from the mobile station MS(x,y) to the i-th receiver (xi, yi) is Ri .

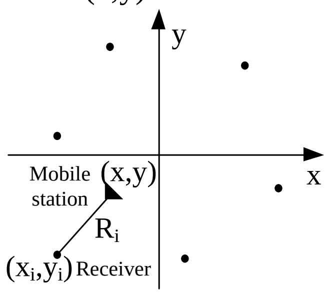

Figure 1. Two-dimensional plane positioning

Let R0i, 1 denote the actual distance difference between the MS and the base station i (i ≠ 1) and the base station 1 (the serving base station). The measured value is denoted as Ri,1.

$$R_{i,1} = cd_{i,1} = R_{i,1}^0 + cn_{i,1} = R_i - R_1 + cn_{i,1} \qquad i = 2,\cdots,M \tag{1}$$

In equation (1): c is the speed of light; di, 1 is the measured value of TDOA; ni, 1 is the noise introduced when measuring TDOA. For convenience, it can be considered as Gaussian white noise with an independent identical distributed variance σ2.

$$R_i = \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{2}$$

From (1), (2) available:

$$R_{i,1} = \sqrt{(x_i - x)^2 + (y_i - y)^2} - \sqrt{(x_1 - x)^2 + (y_1 - y)^2} + cn_{i,1} \tag{3}$$

Among them $dR = \left[R_{2,1}, R_{3,1}, \cdots, R_{M,1}\right]^T$, $R1 = \left[R_2, R_3, \cdots, R_M\right]^T$, $R0 = \left[R_1, R_1, \cdots, R_1\right]^T$.

$$dR = R1 - R0 + cn = \begin{bmatrix} \sqrt{(x_2-x)^2+(y_2-y)^2} - \sqrt{(x_1-x)^2+(y_1-y)^2} \\ \sqrt{(x_3-x)^2+(y_3-y)^2} - \sqrt{(x_1-x)^2+(y_1-y)^2} \\ \text{n} \\ \sqrt{(x_M-x)^2+(y_M-y)^2} - \sqrt{(x_1-x)^2+(y_1-y)^2} \end{bmatrix} + cn \tag{4}$$

In order to make full use of statistical information, the maximum likelihood method is used to determine the mobile station coordinates (x, y). Since each element in dR obeys a Gaussian distribution with a mean of Ri -R1 and a variance of σ2, since each measurement is independent, the likelihood function is:

$$\sum_{i=1}^{M}\left[\frac{1}{\sqrt{2\pi\sigma}}\exp\left[-\frac{(dR_i - R1_i + R0)^2}{2\sigma^2}\right]\right] = \left(\frac{1}{\sqrt{2\pi\sigma}}\right)^2 \exp\left(-\frac{(dR_i - R1_i + R0)^T (dR_i - R1_i + R0)}{2\sigma^2}\right) \tag{5}$$

Finding the maximum coordinate of the likelihood function, the equivalent solved

$$(x,y) = \arg\left\{\min\left[(dR_i - R1_i + R0)^T (dR_i - R1_i + R0)\right]\right\} \tag{6}$$

To solve the value of the coordinates (x, y), the minimum value of the function in equation (6) must be found. It is very difficult to solve the value by the analytical method. For this case, the particle swarm optimization algorithm is used to search the optimal solution in the entire potential solution space to determine the coordinate value.

3. Improved Particle Swarm Optimization Algorithm

As a swarm intelligence optimization algorithm, the PSO algorithm first initializes the population randomly in the feasible solution space. Each particle in the population represents one possible solution to the optimization problem, which corresponds to a fitness value determined by the optimization function. Its spatial geometric position and velocity are represented in vector form. In the each optimization iteration, each particle updates its velocity and position through its own optimal solution (individual extrema) and the optimal solution (global extremum) found by the entire population [5]. The mathematical description of the PSO algorithm is as follows.

Suppose that in an n-dimensional target search space, there are N particles forming a group, where the i-th particle represents a D-dimensional vector xi = [xi1, xi2, ..., xiD]T, i =1, 2 ,... N, the position of each particle is a possible solution. The flight speed of the i-th particle is v i =[vi1, vi2, ..., viD]T .

The optimal position of the i-th particle searched so far is pi =[pi1, pi2,..., piD]T. The optimal position searched by the entire particle group so far is pgi=[pgi1, pgi2, ..., pgiD].TThe PSO algorithm operates on particles using the following formula.

$$\begin{cases} v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (p_g^t - x_i^t) \\ x_i^{t+1} = x_i^t + v_i^t \end{cases} \tag{7}$$

In equation (6), c1 and c2 are learning factors, which are non-negative constants; ω is the inertia weight.

$$\omega = \omega_{\max} - t \times \frac{\omega_{\max} - \omega_{\min}}{T} \tag{8}$$

R1 and r2 are random numbers between [0,1]. The particles are updated through continuous learning. The final pg found is the globally optimal solution. In the PSO algorithm, the fitness function is:

$$fitness(z_i) = (dR_i - R1_i + R0)^T (dR_i - R1_i + R0) \tag{9}$$

The particle coordinate vector is:

$$z_i = \left(X_i, Y_i \right)^T \quad (10)$$

In (10): (Xi, Yi) is the coordinate to be estimated. Based on the improved PSO algorithm, the basic idea of this paper is to first directly enter the first half of the particles with the lowest fitness to the next generation, and then use the PSO algorithm to perform the mutation based on the optimal particle position pg and the optimal velocity for each iteration. Then, based on the degree of fitness, the mutated particles determine whether to replace the particles before the mutation, thereby generating a new particle group.

Equivalent to a screening before the population update, thereby reducing the number of iterations to speed up the convergence rate. The algorithm is simple to implement and the steps are as follows:

Step 1: Initialize the population, determine the population size N, randomly generate the position and velocity of the N particles as the initial position and velocity of the population, and define the particle's position and velocity range; initialize the population's global optimum and individual optimality.

Step 2: Calculate the fitness of the population particles, rearrange the particles in the particle group according to the fitness, and the first half of the particles directly into the next generation.

Step 3: The second half of the particles are mutated according to the following equation, where i1, i2 $\in$ {1, 2, , ..., N} are different from each other in i:

Step 4: Find the global optimal and individual optimal. If the current particle's fitness value is better than the individual optimal, replace the individual optimal position with the current particle position; if the current population particle's fitness value is better than the global optimum, then Replace the global optimization with the current particle position.

Step 5: Use equation (7) to update the particle velocity and position and use equation (8) to update the inertia weight.

Step 6: Terminate the condition. If the maximum number of iterations is reached, stop outputting the result at the same time; otherwise, go to step 2.

4. Computer Simulation and Result Analysis

In order to verify the effectiveness of the TDOA positioning algorithm based on the improved PSO algorithm, this paper analyzes the performance of the improved positioning algorithm under different environments in the COST259 channel model, and is in the same condition as the Chan algorithm[6] and the Taylor algorithm[7]. The performance was compared. The initialization parameters of the algorithm in the simulation are as follows: particle swarm size 20, learning factor c1=c2=2, maximum weighting factor ωmax=0.9, minimum weighting factor ωmin 0.1, and variation factor u=0.5. The total number of iterations is 100. Receiver coordinates:BS2(-$\sqrt{3}$,0), BS3($\sqrt{3}$,0), BS4($\sqrt{3}$/2,3/2), BS5(-$\sqrt{3}$/2,-3/2), BS6(-$\sqrt{3}$/2,3/2), BS7($\sqrt{3}$/2,- $\sqrt{3}$/2), BS8(0,2), BS9(0,-2). Specifically, assume that the mobile station and all base stations are non-line-of-sight transmissions. The TDOA measurement error is an independent, identical, Gaussian random variable with a standard deviation of 0.1us and a mean value of 0. The average estimated coordinate E[(x,y)]; mean squared error MES =E[(x-x0)2 +(y-y0)2] , the independent calculations 1000 times, you can get the estimated coordinates.

The base station is evenly distributed within a sector, and the measurement error obeys an ideal Gaussian distribution with a mean of 0 and standard deviations of 30m, 60m, 90m, 120m, and 150m, respectively.

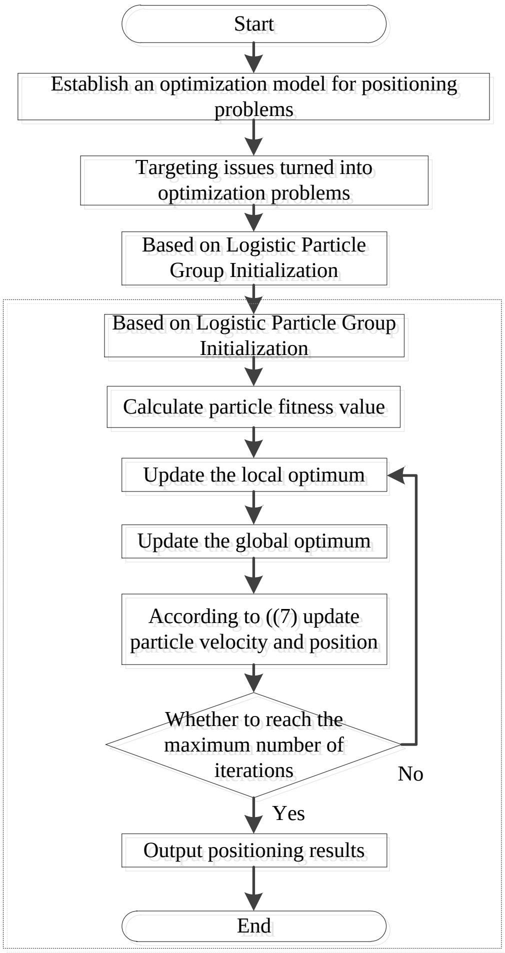

Figure 2. Flowchart of improved particle swarm algorithm

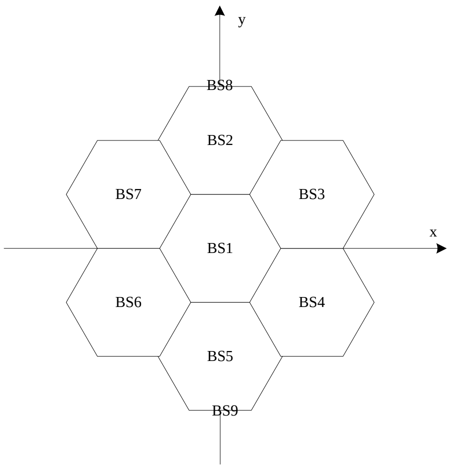

Figure 3. Location of base station and mobile station

As shown in Figure 4, the performance of the Chan algorithm is worse than that of the two PSO algorithms, and as the error variance becomes larger, the gap becomes larger. The main factor is that the Chan algorithm uses two LS algorithms and introduces the second term of error in the first LS algorithm. The PSO algorithm searches for the optimal solution directly against the equation derived from the maximum likelihood method. When the error variance is small, the quadratic term of the error can be ignored, so the Chan algorithm performance is close to the optimal solution. When the error variance increases, the impact of the second term of the error becomes larger and can not be ignored, resulting in the performance degradation of the Chan algorithm. The PSO algorithm is not affected by the quadratic term of the error and its performance is superior to that of the Chan algorithm.

This simulates the performance of the three algorithms in the process of changing the cell radius from 500m to 3000m in the COST259 channel.

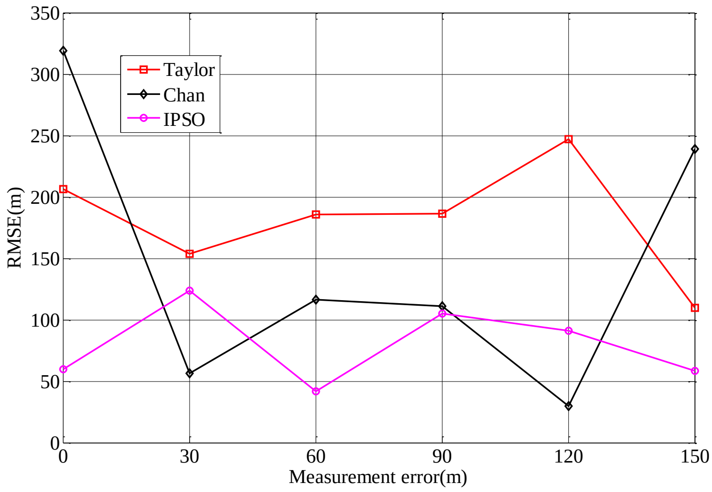

Figure 4. Relationship between measurement error and root mean square error

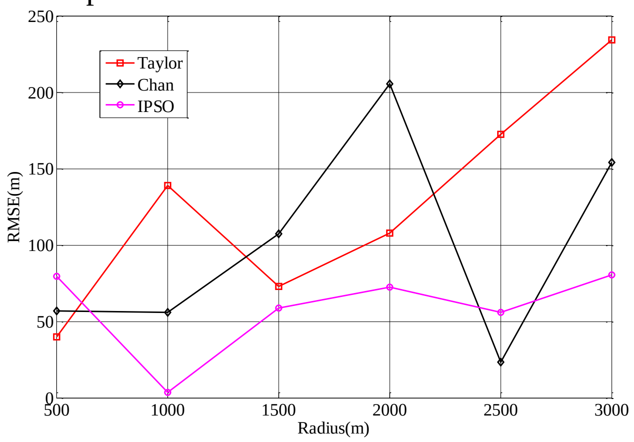

Figure 5. Relationship between radius and root mean square error

As shown in Figure 5, the PSO algorithm exhibits the best performance as the radius increases. This is because the mathematical derivation of the Chan algorithm is based on the small TDOA measurement error and the Gaussian white noise distribution. The actual environment does not satisfy this condition, so the precision of the Chan algorithm is reduced, and the PSO algorithm can reduce the error.

The simulation conditions for selecting the number of base stations are representative, which are 4, 5, 6, and 7, respectively.

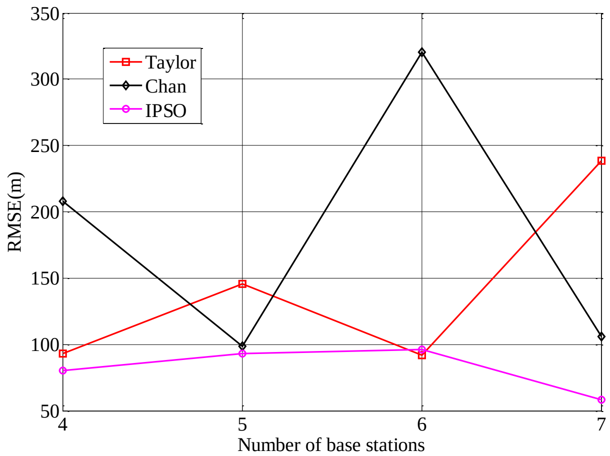

Figure 6. Relationship between base station and root mean square error

As shown in Figure 6, in the Gaussian environment, regardless of the number of base stations, the performance of the improved PSO algorithm is always the best. The performance of the Taylor sequence expansion method is suboptimal, while the Chan algorithm performance is not as good as the first two. That is to say, PSO algorithm and Taylor sequence expansion method can use all TDOA information to obtain the most accurate solution. Therefore, they can adapt to different measurement environments.

5. Conclusion

Aiming at the problem of NLOS in indoor positioning process, a TDOA indoor location algorithm based on improved PSO algorithm is proposed. Utilizing the characteristics of iterative optimization of the improved PSO algorithm, the non-line-of-sight errors of multiple base station TDOA measurements are corrected to be close to the value in the line-of-sight environment, and the TOA of the base station and the mobile station are close to the correct measurement values. TDOA value, and use TDOA algorithm to achieve the original positioning of the mobile station, and then use the improved PSO algorithm to optimize the original positioning coordinates to obtain the final positioning results. The simulation results show that the TDOA positioning algorithm based on improved particle swarm algorithm and the traditional Chan algorithm are proposed in this paper. Compared with the Taylor algorithm, the positioning accuracy is obviously improved.

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References

[1] Li Ming, Pan Junchen. UWB indoor positioning principle and TDOA positioning algorithm[J]. Scientific Innovation and Application, 2017(2):57-57.

[2] Shi Xiaohong. Wireless location method based on TDOA and its performance analysis[J]. Journal of Southeast University(Natural Science Edition), 2013, 43(2):252-257.

[3] Li Zhaohua, Wang Wei, Shao Qing. TDOA 3D Positioning Algorithm Based on Chan[J]. Modern Telecommunication Science and Technology, 2014(11):36-40.

[4] Ma Chunguang, Zhang Chenglong. Design of Mine Resources Real-time Positioning System Based on UWB Technology[J]. Information and Computer(Theory), 2017(19).

[5] Zhao Tiantian, Wang Siming. Path Planning of Mobile Robot Based on Improved PSO Algorithm[J]. Transducer and Microsystem, 2018(2).

[6] Zhong Jiangtao, Qin Bin, Wu Jianchun, et al. Improvement of Chan Indoor Location Algorithm Based on Kalman Filtering[J]. Communications Technology, 2017, 50(10):2223-2228.

[7] Zhao Hongxu, Yang Wenshuai. Analysis and Comparison of Chan Algorithm and Taylor Algorithm Based on TDOA[J]. Electronic world, 2017(9):176-177.