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RESEARCH ON TDOA LOCALIZATION TECHNOLOGY BASED ON IMPROVED DUNG BEETLE OPTIMIZER

GUANWU JIANG*, XU WANG, BO LIU, AND KEQIANG BAI†

Abstract. With advancements in electronic technology, high-precision positioning and navigation of indoor mobile devices have been achieved. By solving the nonlinear Time Difference of Arrival (TDOA) problem, an Improved Dung Beetle Optimization (IDBO) algorithm has been proposed to enhance the performance of positioning algorithms. Firstly, during the population initialization stage, Bernoulli mapping is employed to initialize the dung beetle population positions, replacing the traditional random initialization method. This approach addresses issues of uneven population distribution and limited search range. Next, a fitness function tailored to the TDOA localization problem is designed to improve localization accuracy and make the algorithm more targeted. The golden sine strategy is then introduced into the position update process of the ball-rolling dung beetle to enhance the algorithm's local optimization capabilities. Finally, a self-adaptive Levy flight strategy is utilized to randomly update the dung beetle's position, mitigating the impact of local extrema and improving the algorithm's resistance to localization noise. Simulations of the IDBO algorithm demonstrate that it can converge quickly and stably to the target position in two-dimensional TDOA localization scenarios.

1. Introduction

With the rapid development of wireless communication and positioning technology, the demand for both indoor and outdoor positioning is constantly increasing. Time Difference of Arrival (TDOA) is a positioning technique based on time differences, determining the position of the target by calculating the time difference of the signal reaching different receivers. TDOA technology offers high positioning accuracy and wide applicability, and is widely used in wireless communication, intelligent transportation, military and other fields.

Traditional TDOA localization methods typically use iterative optimization algorithms. However, these algorithms often suffer from slow convergence speeds and a tendency to get stuck in local optima, resulting in low positioning accuracy [3]. Therefore, improving the Dung Beetle Optimizer (DBO) as a novel optimization algorithm has been introduced into TDOA positioning technology to enhance positioning accuracy and convergence speed. The mathematical principle of TDOA is

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*†Corresponding author.

based on the difference in signal propagation speeds between multiple receivers [15]. Although theoretically feasible, solving the TDOA equation system requires special algorithms and techniques due to its nonlinear characteristics [8].

The TDOA system, characterized by its nonlinear nature, is a set of equations based on time differences [5]. To solve the nonlinear optimization process of the target, it is often necessary to convert it into a linear equation system. Traditional TDOA positioning is mainly solved via analytical algorithms such as the Fang algorithm [4], Chan algorithm [19], Taylor algorithm [7], and Gaussian-Newton (GN) algorithm [1]. The Fang algorithm is limited to two-dimensional three-base station or three- dimensional four-base station positioning and cannot fully utilize redundant data [14]. Various methods, such as phase difference compensation and TDOA estimation based on reference signal integration, have been proposed to enhance accuracy [2]. However, the accuracy of the Taylor and GN algorithms is limited by the initial position of the series expansion, which may result in non-convergence [16,17]. Recent studies have proposed algorithms such as an indoor 3D positioning algorithm based on multiple swarm sparrow algorithms [9], and a DV-Hop sensor positioning algorithm improved by the grey wolf optimization algorithm [12], both of which improve positioning accuracy and convergence speed. Additionally, an improved whale optimization algorithm has been proposed for solving TDOA, enhancing algorithm robustness [11].

These algorithms do not require constructing a system of equations but only need an appropriate fitness functionṪhrough algorithm search strategies, an optimal estimated position can be achieved, yielding higher positioning accuracy. However, according to the No Free Lunch (NFL) theory [13], no single intelligent algorithm is universally applicable to all optimization problems. In the application of TDOA algorithms, intelligent algorithms often face challenges such as excessive control parameters, slow convergence in later stages, and susceptibility to local optima. Therefore, finding a suitable intelligent algorithm model for TDOA positioning and addressing its shortcomings in a targeted manner is crucial. A new metaheuristic algorithm, the Dung Beetle Optimizer (DBO), has been proposed, exhibiting fast convergence speed and high solution accuracy [18].

This article aims to study TDOA localization technology based on an improved dung beetle algorithm. Firstly, a detailed introduction to TDOA positioning technology is provided, covering its principles, application areas, and existing problems. Secondly, an analysis of traditional TDOA positioning algorithms is conducted, highlighting their limitations. Then, a TDOA localization method based on the improved dung beetle algorithm is proposed, detailing the algorithm steps and optimization strategies. Finally, the advantages of the improved dung beetle algorithm in TDOA localization are verified through experimental simulation and comparative analysis. The research results are significant for improving the accuracy and reliability of TDOA positioning technology. By enhancing the dung beetle algorithm, the search strategy of the localization algorithm can be optimized to improve localization accuracy. Looking ahead, TDOA positioning technology based on improved dung beetle algorithms can be combined with other positioning technologies to further enhance the performance of multi-mode positioning systems and achieve wider applications.

2. TDOA positioning model

The TDOA (Time Difference of Arrival) localization model is a time-based method used to determine the position of a target in two-dimensional or three-dimensional space. This model relies on measuring the time differences of the target signal reaching multiple receivers and estimates the target's position by calculating the differences in distances. This section focuses on two-dimensional positioning; the principles can be extended to three-dimensional coordinates. Assuming the coordinates of the target are $P(x, y)$, there are N base stations participating in the localization solution, with their coordinates being $R_1(X_1, Y_1)$, $R_2(X_2, Y_2)$,$\cdots R_i(X_i, Y_i)$, $i = 1, 2...N$. The actual distance between the test tag and the i_{th} base station is d_i. The geometric model of TDOA positioning for multiple base stations is shown in Fig. 1.

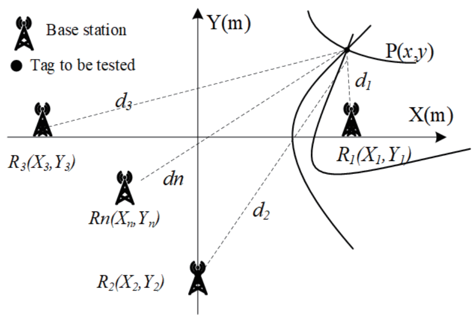

FIGURE 1. Geometric model of multi base station TDOA positioning.

Assuming there is a target with two-dimensional position coordinates (P_x, P_y), and there are N receivers $R_1(X_1, Y_1)$, $R_2(X_2, Y_2)$,$\cdots R_n(X_n, Y_n)$. The true time for the tested tag to send a signal to reach the i_{th} base station is t_i. The expression for t_i and d_i as follows:

$$d_i = ct_i = \sqrt{(x - X_i)^2 + (y - Y_i)^2}. \tag{2.1}$$

Between the signal reaching each receiver can be expressed as:

$$t_i = (d_i - d_{ref} i)\, c. \tag{2.2}$$

Here, $d_{ref} i$ represents the reference distance of the i_{th} point, and c denotes the signal propagation speed.

The TDOA positioning model needs to consider factors such as the accuracy of receiver position, sensor clock synchronization, and uncertainty in signal propagation speed. Due to the presence of noise during signal transmission and e_i is the noise error. The measurement time for the signal to reach base station i is T_i, the measurement distance is D_i, and the expression can be obtained:

$$\begin{cases} T_i = t_i + e_i \\ D_i = cT_i = c(t_i + e_i) \end{cases}. \tag{2.3}$$

Let the distance measurement error be E_i, and the difference between the distance measurement values between the label distance base station i and base station j is

$D_{i,j}$, the expression [10] can be obtained:

$$\begin{cases} E_i = ce_i \\ D_{i,j} = D_i - D_j = cT_i - cT_j \end{cases}. \tag{2.4}$$

Joint announcement 1-4 can obtain the distance and position relationship between the target label and the base station:

$$D_{i,j} = c\left(T_i - T_j\right) = d_i - d_j + E_i - E_j. \tag{2.5}$$

A hyperbolic equation system can be established based on measurement data to estimate the position of the tested label and construct a fitness function.

3. Improved dung beetle optimization algorithm

3.1. **Description of Dung Beetle Optimization Algorithm.** The Dung Beetle Optimizer (DBO) is an intelligent optimization algorithm derived from the rolling, dancing, breeding, foraging, and stealing behaviors. Based on these behaviors, the DBO algorithm designs five different update rules [6].

(1) Dung beetle rolling behavior

Dung beetles make a living by rolling dung balls in nature. They use light to determine their travel trajectory, and their updated position as follows:

$$\begin{cases} x_i\left(t+1\right) = x_i\left(t\right) + \alpha \times k \times x_i\left(t-1\right) + b \times \Delta x \\ \Delta x = \left|x_i\left(t\right) - X^w\right| \end{cases}. \tag{3.1}$$

Among them, t is the number of iterations, $x_i\left(t\right)$ is the i dung beetle during iteration, k is the deflection coefficient, b is a constant, α is the natural coefficient, X^w is the global worst position, and Δx is the degree of change in light intensity.

(2) Dancing behavior of dung beetles

When the dung beetle is unable to move forward due to obstacles, it dances to obtain a new path forward. By simulating dance, use relevant functions to obtain new rolling directions. Once the new direction is successfully determined, the fecal ball will continue to roll backwards. Therefore, its position update method can be expressed as:

$$x_i\left(t+1\right) = x_i\left(t\right) + \tan\left(\theta\right)\left|x_i\left(t\right) - x_i\left(t-1\right)\right|. \tag{3.2}$$

Among them, θ For deflection angle, $\theta \in (0, 2\pi)$.

(3) Reproductive behavior of dung beetles

For the DBO algorithm, female insects produce one egg in each iteration. Which can prevent the algorithm from falling into local optima. The position of the incubated fecal balls is also dynamically changing during the iteration process, and its definition is as follows:

$$B_i\left(t+1\right) = X^* + b_1 \times \left(B_i\left(t\right) - Lb^*\right) + b_2 \times \left(B_i\left(t\right) - Ub^*\right). \tag{3.3}$$

Among them, $B_i(t)$ is the position of the i-th incubated egg fecal ball at the t-th iteration, and b_1 and b_2 represent sizes of 1×2independent random vectors of D, where D represents the dimension of the optimization problem.

(4) The foraging behavior of dung beetles

After hatching, newly hatched dung beetles need to ingest nutrients and start foraging. The foraging area includes a range constraint, and the optimal foraging area is defined as follows:

$$\begin{cases} Lb^b = \max\left(X^b \times (1-R), Lb\right) \\ Ub^b = \min\left(X^b \times (1+R), Ub\right) \end{cases}. \tag{3.4}$$

Among them, X^b is the global optimal position, and Lb^b and Ub^b are the optimal foraging area. After the position update method for the dung beetle can be defined:

$$x_i(t+1) = x_i(t) + C_1\left(x_i(t) - Lb^b\right) + C_2\ (x_i\ (t) - Ub^b\ ). \tag{3.5}$$

Here $x_i(t)$ represents the position of the i_{th} beetle at the t_{th} iteration, C_1 represents a random number that follows a normal distribution, and C_2 represents a random vector belongs to $(0,1)$.

(5) Dung beetle theft behavior

Dung beetles are known as theft behavior. The updated definition of their location is as follows:

$$x_i(t+1) = X^b + X \times b_3 \times |x_i(t) - X^*| + z \times b_3 \times |x_i(t) - X^b|. \tag{3.6}$$

Among them, Z is a constant, b_3 is size of the random vector of $1 \times D$ and follows a normal distribution.

3.2. **Fitness function.** In the TDOA positioning problem, it is required for the number N of base stations to be greater than 3, assuming base station $R_1(X_1, Y_1)$ as the main base station $D_{i,j}$ follows a mean of 0 and a variance of $\delta_d^2 = 2\delta_{new}^2$ of Gaussian distribution, all measured values that are independent of each other. The maximum likelihood estimation method is used to determine the position of the tested label, and its likelihood function is as follows:

$$\begin{aligned} L &= \prod_{i=2}^{N} \left\{ \frac{1}{\sqrt{2\pi}\delta_d} exp\left[-\frac{(D_{i,1}-d_i+d_1)^2}{2\delta_d^2} \right] \right\} \\ &= \left(\frac{1}{\sqrt{2\pi}\delta_d} \right)^{N-1} \times exp\left[\frac{\sum_{i=2}^{N}(D_{i,1}-d_i+d_1)^2}{-2\delta_d^2} \right]. \end{aligned} \tag{3.7}$$

The coordinate value of the maximum likelihood function can be equivalent to:

$$(\hat{x}, \hat{y}) = argmin\left[\sum_{i=2}^{N} (D_{i,1} - d_i + d_1)^2 \right]. \tag{3.8}$$

The fitness function can be obtained as:

Among them, $(\hat{x}, \hat{y})$ is the estimated position of the label to be tested, where the “argmin” function represents obtaining the minimum parameter value within its defined domain.

The fitness function can be obtained as:

$$fitness = \sum_{i=2}^{N} (D_{i,1} - d_i + d_1)^2. \tag{3.9}$$

Face to this situation, the fitness function is designed as follows:

$$F_j = \sum_{i=1}^{N} (D_{i,j} - d_i + d_j)^2. \tag{3.10}$$

Then, $j \neq i, j \in \{1, 2, \ldots, N\}$.

The improved fitness function calculates the fitness function values for each base station as the main base station, and then obtains the minimum fitness function value for each main station, which is used as the improved fitness function and can be expressed as:

$$\begin{cases} fitness = min(F_1, F_2, \ldots, F_N) \\ (\hat{x}, \hat{y}) = argmin[fitness] \end{cases}. \tag{3.11}$$

The DBO algorithm initializes the position of the population by generating random numbers during the population initialization stage, resulting in uneven distribution of beetle positions in the population, which cannot guarantee the algorithm's global search ability. This article introduces Bernoulli mapping, incorporating features such as randomness, nonlinearity, and traversal, and initializing the population using its generated chaotic number to achieve better optimization performance. The mapping expression is as follows:

$$p_{k+1} = \begin{cases} \frac{p_k}{1+\lambda} & 0 < p_k \leq 1 - \lambda \\ \frac{p_k - (1-\lambda)}{\lambda} & 1 - \lambda < p_k < 1 \end{cases}. \tag{3.12}$$

Among them, p_k is the current value of the k_{th} generation chaotic sequence, λ is a control parameter.

3.3. **Improved DBO optimization.** DBO optimization improvements were made to the rolling and stealing behavior of dung beetles, introducing the golden sine strategy to optimize rolling behavior and the adaptive Levi flight strategy to optimize stealing behavior, increasing local search ability and ensuring the algorithm's noise resistance.

(1) Optimizing Rolling Ball Behavior with Golden Sine Strategy

The algorithm utilizes the scanning characteristics of the sine function within the unit circle, reduces the search space through the golden ratio, improves search speed and accuracy, and introduces the golden sine strategy to improve the rolling behavior of beetles in the DBO optimization algorithm. The improved formula is:

$$\begin{cases} x_i\left(t+1\right) = x_i\left(t\right)\left|sin\left(g_1\right)\right| - g_2 sin\left(g_1\right)\left|g_1 X_i\left(t\right) - g_2 x_i\left(t\right)\right| \\ g_1 = -\pi + 2\pi \times (1-h) \\ g_2 = -\pi + 2\pi h \\ h = \frac{\sqrt{5}-1}{2} \end{cases}. \tag{3.13}$$

Among them, g_1 and g_2 is the golden ratio coefficient, h is the segmentation rate, and $X_i\left(t\right)$ is the optimal position of the i_{th} dung beetle after t iterations. (2) Adaptive Levy Flight Optimization for Theft Behavior By using the Levy flight probability distribution model and incorporating high-frequency short distance walks and low-frequency long distance jumps, flight strategies are typically represented by a power-law distribution:

$$L\left(S\right) \ \left|S\right|^{-1-\beta} \quad (0 < \beta < 2). \tag{3.14}$$

Among them, S is the step size, and $L\left(S\right)$ is the moving step size probability. Then, the Mantegna method is used to generate a random step size that follows a

Levy distribution:

$$S = \frac{u}{|v|^{\frac{1}{\beta}}}. \tag{3.15}$$

Among them, u and v follow a normal distribution:

$$\sigma_u^2 = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{2^{\frac{\beta-1}{2}} \times \beta \times \Gamma\left(\frac{1+\beta}{2}\right)} \right)^{\frac{1}{\beta}}. \tag{3.16}$$

In the formula, β for the scaling factor, σ_u is the standard deviation of u, with a value range of $N(0,1)$ for v and a value range of $N\left(0,\sigma_u^2\right)$ for u. Introducing Levy flight strategy into dung beetle theft and adding adaptive links to balance search diversity and convergence accuracy, the improved formula (3.4) is:

$$x_i(t+1) = X^b + Z \times b_3 \times |x_i(t) - X^*| + Z \times b_3 \times |x_i(t) - \zeta X^b| + \zeta L(S). \tag{3.17}$$

Among them, $L(S)$ is the flight step length, ζ for the adaptive movement factor, t is the number of iterations.

4. Simulation results and analysis of the experiment

This article investigates the simulation and testing of TDOA localization performance using the IDBO algorithm in the Matlab environment. Simulation testing can help evaluate the accuracy, stability, and robustness of algorithms, and optimize and analyze different parameter settings.

4.1. Convergence performance analysis.

To verify its convergence performance, Sparrow Algorithm (SSA), Whale Algorithm (WOA), Grey Wolf Algorithm (GWO), and the unimproved DBO algorithm were compared with the IDBO algorithm. When the population size is 40 and the noise power is $-40dB$. When the noise standard deviation $\sigma_d = 0.01m$, analyze the convergence performance of the algorithm by comparing the changes in its fitness value and root mean square error (RMSE).

New experiments were conducted to explore the impact of population size on RMSE values in heuristic optimization algorithms. As shown in Fig. 2, the relationship between RMSE and population size is illustrated.

Analyzing the graph, it can be seen that the LDBO algorithm converges when the population size is between 20 and 30, and is less affected by the population compared to the DBO algorithm; Similarly, the SSA algorithm has relatively stable localization data when the population size is small, but its RMSE value is slightly higher than that of the LDBO algorithm; The WOA algorithm and GWO algorithm require a population size of 80 or even higher to achieve convergence and obtain relatively stable RMSE values.

As shown in Fig. 3, the RMSE values of each algorithm decrease with increasing iteration times and then tend to stabilize. Among them, WOA and GWO require more than 80 iterations to converge, and the RMSE value at convergence is much higher than other algorithms; The SSA algorithm tends to converge after about 50 iterations, while DBO and IDBO tend to converge after about 20 iterations. The number of convergence iterations and the RMSE value of convergence indicate

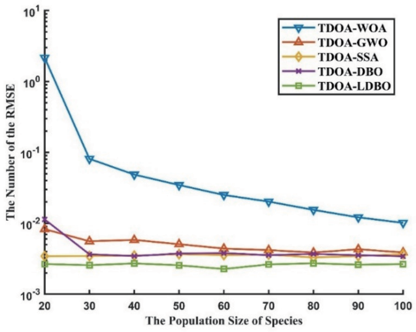

FIGURE 2. Relationship between RMSE and population size.

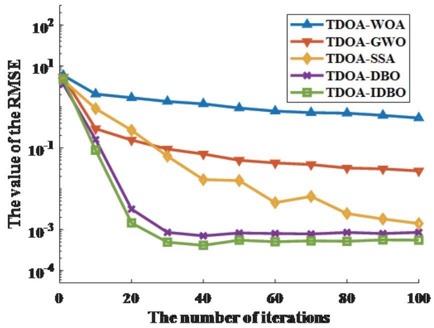

FIGURE 3. Relationship between RMSE and Iteration Times.

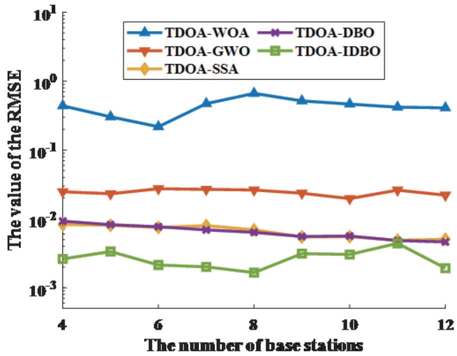

FIGURE 4. Comparison of positioning accuracy under different numbers of base stations.

that the IDBO algorithm can achieve good optimization results. Requiring 20-40 iterations to obtain stable optimization results, and the optimization results are more in line with the requirements of TDOA solution, with good convergence performance.

4.2. **Precision Analysis.** For our first experimentation, the population size was set to 40 and the number of iterations to 500. To verify the positioning accuracy of the algorithm, SSA, GWO, WOA, DBO, and IDBO algorithms were selected for comparison of positioning accuracy.

When analyzing the performance of distance noise standard deviation $\sigma_d = 0.01m$, in addition to the existing 4 base stations, an additional 8 base stations are arranged. Set the base station (0,0) as the main base station, and the other three base stations as slave stations. The positions of the near point to be tested labels are (15,15) and the far point to be tested labels are (40,40). Conduct two sets of experiments, namely, near point distance measurement and far point distance measurement. The coordinates of the 8 additional base stations are: (0,15), (15,0), (35,50), (50,35), (0,35), (35,0), (15,50), and (50,15). Fig. 4 shows the comparison of positioning accuracy under different numbers of base stations.

As the number of base stations increased from 4 to 12, the RMSE of SSA, WOA, GWO, DBO, and IDBO decreased by 42.67%, 3.78%, 1.28%, 42.75%, and 89.60%, respectively. This indicates that compared to other intelligent algorithms, the IDBO algorithm can better utilize redundant measurement data from excess base stations and improve measurement accuracy.

Set the measurement distance noise is $\sigma_d \in [0.1, 1.0]\,m$, experimental comparison of positioning accuracy was conducted for various algorithms in different noise environments, with 1000 positioning experiments conducted for each group. Set the base station (0,0) as the main base station, and the other three base stations as slave stations. The position of the near point test label is (5,5), and the position of the far point test label is (40,40). As shown in Table 1, the RMSE comparison table of the near point test label under different noises is presented.

Table 1. Comparison of RMSE under Different Noises (Near Point).

θ_d	RMSE					CRLB
	WOA	GOW	SSA	DBO	IDBO	
0.1	1.1739	0.3809	0.3652	0.3712	0.2990	0.0772
0.2	1.0571	0.4837	0.4932	0.4762	0.4231	0.1545
0.3	1.0603	0.5562	0.5799	0.5632	0.5213	0.2318
0.4	1.1780	0.7042	0.6496	0.6609	0.6065	0.3091
0.5	1.1362	0.7161	0.7250	0.7489	0.6838	0.3864
0.6	1.2624	0.7837	0.7919	0.7670	0.7371	0.4637
0.7	1.4146	0.9142	0.8808	0.8291	0.8210	0.5409
0.8	1.3489	0.8735	0.8743	0.8920	0.8423	0.6182
0.9	1.5189	0.9391	0.9436	0.9698	0.9276	0.6955
1.0	1.5297	0.9844	1.0306	1.0258	0.9186	0.7728

As shown in Table 2, the RMSE comparison table for the far point test label under different noises is presented.

According to Tables 1 and 2, as the distance noise standard deviation increases, the positioning error of each algorithm also increases. The Chan algorithm has a large error, while intelligent algorithms have errors below $1.1m$, with the IDBO algorithm having the smallest error. For both near point and far point measurements, the RMSE of the IDBO algorithm remains around $0.02m$, whereas other intelligent algorithms have errors around $0.2m$. This indicates that in the IDBO algorithm, the influence of the main base station is equivalent to that of the slave stations, resulting in more stable and accurate measurement accuracy compared to other algorithms.

In summary, the IDBO algorithm achieves higher positioning accuracy in different noisy environments and positioning positions.

Table 2. Comparison of RMSE under Different Noises (Far Point).

θ_d	RMSE					CRLB
	WOA	GOW	SSA	DBO	IDBO	
0.1	0.5755	0.3701	0.3782	0.3533	0.2811	0.0917
0.2	0.6350	0.4712	0.4755	0.4721	0.3889	0.1835
0.3	0.6693	0.5583	0.5733	0.5549	0.4823	0.2752
0.4	0.7483	0.6550	0.6432	0.6404	0.5732	0.3670
0.5	0.7683	0.7134	0.6872	0.6940	0.6301	0.4587
0.6	0.8433	0.7770	0.7630	0.7461	0.6701	0.5505
0.7	0.9266	0.8288	0.8216	0.8239	0.7650	0.6422
0.8	0.9453	0.8409	0.8346	0.8939	0.8077	0.7340
0.9	0.9914	0.9526	0.9210	0.9180	0.8837	0.8257
1.0	1.0234	0.9625	0.9778	0.9747	0.9288	0.9174

5. Conclusion

To address the issues of insufficient accuracy and slow speed in traditional Time Difference of Arrival (TDOA) positioning algorithms, this paper enhances the application of the Dung Beetle Optimization Algorithm (DBOA) for TDOA positioning. The improved algorithm demonstrates good positioning accuracy under various signal-to-noise ratio and measurement error conditions.

We enhanced the DBOA by introducing a probability distribution function to account for TDOA measurement errors and refining the algorithm's evaluation function. These improvements better consider the impact of measurement errors on positioning accuracy and increase the algorithm's robustness. Additionally, an adaptive weight adjustment strategy was adopted to improve the algorithm's convergence, and a dynamic weight adjustment mechanism was introduced to enhance its global search capability, making it easier to find the global optimal solution.

The effectiveness of the proposed improved algorithm was verified through comparative analysis with other commonly used optimization algorithms, showing superior positioning accuracy under various measurement error conditions. Future work will focus on implementing the algorithm on embedded hardware platforms to optimize size, power consumption, and hardware filtering capabilities. Additionally, fusion thinking will be used to integrate other positioning sensors with UWB modules for enhanced positioning.

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G. Jiang
School of Information Engineering, Southwest University of Science and Technology, Mianyang, 621010, China;
Engineering Research Center of Integration and Application of Digital Learning Technology, Ministry of Education, Beijing, 100039 China
E-mail address: jgwu0816@mail.ustc.edu.cn

X. Wang
School of Information Engineering, Southwest University of Science and Technology, Mianyang, 621010, China
E-mail address: 1224589721@qq.com

B. Liu
School of Information Engineering, Southwest University of Science and Technology, Mianyang, 621010, China
E-mail address: 1822442579@qq.com

K. Bai
School of Information Engineering, Southwest University of Science and Technology, Mianyang, 621010, China
E-mail address: baikeqiang@swust.edu.cn