An Improved TOA Model based on Error Correction and Self-Genetic Algorithm

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Abstract

In this paper, we propose an improved TOA model in the indoor three-dimensional positioning of wireless communication base station. By adding an error correction function to the existing TOA location model, the search domain of solutions is narrowed down. In addition, we design an adaptive genetic algorithm to solve the objective function. The simulation results further demonstrate that the proposed algorithm can not only improve the positioning accuracy compared with the existing DTOA, but also has the characteristics of fast convergence speed and strong robustness. The average localization error of the model is only 1.4041m.

Keywords: indoor positioning; TOA positioning model; error correction; adaptive genetic algorithm

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1. Introduction

With the rapid development of mobile Internet and wireless communication technology, LBS (Location Based Services) [1] has seamlessly integrated into people’s daily lives. Meanwhile, it plays a crucial role in promoting the development of Internet of things technology. Indoor positioning is the technology of confirming information users’ location through wireless terminal equipment and wireless sensor networks. Currently, the common indoor positioning technology [2] includes ultrasound, RF, Zigbee, and Wireless fidelity (WI-FI). However, due to the complexity and diversity of indoor scenes, pre-existing indoor location technologies have their own limitations and have not formed a universal solution similar to GNSS.

Nowadays, TOA (time of arrival) is one of the most common radio frequency ranging technologies. It is based on a ranging algorithm and has relatively high positioning accuracy in wireless sensor networks. The principle of TOA is a method of ranging between the sender and the receiver [3-6] by measuring the signal transmission time. The ranging error of TOA mainly depends on the state of the transmission channel. Classical positioning algorithms such as CHAN’s algorithm [7] can solve TOA positioning accuracy in certain cases of a wireless sensor network. However, the test time is influenced by environmental factors and hardware influence (such as clock accuracy), which makes the TOA measurement value deviate. Meanwhile, the solution of hyperbolic equations is irresolvable, and this decreases the performance of the localization algorithm. Furthermore, the positioning accuracy of TOA needs to be improved.

This paper uses the potential relationship between the true and measured value to derive the error correction function, which reduces the effect of positioning accuracy and results from NLOS greatly. Then, an error correction function is added to the model of existing TOA positioning, reducing the search domain of the solution. Furthermore, the improved TOA model is proposed to be solved by using an adaptive genetic algorithm. The results show that the model not only has higher positioning accuracy than the existing DTOA model, but also has the characteristics of fast convergence and strong adaptability.

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2. Related Work

2.1. Introduction to the Basic TDOA Location Model

2.1.1. Symbols and Descriptions Appearing in this Article

Symbols and descriptions appearing in this article are shown in Table 1 below.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_i$</td>
<td>The distance from the terminal to the $i$th base station</td>
<td>m</td>
</tr>
<tr>
<td>$R_{i,0}$</td>
<td>The distance from the $i$th base station to the master station</td>
<td>m</td>
</tr>
<tr>
<td>$c$</td>
<td>Speed of electromagnetic wave propagation</td>
<td>m/s</td>
</tr>
<tr>
<td>$\tau_{i,0}$</td>
<td>The difference of TOA between the $i$th base station and the master station from the terminal</td>
<td>s</td>
</tr>
<tr>
<td>$BS_i$</td>
<td>I base station</td>
<td>-</td>
</tr>
<tr>
<td>$T_i$</td>
<td>TOA of the $i$th base station from the terminal</td>
<td>s</td>
</tr>
<tr>
<td>$\mu$</td>
<td>TOA error value</td>
<td>s</td>
</tr>
<tr>
<td>$TOA_i^{\text{real}}$</td>
<td>The actual TOA from the terminal to the $i$th base station</td>
<td>s</td>
</tr>
<tr>
<td>$TOA_i^{\exp}$</td>
<td>TOA measured by the terminal to the $i$th base station</td>
<td>s</td>
</tr>
<tr>
<td>$R_i^{\text{real}}$</td>
<td>The actual distance from the terminal to the $i$th base station</td>
<td>m</td>
</tr>
<tr>
<td>$R_i^{\exp}$</td>
<td>Estimated distance from the terminal to the $i$th base station</td>
<td>m</td>
</tr>
<tr>
<td>$\Delta R_i$</td>
<td>The absolute error of the distance from the terminal to the $i$ th base station</td>
<td>m</td>
</tr>
<tr>
<td>$\Delta TOA_i$</td>
<td>The absolute error of the TOA to the $i$th base station from the terminal</td>
<td>s</td>
</tr>
<tr>
<td>$TOA_i^{\text{cor}}$</td>
<td>The error-corrected $TOA_i^{\exp}$</td>
<td>s</td>
</tr>
<tr>
<td>$R_i^{\text{cor}}$</td>
<td>After error correction $R_i^{\exp}$</td>
<td>m</td>
</tr>
</tbody>
</table>

2.1.2. The Principle of TDOA Positioning

The technology of TDOA positioning is a method to locate the target by measuring the time difference between the signal that was sent by the terminal and the base station [8]. The basic principle of TDOA positioning technology is to measure the difference of the arrival times from the signals sent by the terminal to different base stations, and according to the geometric principle, the difference of time from the signals sent by the terminal to two base stations can determine a hyperboloid that focuses on base stations of two ground participating in the TDOA measurement, and the target is to be located on a branch of the pair of hyperboloids.

Therefore, if there are four base stations, then the three-dimensional coordinates of the target space, namely the target position [9], can be determined by solving the intersection of three pairs of hyperboloid formed by three TDOA measurements.

Assuming that the spatial location of the target to be measured is $P(x, y, z)$, the spatial location of the base station is $A_i (x_i, y_i, z_i)$, where $i = 0, 1, 2, 3$, as shown in Figure 1.

![Figure 1. The target TDOA positioning diagram](image-url)
The mathematical model of the target location by using TDOA measurements is:

$\begin{align*}
R_0^2 &= (x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2 \\
R_i^2 &= (x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 \\
R_{i0} &= R_i - R_0 = cT_{i0} \\
i &= 1, 2, 3
\end{align*}$

(1)

In the middle of this, $c$ is the propagation speed of electromagnetic waves, taken as $3 \times 10^8$ m/s. The above equation shows that terminal positioning solves the solution of the nonlinear equations, as shown in Equation (1).

2.1.3. Without Considering NLOS DOA Location Algorithm

The radio signal propagation time measuring a radio signal from a handset until the base station receives the signal is the signal arrival time (time of arrival, TOA), which is mainly measured by the propagation delay of the radio frequency signal. The response delay of the terminal and the error of the clock are not synchronized. Because radio waves in the air at the speed of light $c$ communication, base station, and the terminal, the distance between the valuation $R_i = c \cdot TOA_i$ [10]. When there are three base stations involved in the measurement, according to triangulation method, you can determine the area where the terminal is located. Generally, if there are multiple base stations in two-dimensional space, each base station takes the base station as the center of the circle and the estimated distance from the base station to the terminal as a radius, which forms a circular area. Ideally, all base stations correspond to the round at a little, and this point is for the location of the terminal, as shown in Figure 2.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{The ideal situation for locating three base stations in a dimension space}
\end{figure}

Assuming that there are any $n$ base stations in the three-dimensional space, where the mobile terminal (mobile station, MS) is located at $(x, y, z)$ and the position of the $i$th base station is $(x_i, y_i, z_i)$, the estimated distance from the terminal to the $i$th base station is $R_i$:

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

(2)

At this point, if we can obtain $N$ values in the case of $N$-base station coordinates, the solution is composed of the nonlinear equations of the upper form, that is, the estimated terminal position $(X, Y, Z)$ can be obtained, as shown in Equation (2).

2.1.4. Introduction to Genetic Algorithms

In the next chapter, the improved TOA positioning model is described as a nonlinear equation group with constraints. For the TOA positioning method, if multiple base stations are located on a straight line, there are many optimal processing methods [11]. However, if the receiver is in the spatial random distribution, the situation is more complicated, and we will have difficulty solving the nonlinear equations. The exact solution to the number of measured parameters and the number of source signal coordinates is given in literature [12]. However, when the number of measurement parameters is redundant, this method cannot fully use the statistical information given by the redundant measurement parameters to improve the positioning accuracy. In paper [13], the iterative algorithm using Fourier series is given, which requires a good initial value; otherwise, it is easy to fall into the local minimum point, and convergence cannot be guaranteed. A two-step weighted LS
method is proposed in paper [14]. When the error of measurement parameter is very small, the performance is approximate to the optimal value, but because of the introduction of the square term of the measurement parameter, when the measurement error is large, the two items of noise cannot be neglected and the performance will deteriorate.

The genetic algorithm (GA) [15-17] is an adaptive probabilistic optimization technique based on biological genetic and evolutionary mechanisms and is suitable for optimization calculation of complex systems. As an intelligent optimization algorithm, its robustness is strong, simple, and generalized, with strong fault-tolerant ability, and it can be approximated to the optimal solution by selection, crossover, mutation, and other operations. Using the genetic algorithm is the best way to develop and explore the search space, that is, to maintain a potential solution while exploring the search space. This feature is beneficial for finding the best option in the whole picture.

2.2. Improved TDOA Positioning Model

2.2.1. Selection of the Number of Base Stations

Because the TOA algorithm that does not consider NLOS is based on time, the increase of transmission delay caused by the multipath effect and NLOS is the main cause of ranging and locating error [17]. Therefore, in the actual system, the result of ranging is generally greater than the actual distance between the base station and the terminal, as shown in Figures 1 and 2. In order to overcome the adverse effects of NLOS and multipath effects and improve the positioning accuracy, the number (N) of base stations participating in the same position in three-dimensional space is generally greater than four, which reduces the area of the circle-intersecting area in Figure 3.

2.2.2. Establishment of Indoor Base Station Location Error Equation

NLOS, multipath effect, and clock synchronization problems will bring certain errors to TOA measurement. Assuming that the error in TOA measurement is \( \mu \), the relationship between the measured value \( TOA^{exp} \) and value \( TOA^{real} \) of real TOA is:

\[
TOA^{exp} = TOA^{real} + \mu
\]  
(3)

The relationship between the estimated distance from the base station to the terminal and the real TOA is as follows:

\[
R_i^{exp} = (TOA_i^{real} + \mu_i) \cdot c
\]  
(4)

The error \( \mu \) is closely related to the environment in which the terminal is measured. If we can estimate the \( \mu \) value in the current environment, we can make the error correction of the measured data, eliminate the error caused by various factors, and get a more accurate solution, as shown in Equation (4).

For a given set of five test cases [18], it contains the base station coordinates, the TOA value measured at a point by the terminal, and the coordinates of the actual measurement point (assuming the result of the use case is the real position). The estimated distance between the measuring point and the base station (including the error) is obtained by the measured TOA value, as shown in Equation (5):

\[
R_i^{exp} = TOA_i^{exp} \cdot c
\]  
(5)

The real distance \( R_i^{real} \) between the terminal and the base station can be obtained through the real coordinates of the terminal \((x_0, y_0, z_0)\) and the coordinates of the base station \((x_i, y_i, z_i)\), as shown in Equation (6):

\[
R_i^{real} = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}
\]  
(6)

The difference between the real distance and the estimated distance \( \Delta R_i \) as the absolute error of the distance between the base station I and the terminal is shown as follows:

\[
\Delta R_i = R_i^{exp} - R_i^{real}
\]  
(7)

\[
\Delta TOA_i = \mu_i = \frac{\Delta R_i}{c}
\]  
(8)

\( \Delta TOA_i \) (8) is a TOA absolute error for the base station I to the terminal, as shown in Equations (7) and (8).
Five sets of test cases are analyzed by using the above method. First, testing the different terminals of a single environment (that is, a single test case), and analyzing the test case “sample_case001” (three-dimensional space, 30 base stations, 1100 sets of TOA at different terminals), we can draw the relationship between each terminal $\Delta R_i$ and $R_i^{exp}$ at each base station as shown in Figure 4:

For five sets of use cases in other test environments, we obtain the relationship between all $\Delta R_i$ and $R_i^{exp}$ in each environment, as shown in Figure 5.

Analyzing the relationship between the five test cases $\Delta R_i$ and $R_i^{exp}$, it can be clearly seen that they show a strong linear relationship. From Figure 4, for a single environment with a fixed base station, although the positions of the terminals in the environment are different, the error relationship with the distance between them and the base stations is the same. From Figure 5, it can be seen that the distance error between the terminal and the base station in different environments is still linearly related to the estimated distance from the base station.

From this, we can construct a linear relationship between $\Delta R_i$ and $R_i^{exp}$, as shown in Equation (9):

$$\Delta R = k \cdot R_i^{exp} + b$$

(9)

Furthermore, we can obtain the linear relationship between $\Delta TOA$ and $TOA^{exp}$, as shown in Equation (10):

$$\Delta TOA = k \cdot TOA^{exp} + b$$

(10)

Among this, $k$ and $b$ are unknown parameters, and for the same environment, $k$ and $b$ from the relationship always remain unchanged.

To sum up, positioning of the wireless communication base station in the indoor is three-dimensional, and the TOA error equation between the terminal and the base station is shown in Equation (11).

$$\mu = k \cdot TOA^{exp} + b$$

(11)

2.2.3. Narrow the Search Field

The test case shows the error of TOA data in the actual scene: the error caused by the clock asynchronous problem is less than 200ns, and the delay caused by NLOS may exceed 400ns [19].

Analysis of this TOA average delay is shown in Equation (12).

$$\bar{\mu} = \frac{(-200) + (200 + 400)}{2} = 200\text{ns}$$

(12)

Therefore, the error of TOA data must be greater than the actual value in the vast majority of cases, that is, the error $\bar{\mu}$ must be non-negative. This view is also shown in [20].

By analyzing the test data, it is found that the true position of almost all the terminals falls into the sphere with the base
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station as the center and the corresponding $R_{\text{exp}}$ as the radius (the base station with the smallest $TOA_{\text{exp}}$ value $TOA_{\text{min}}$ is the center of the sphere, while $R_{\text{min}}$ is the radius of the sphere), as shown in Figure 7. This also shows that TOA measurements are generally larger than their true values.

To sum up, in the positioning process, the search domain of the terminal position is reduced to the sphere center of the $TOA_{\text{exp}}$ obtained by the terminal, and the corresponding $R_{\text{exp}}$ is the radius of the sphere (the shaded part in Figure 7). The constraints are shown in Equation (13).

$$\begin{align*}
x &< R_{\text{min}} \sin \theta \lambda \\
y &< R_{\text{min}} \sin \theta \lambda \\
z &= R_{\text{exp}} \\
0 &\leq \theta \leq 2\pi \\
0 &\leq \varphi \leq \pi
\end{align*}$$

(13)

2.2.4. Improved TOA Positioning Model

Section 2.2 analyzes the relationship between the error generated in the case of indoor base station location and the TOA value $TOA_{\text{exp}}$ measured by the real $\mu$, so we get the TOA error equation. Based on $TOA_{\text{exp}}$ correction in this error equation, we can obtain more accurate estimates of the measured $TOA_{\text{cor}}$, as shown in Equation (14).

$$TOA_{\text{cor}} = TOA_{\text{exp}} - (k \cdot TOA_{\text{exp}} + b)$$

(14)

This corresponds to a more accurate measurement of radius $R_{\text{cor}}$, as shown in Equation (15).

$$R_{\text{cor}} = R_{\text{exp}} - (k \cdot R_{\text{exp}} + b)$$

(15)

Then, the revised estimated measurement value is substituted into the basic TOA positioning model to correct the NLOS error, as shown in Equation (16).

$$R_{\text{exp}} = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 + (k \cdot R_{\text{exp}} + b)}$$

(16)

If there are $n$ sets of TOA data at this time, then the error-corrected TOA positioning model is $n$ nonlinear equations:

$$\begin{align*}
R_{1_{\text{exp}}} &= \sqrt{(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2 + (k \cdot R_{1_{\text{exp}}} + b)} \\
R_{2_{\text{exp}}} &= \sqrt{(x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2 + (k \cdot R_{2_{\text{exp}}} + b)} \\
&\vdots \\
R_{n_{\text{exp}}} &= \sqrt{(x - x_n)^2 + (y - y_n)^2 + (z - z_n)^2 + (k \cdot R_{n_{\text{exp}}} + b)}
\end{align*}$$

(17)

$(x_i, y_i, z_i)$ are the coordinates of the $i^{th}$ base station, as shown in Equation (17).

In conjunction with the discussion of locating search spaces in Section 2.3, the constraints of the locating space are added to the non-linear Equations (3):

$$\begin{align*}
R_{1_{\text{exp}}} &= \sqrt{(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2 + (k \cdot R_{1_{\text{exp}}} + b)} \\
R_{2_{\text{exp}}} &= \sqrt{(x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2 + (k \cdot R_{2_{\text{exp}}} + b)} \\
&\vdots \\
R_{n_{\text{exp}}} &= \sqrt{(x - x_n)^2 + (y - y_n)^2 + (z - z_n)^2 + (k \cdot R_{n_{\text{exp}}} + b)} \\
x &< R_{\text{min}} \sin \theta \lambda \\
y &< R_{\text{min}} \sin \theta \lambda \\
z &= R_{\text{min}} \cos \lambda \\
0 &\leq \theta \leq 2\pi \\
0 &\leq \varphi \leq \pi
\end{align*}$$

(18)
We can get nonlinear equations with constraints, which is the final modified TOA localization model. For a fixed situation, if we use this model to solve, then it contains \( x, y, z, k, b \), and these five parameters are unknown, as shown in Equation (18).

### 2.2.5. Genetic Algorithm based on iTOA Location Model

In this paper, the corresponding non-linear equation system of the iTOA positioning model is transformed into the following Equation (19).

\[
\begin{align*}
\Delta R_1 &= |R_{1\text{exp}} - \sqrt{(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2} - (k \cdot R_{1\text{exp}} + b)| \\
\Delta R_2 &= |R_{2\text{exp}} - \sqrt{(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2} - (k \cdot R_{2\text{exp}} + b)| \\
\vdots \\
\Delta R_n &= |R_{n\text{exp}} - \sqrt{(x-x_n)^2 + (y-y_n)^2 + (z-z_n)^2} - (k \cdot R_{n\text{exp}} + b)|
\end{align*}
\]

\( \Delta R_i \) is the absolute error between the real distance and the corrected distance from the terminal to the base station \( i \). Then, take the sum of the absolute errors as the optimization target. The optimization model is as follows (considering the search area limitation):

\[
\begin{align*}
\min_{\mathbf{x}} \quad G &= \sum_{i=1}^{n} \Delta R_i \\
\text{s.t.} \quad &x < R_{\text{min}} \sin \theta \cos \lambda \\
&y < R_{\text{exp}} \sin \theta \cos \lambda \\
&z = R_{\text{exp}} \cos \lambda \\
&0 \leq \theta \leq 2\pi \\
&0 \leq \varphi \leq \pi
\end{align*}
\] (20)

For the above optimization model, if the sum \( G \) of absolute errors of the current location \((x, y, z)\) from the corrected measured distance from each base station to the terminal is smaller, the closer the current location is to the location of the real terminal that we can prove. Therefore, when the constraint value is satisfied, the smaller the \( G \) value, the higher the accuracy of obtaining the terminal position, as shown in Equation (20).

Using the improved genetic algorithm to solve the above optimization model, we can set the parameters as follows:

1. **Search space.** In this paper, an improved genetic algorithm is proposed, which uses the reduced positioning space in Section 3.2 as the searching space of the algorithm and then uses the estimated point to each fitness function and floating-point number coding. Then, it takes each component in the chromosome vector to represent the undetermined coordinates, so genetic algorithm can search within the specified coordinate range.

2. **Genetic code.** The traditional genetic algorithm uses a binary coding method to meet the high precision requirements by increasing the number of encoding bits. Because of the increase of the encoding bits, the decoding delay will increase, and when the solution space is unknown, binary encoding cannot be performed. Therefore, the improved genetic algorithm uses floating-point encoding, that is, each chromosome vector is encoded as a floating-point vector, and the solution vector has the same length.

3. **Mutation operator.** In order to improve the accuracy, this paper uses a non-uniform mutation operator, that is, when the search time increases, the mutation operator dynamically changes from full-space mutation to partial fine-tuning. This mutation operator is shown in Equation (21).

\[
\hat{Z}_{t+1} = \begin{cases} 
\hat{Z}_{t} + N_{M \times M}(UB - \hat{Z}_{t}) \left(1 - \frac{t}{T}\right)^b, & \text{When the random number is 0} \\
\hat{Z}_{t} - N_{M \times M}(L\hat{Z} - LB) \left(1 - \frac{t}{T}\right)^b, & \text{When the random number is 0}
\end{cases}
\] (21)

4. **Fitness function.** Because the optimization model has fewer constraints on the solution, the objective function is directly selected as the fitness function to evaluate the fitness of each individual.
Experimental results show that the proposed algorithm is stable, and the solution to the global optimal point can be found by reasonably setting the population size and mutation rate. Compared with the other algorithms, the proposed algorithm has higher accuracy. Since the performance of the proposed method in [17, 21] is better than the other methods mentioned above, the comparison between the proposed algorithm and the TDOA algorithm in [17, 21] is given in this paper.

3. Analysis and Comparison of Experimental Data

All the test data in this experiment are from the 2016 Master Mathematical Contest [17, 21] provided by China Huawei Technologies Co., Ltd. As a matter of convenience, this paper ignores the z-axis when plotting and transforms the data into two-dimensional coordinates due to the small value of the data in the z-axis. According to the principle of TOA positioning, as shown in Figure 6, a circle with a radius from the TOA of each base station is made.

Using the genetic algorithm to solve the improved TOA model, the coordinates of the base station are obtained as \( x = -21.200 \), \( y = 4.483 \), and \( z = 1.1250 \). The error function parameters are \( k = 0.29168 \) and \( b = 0.93600 \). The circle obtained from the true TOA value in Figure 7 is corrected by the error equation \( \mu = 0.29168 \cdot \text{TOA}^{\text{exp}} + 0.93600 \). The result is shown in Figure 7.

The figure shows that the circle of each base station does not meet a point because of the error of the TOA value before it is corrected, but after the correction, all the circles are almost at one point. Figure 8 shows the enlargement of the circle intersection area in Figure 7. It can be seen from the result that the position calculated by this algorithm is close to the real position \( x = -21.19 \), \( y = 4.48 \), \( z = 1.48 \), and the Euclidean distance between them is only:

\[
\sqrt{(-21.200 + 21.19)^2 + (4.483 - 4.48)^2 + (1.1250 - 1.48)^2} = 0.3661
\]

The difference between the iTOA positioning result and the real position is 0.3661m, which shows the effectiveness of the proposed algorithm.
For the five benchmark test cases, the positioning results are obtained by using the improved TOA positioning model. The simulation results of 1200 terminals in case 1 are shown in Figure 9.

The frequency histogram of the errors is shown in Figure 10. It is found from the figure that the Euclidean distance between the experiment results and the true locations obeys the Poisson distribution with \( \lambda = 1.4041 \), which means the average error of the model is 1.4041m and the accuracy is high.

![Figure 9. The distance between each terminal location and its true location](image1)

![Figure 10. Terminal positioning error frequency histogram](image2)

Test case 1 was located by using the DTOA positioning model, and the DTOA was solved by using the classical Chan algorithm, resulting in an average error of 26.3549m. The results are shown in Figure 11.

![Figure 11. Comparison of the error between the improved TOA model and the DTOA model](image3)

![Figure 12. Box diagram of the improved TOA positioning and DTOA positioning model in this paper](image4)

From Figure 11 and Figure 12, the iTOA positioning model proposed in this paper has higher accuracy than the classic DTOA model in the indoor positioning. In general, iTOA can meet real-world needs, such as indoor navigation and crowd traffic analysis.

4. Conclusion

In this paper, an improved TOA positioning model that constrains the search space and introduces the NLOS error correction function was proposed. Compared to the traditional TOA positioning model, the proposed model is more adaptable than the classical location method considering the indoor location condition, and it has the advantages of simple calculation, fast convergence, and high positioning accuracy.

Simulation results show that the proposed algorithm has higher efficiency and robustness than the existing classical algorithms. However, this model only considers the given data in the standard test sample. In the future, we can continue to optimize the improved TOA model and consider more real-world application scenarios.
Xuyang Wang is a professor and Master’s tutor. Since 2008, she has been employed by Lanzhou University of Technology and has tutored more than 20 Master’s graduate students. She has also hosted and participated in the completion of a number of provincial-level research projects. Her main research areas are intelligent information processing, data mining, and knowledge engineering.

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