Real Time Tracking of the Position of Intelligent Logistics Cold Chain Transportation Vehicles Based on Wireless Sensor Networks

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Abstract. In order to more effectively track intelligent logistics cold chain transportation vehicles in real-time, This article proposes a real-time tracking algorithm for the position of intelligent logistics cold chain transportation vehicles based on wireless sensor networks. In the first stage, the received RSSI value of the anchor node is directly used for coarse positioning. In the second stage, the coarse positioning value is used as the initial solution optimization iteration of the wireless sensor network. In addition, this article also conducts research on the prediction and tracking of location nodes for smart logistics cold chain transportation vehicles, and discusses real-time tracking algorithms for EKF and wireless sensor networks. In view of the fact that EKF algorithm needs to abandon the information of higher order items of the system when approaching the nonlinear, which has caused error accumulation to some extent, the real-time tracking algorithm of wireless sensor network uses UT transformation and deterministic sampling strategy to linearly map the nonlinear system, which retains the information of the system to the greatest extent, and realizes effective prediction and real-time tracking of the nonlinear system.

Keywords: Wireless Sensor Network · Smart Logisticsm · Cold Chain Transportation · Vehicle Position Tracking

1 Introduction

In this paper, the wireless sensor network is used to track the location of intelligent logistics cold chain transport vehicles in real time, so as to timely understand the location information of cold chain transport vehicles. The smart logistics cold chain transport vehicle location real-time tracking method based on wireless sensor network has the characteristics of miniaturization and low price [1]. They have the characteristics of wireless communication and AD hoc network, which makes the smart logistics cold chain vehicle location real-time tracking method based on wireless sensor network has significant advantages over the traditional tracking method, which is reflected in the following aspects: (1) more precise tracking. Due to the dense deployment of wireless

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sensor network nodes and the characteristics of deeply embedded environment, it can realize the accurate perception, tracking and control of moving targets in close range, so as to obtain more detailed information about targets. (2) tracking can be opened. Wireless sensor networks have the characteristics of self-organization, self-configuration and intensive deployment, which makes the target tracking method of wireless sensor networks have higher reliability, fault tolerance and robustness. (3) Distributed tracking. The distributed nature of wireless sensor network makes real-time tracking based on its position without calculation and control, and reduces the risk of single point failure. It has the characteristics of small tracking delay and good scalability.

Wireless sensor network plays a huge advantage in the real-time tracking method of cold chain transport vehicle position in intelligent logistics, and has a better prospect and future because of its little overhead, low error and targeted data measurement ability.

2 Intelligent Logistics Cold Chain Transport Vehicle Location Real-Time Tracking Algorithm

2.1 Cost Analysis of Intelligent Logistics Cold Chain Transportation

There are many inevitable factors and unexpected situations in smart logistics cold chain transportation, such as weather conditions, traffic conditions, and sudden vehicle damage [2, 3]. These influencing factors have a certain impact on the transportation process in reality.

(1) Vehicle fixed cost.

Fixed costs include vehicle maintenance and repair costs, driver salaries, etc., which are necessary costs for using the vehicle. The formula for fixed cost is:

$$C_1 = \sum_{k=1}^{K} f_k \tag{1}$$

where, C_1 represents the Fixed cost of transport vehicles; f_k represents the fixed cost of car k; K represents the number of cold chain delivery vehicles, K represents the vehicle serial number $(1 \cdots k)$.

Driving cost refers to the cost of fuel consumption and passing expenses incurred during the transportation of goods. The formula of driving cost is as follows:

$$C_2 = \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha d_{ij}^{k} X_{ij}^{k} \tag{2}$$

Among them,

$$X_{ij}^{k} = \begin{cases} 1(\text{Cold chain delivery vehicle k from customer i to j}) \\ 0(\text{Cold chain delivery vehicle k does not go from customer i to j}) \end{cases}.$$

Where, C_2 represents the total transportation cost of all cold chain transportation vehicles; α represents the transportation cost per unit of transportation distance generated by transportation vehicles; d_{ij}^{k} represents the distance traveled by the k vehicle during the delivery process from customer i to j; N represents the customer Total Collection $N = \{i, j/i, j = 1, 2, \ldots, N\}$; X_{ij}^{k} represents the evaluation coefficient.

(2) refrigeration cost.

Cold chain transport vehicles will transport goods due to the particularity of transport products, vehicles in the process of driving and loading and unloading must ensure the quality of transport goods, because the goods must be in low temperature conditions to maintain product safety and quality, so each cold chain transport vehicle will use a certain fuel consumption to ensure the temperature state, resulting in a certain refrigeration cost, refrigeration cost formula is as follows:

$$C_3 = \sum_{k=1}^{K} \sum_{j=1}^{N} X_j^k Q_j \beta t_{ij} \tag{3}$$

Among them, $X_J^K = \begin{cases} 1(\text{The k vehicle serves customer j}) \\ 0(\text{The k vehicle does not serve customer j}) \end{cases}.$

Where, C_3 represents the total cooling cost generated by all vehicles in this experiment; β represents the refrigeration oil consumption price per unit product per unit time; t_{ij} represents the time for transportation vehicles from i to j; Q_j represents the total amount of fresh agricultural products ordered by customer j ($j = 1, 2, \ldots, N$); X_J^K represents the evaluation coefficient.

(3) Cost of goods loss.

Freight damage cost is an important cost expenditure in the process of cold chain transportation. Due to the characteristics of cold chain products, there is a certain loss rate of products due to temperature changes in the process of transportation and loading and unloading [4]. The formula of freight damage cost is as follows:

$$C_4 = \sum_{k=1}^{K} \sum_{j=1}^{N} p q_j X_J^K e^{-\phi - t_{jk}} \tag{4}$$

Among them, $X_J^K = \begin{cases} 1(\text{The k vehicle serves customer j}) \\ 0(\text{The k vehicle does not serve customer j}) \end{cases}.$

Where, C_4 represents the total cost of goods damage incurred by all delivery vehicles during the delivery process in this experiment; p represents the price of Cold Chain Goods; q_j represents the customer j's demand for goods ($j = 1, 2, \ldots, N$); ϕ represents the sensitivity coefficient of the quality of cold chain goods to time; t_{jk} represents the time when the k transport vehicle arrived at customer point j.

(4) Time window penalty cost.

Penalty cost refers to the penalty cost incurred when the delivery vehicle fails to arrive at the distribution point in time according to the customer's time requirements [5].

The formula of penalty cost is:

$$C_5 = P\left(t_j^k\right) = \begin{cases} M, t_j^k < t_1 \ \text{ or } \ t_1 > t_4 \\ \theta_1\left(t_1 - t_j^k\right), t_1 < t_j^k < t_2 \\ 0, t_2 \le t_j^k \le t_3 \\ \theta_2\left(t_j^k - t_3\right), t_3 < t_j^k < t_4 \end{cases} \tag{5}$$

where, C_5 represents the total penalty cost of all transportation vehicles during the delivery process in this experiment; t_1 represents the earliest time that customers can accept vehicles transporting goods to reach the delivery point; t_2 represents the earliest time the customer requires the vehicle to deliver the goods to reach the delivery point; t_3 represents the customer requests the latest time for the vehicle transporting the goods to reach the delivery point; t_4 represents the latest time that customers can accept vehicles transporting goods to reach the delivery point; θ_1 represents the penalty coefficient for vehicles transporting goods reaching the delivery point is between t_1 t_2; θ_2 represents the penalty coefficient for vehicles transporting goods reaching the delivery point is between t_3 t_4; θ_1, θ_2 is the parameter, and its value depends on customers' demand for delivery time; M is a larger positive number. The time outside t_1 t_4 refers to the time when the customer does not accept the goods. The arrival of the vehicle within this interval requires paying a large penalty fee or being rejected by the customer; t_2 t_3 is the customer's ideal distribution time range. When the delivery vehicle arrives within this period, no penalty fee will be paid; t_1 t_2 and t_3 t_4 are the time range within which the customer can accept the delivery of the vehicle, subject to the payment of penalty charges. When the delivery vehicle arrives within the t_1 t_2 range (earlier than the ideal delivery time), it will not have a significant impact on product quality and sales, and the impact factor is relatively small; When the delivery vehicle arrives within the t_3 t_4 range (later than the ideal delivery time), it has a significant impact on the freshness of the goods and has a significant impact factor.

2.2 Real Time Tracking of Vehicle Position Nodes in Wireless Sensor Networks

The first step is to measure the distance. Distance measurement is the basis of real-time tracking algorithm for intelligent logistics cold chain transport vehicles based on wireless sensor network [6–8]. The accuracy of distance measurement will directly affect the accuracy of positioning results of such algorithms. In practical application, there are many methods for distance measurement [9]. At present, the commonly used methods include Time of arrival (TOA), Time Difference of arrival (TDOA), There are three Received signal strength indications (RSSI).

(1) Time of Arrival (TOA).

The basic principle of this method is that the sending node sends the ranging signal to the receiving node, and the receiving node uses the transmission time and speed of the signal to calculate the distance between itself and the sending node. TOA is currently one of the most widely used ranging methods [10, 11]. The commonly used ranging signals include acoustic signals and radio frequency signals. The TOA method has high ranging accuracy, but it requires precise clock synchronization and high-precision clock frequency from both the transmitter and receiver, thus requiring high hardware requirements for sensor nodes [12]. Recently, due to the emergence and development of UWB technology, TOA technology has broader application prospects.

(2) Arrival time difference (TDOA).

In the TDOA ranging mechanism, the sending node simultaneously sends two wireless signals with different propagation speeds, and the receiving node calculates the distance from the sending node to itself according to the time difference between the arrival of the two signals and the propagation speed of the two signals [13–15]. This works as shown in Fig. 1.

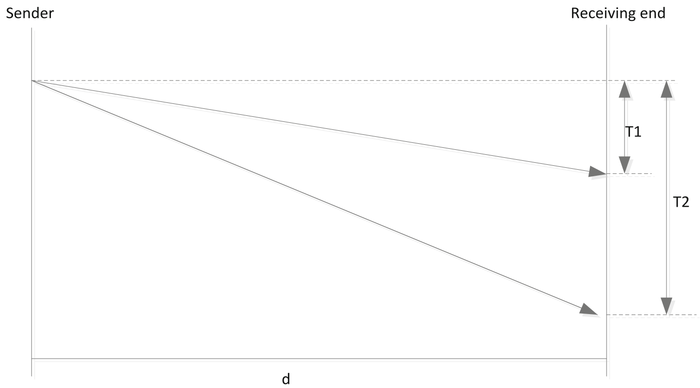

Fig. 1. TDOA measurement principle diagram

The distance between two nodes can be calculated according to (6):

$$d = (T_2 - T_1)\frac{v_1 v_2}{v_1 - v_2} \tag{6}$$

Among them, T_1, T_2 and v_1, v_2 represent the transmission time and speed of the two signals, respectively.

The ranging accuracy of TDOA technology is higher than that of TOA method, but additional hardware equipment must be installed at the node. In practical applications, the two types of signals commonly selected for transmission are electromagnetic waves and ultrasonic waves. Nodes must install ultrasonic transceivers, which greatly increases the cost and power consumption of nodes. In addition, ultrasonic signals are easily affected by the environment, and humidity, temperature, and wind speed can all affect the accuracy of measurement.

(3) Received signal strength (RSSI).

The idea of RSSI ranging is that the receiving node measures the power intensity of the received signal and calculates the distance information according to the strength of the received signal according to the path loss model. The calculation formula is as follows:

$$d = d_0 * 10^{(RSS_0 - RSS)/10n_p} \tag{7}$$

Among them, represents the signal strength received by RSS, RSS_0 represents the signal strength after transmitting a reference distance d_0, and n_p is the path loss index, which varies according to the surrounding environmental conditions and is generally taken as 2–4.

The strength of the received signal can be obtained directly by the node without additional hardware equipment. At the same time, the method requires the least calculation in the actual ranging process, and the distance estimate can be obtained only by looking up the comparison table of signal strength and distance or by estimating according to the fitting curve. Therefore, the application of this method is studied the most. However, this method also has its shortcomings. For example, drawing the fitting curve requires a lot of preparation and measurement work, and this method is sensitive to the environment. Changes in environmental factors will cause large positioning errors in the data model obtained in advance, so it must be re-measured, which increases the workload.

The above three ranging methods have their own advantages and disadvantages, and can be flexibly selected according to the required positioning accuracy in practical applications. When high accuracy is required, TDOA method is generally chosen, but this method requires high energy consumption and cost; When the accuracy requirement is not high, choose the RSSI method, which is simple to implement and does not require additional equipment.

After using the vehicle position real-time tracking algorithm proposed in this article to calculate the estimated value of the target node, it is used as the initial position of each target node for iterative optimization based on the initial value. The algorithm process is as follows:

(1) Initialize the population.

The estimated value obtained in the first step is used as the initial solution of the population to find the optimal solution. Based on the initial solution, the population is initialized using the uniform distribution function.

Assuming that the coordinate of the target node obtained by the weighted centroid algorithm based on RSSI is $A_0(A_{0x}, A_{0y})$ in the first step, it is taken as the initial solution to initialize the population, and the initial value is added to improve the performance of the evolutionary algorithm, reduce the computing time and improve the efficiency.

Using the uniform distribution probability function, the population is initialized as:

$$\begin{aligned} X_{1i,G} &= rand[0, N(0,1)(B-A)](B-A) + A_{0x} \\ X_{2i,G} &= rand[0, N(0,1)(B-A)](B-A) + A_{0y} \end{aligned} \tag{8}$$

where, A and B are variable boundaries that utilize the distance between the target node and the anchor node; $N(0, 1)$ represent a standard Normal distribution.

(2) Mutation operation:

In numerous literature, through extensive experimental function testing, it has been found that different modes of differential evolution algorithms have certain differences in simulation performance. However, a large number of experiments have shown that Mode 1 and Mode 4 have the best performance, but Mode 1 is simpler compared. Therefore, in this algorithm, we chose the standard DE algorithm, which is the mutation mode using:

$$V_{i,G} = X_{1i,G} + F * \left(X_{1i,G} - X_{2i,G}\right) \tag{9}$$

In the equation, F represent the coefficient of variation.

(3) Cross operation:

The crossover operation is to increase the diversity of the newly generated population. According to the newly generated individual $V_{i,G+1}$, part of the code is exchanged between the old and new individuals according to the crossover strategy, so as to form a new individual.

Three different individuals r_i are randomly selected in the population, and a random index $R = (1, 2, \cdots, N)$ is selected. For each i $U(0, 1)$, the following operations are performed:

$$u_{ji,G+1} = \begin{cases} V_{ji,G+1}, j = i \\ X_{ji,G+1}, j \neq i \end{cases} \tag{10}$$

The formation of new individuals:

$$U_{i,G+1} = \left(u_{1i,G+1}, u_{2i,G+1}, \cdots, u_{ji,G+1}\right)$$

In order to determine whether the newly generated individual $V_{i,G+1}$ will be left to participate in the evolution of the new generation $G + 1$ or eliminated, a selection operation is carried out.

Calculate the fitness function of $U_{ji,G+1}$ and $X_{ji,G+1}$ respectively, and compare their values according to the following formula to determine the survival of the fittest.

If $f\left(X_{ji,G+1}\right) < f\left(U_{ji,G+1}\right)$, $X_{ji,G+1}$ will be eliminated, but instead $U_{ji,G+1}$ will enter the next generation.

(4) Set the fitness function to

$$f = \sqrt{(x_m - x)^2 + (y_m - y)^2} - d \tag{11}$$

In Formula (11), (x_m, y_m) is the coordinate value of the anchor node with the largest RSSI value, (x, y) is the vector involved in evolution, and d is the distance calculated according to the RSSI value.

In this way, after the completion of the set number of iterations, the output is the optimal solution, that is, the exact coordinates of the target node. Of course, the larger the number of iterations, the more accurate the value will be, but at the same time, it will increase the amount of calculation. Generally, 30~50 times of generation selection will be selected.

In summary, the real-time location tracking algorithm of wireless sensor network can more accurately calculate the real-time location information of intelligent logistics cold chain transport vehicles.

3 Experimental Analysis

3.1 Analysis of Real-Time Tracking Algorithms for Wireless Sensor Networks

For the establishment of target tracking simulation model, the nonlinear dynamic model is adopted. In this model, it is assumed that the target node only moves along the x-axis direction, then the dynamic null of this model can be expressed as:

$$x_{k+1} = \alpha x_k + \beta \frac{x_k}{1 + (x_k)^2} + \gamma \cos(1.2k) + w(k) \tag{12}$$

Simultaneously construct its observation equation as follows:

$$z_k = \frac{(x_{k+1})^2}{20} + v(k) \tag{13}$$

Among them, $x(k)$ represent the movement distance of target node k; $\gamma \cos(1.2k)$ are the loading terms of the system, $w(k)$ is the noise level of the state equation, and $v(k)$ is the noise level of the observation equation; α,β and γ represent parameter factors separately.

In the simulation experiment, the real-time tracking algorithm of wireless sensor networks is used for symmetric sampling strategy. Before testing, the effectiveness of the proposed method is verified and relevant experimental parameters are set as shown in Table 1.

Table 1. Parameter Settings

Parameter	Value
α	0.5
β	2
γ	8
Total time step N	100
$w(k)$ variance of noise level of Equation of state	4
The noise level $v(k)$ variance of the observation equation	0.04

Next, real-time tracking simulation will be conducted based on the above parameter settings. The tracking simulation results without parameter adjustment and after adjustment, as well as the tracking error, are shown in the following figure.

From Figs. 2 and 4, it can be seen that there is a significant difference between the tracked trajectory and the true trajectory of the target node before parameter adjustment. However, after appropriate parameter adjustments are made to the real-time tracking algorithm of the wireless sensor network, the filtering trajectory of the real-time tracking algorithm of the wireless sensor network is basically consistent with the true trajectory of the target node, achieving good tracking results.

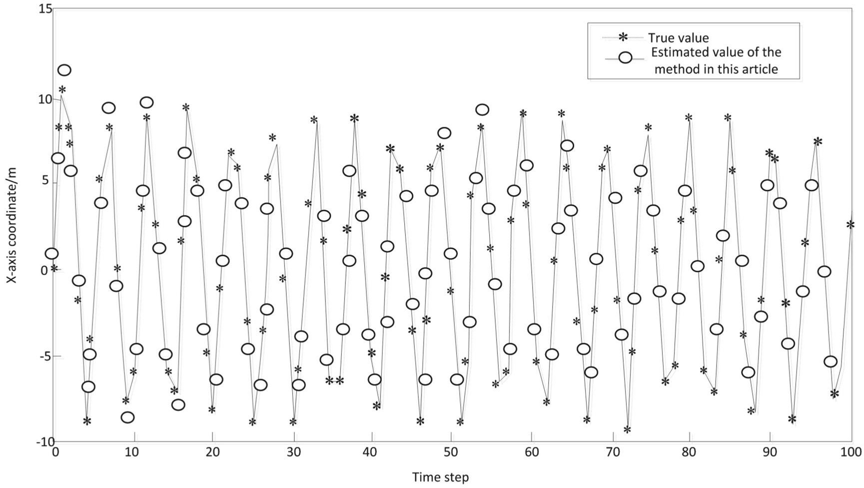

Fig. 2. Real time tracking simulation diagram

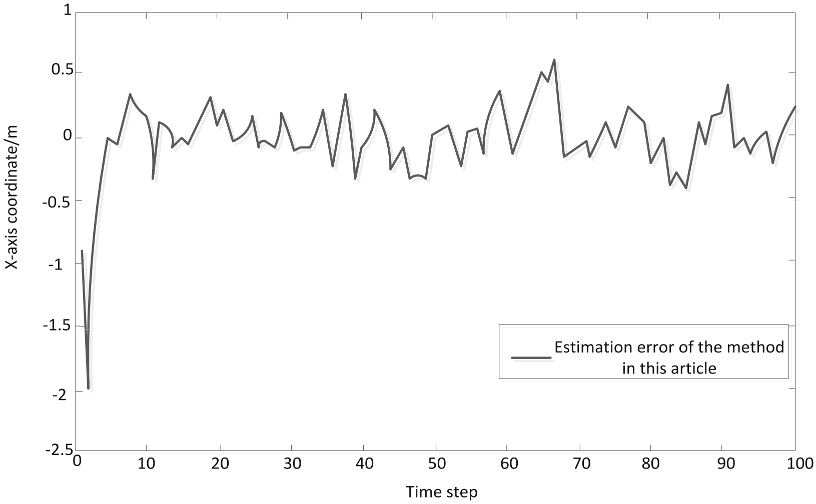

Fig. 3. Real time tracking error diagram

From Figs. 3 and 5, it can be seen that before parameter adjustment, the tracking prediction error fluctuates between [−2, 0.5], with a large fluctuation amplitude. However, after appropriate parameter adjustment of the real-time tracking algorithm for wireless sensor networks, the tracking prediction error fluctuates between [−0.5, 0.5], and the fluctuation fluctuation is small. Based on the above results, it can be concluded that the real-time tracking algorithm filtering algorithm based on deterministic symmetric sampling in wireless sensor networks has high tracking accuracy, can achieve efficient prediction and tracking in nonlinear models, and is effective.

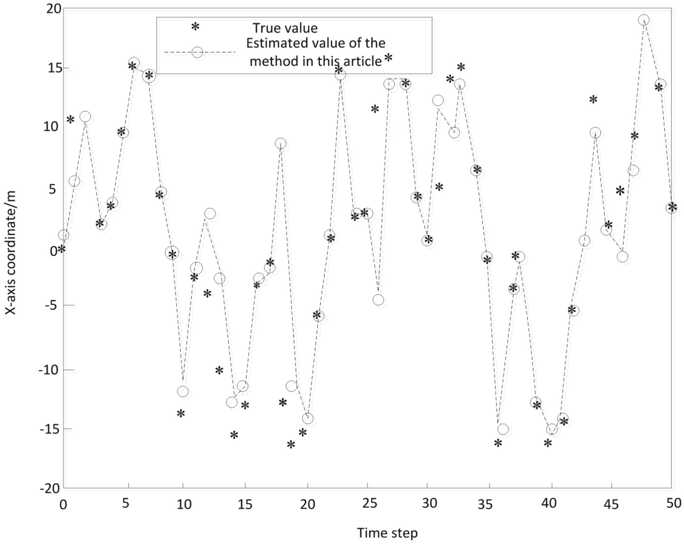

Fig. 4. Real time tracking simulation diagram with time step size = 50

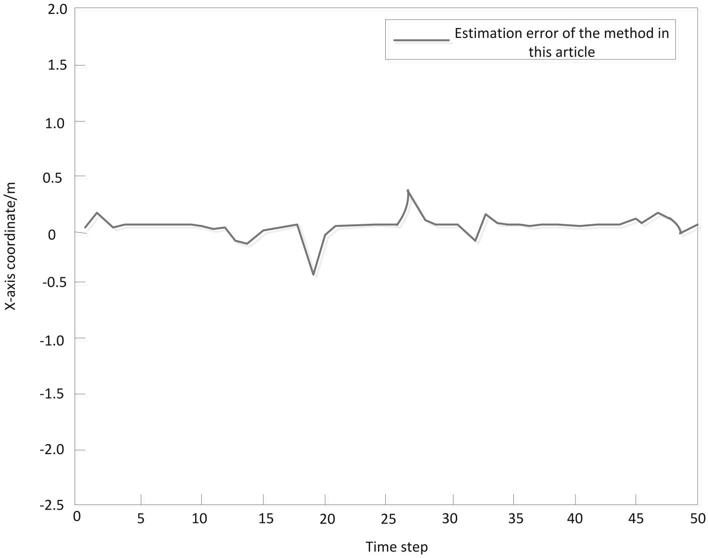

Fig. 5. Real time tracking error chart with time step size = 50

3.2 Comparison Simulation Experiment Between Real-Time Tracking Algorithm and EKF of Wireless Sensor Network

Next, to further verify the superiority of the proposed real-time tracking algorithm for wireless sensor networks, the real-time tracking algorithm for wireless sensor networks and the tracking performance of EKF on the same system model are analyzed. The results are shown in the following figure.

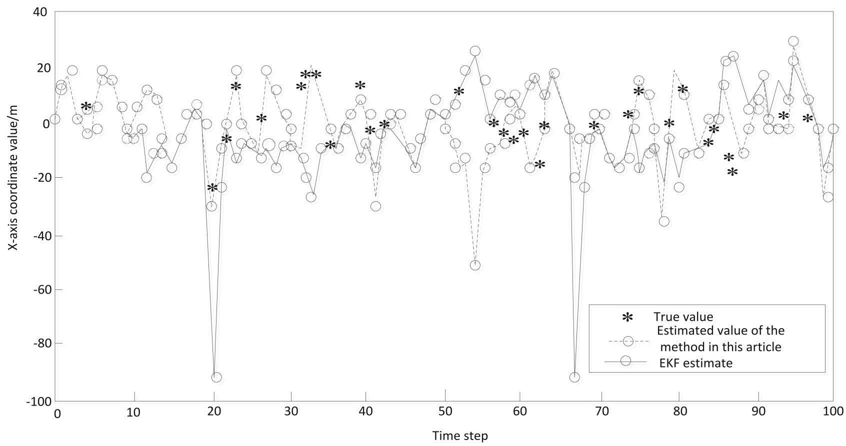

Fig. 6. Simulation of Real Time Tracking Algorithm and EKF Comparison for Wireless Sensor Networks with Time Step = 100

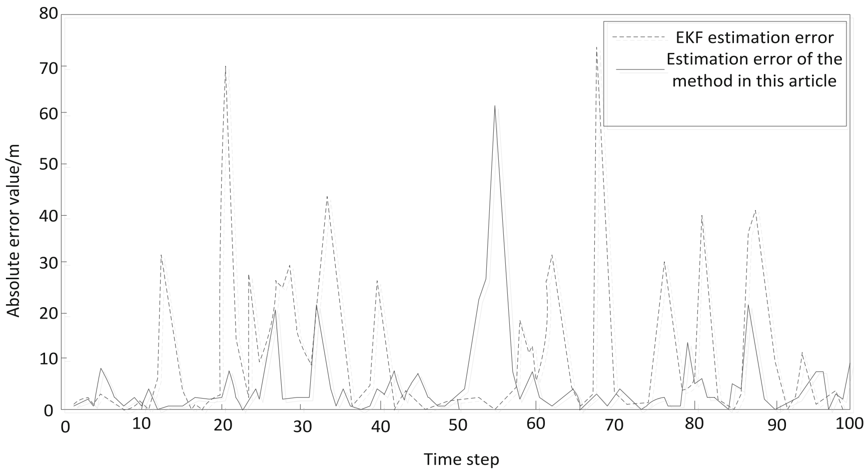

Fig. 7. Comparison error diagram of real-time tracking algorithm and EKF for wireless sensor networks with time step size of 100

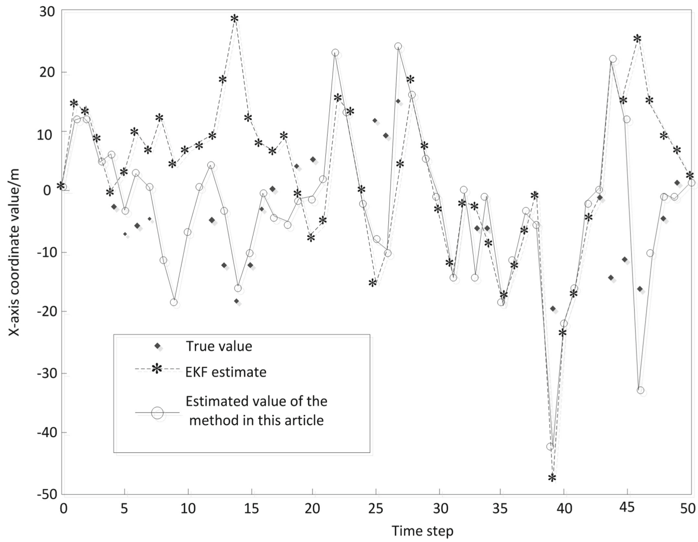

Fig. 8. Simulation of Real Time Tracking Algorithm and EKF Comparison for Wireless Sensor Networks with Time Step = 50

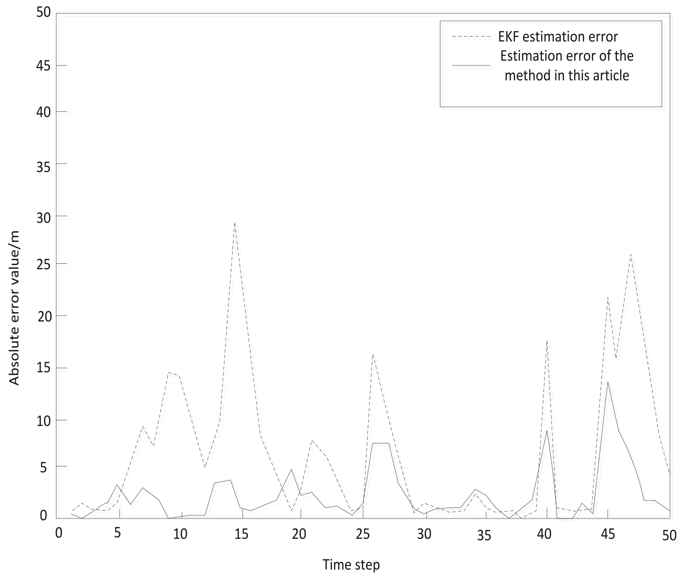

Fig. 9. Comparison error diagram of real-time tracking algorithm and EKF for wireless sensor networks with time step size of 50

Figure 6 and Fig. 8 respectively compare the tracking simulation effects of the system model with the time of 100 and 50. From the figure, it can be seen that in both cases, the real-time tracking algorithm of wireless sensor networks generally outperforms the

EKF algorithm in terms of tracking performance, and its tracking trajectory is closer to the actual trajectory, indicating that the real-time tracking algorithm of wireless sensor network adopts definite line sampling and UT transform to overcome the nonlinear transmission in EKF algorithm to a certain extent, and also proves that UT transform can describe the nonlinear characteristics of the system more accurately by using symmetric sampling strategy.

Figure 7 and Fig. 9 show the tracking errors for two scenarios with time steps of 100 and 50, respectively. It can be seen that there are errors in both the real-time tracking algorithm of wireless sensor networks and EKF in the tracking and prediction process, regardless of the scenario. However, compared to the two methods, the proposed method can effectively reduce tracking error, which can be controlled below 15. Although the EKF algorithm can also reduce the error, its error control results are still higher than the proposed method. Therefore, it indicates that the real-time tracking algorithm of wireless sensor networks has achieved more accurate predictions with smaller overall errors.

4 Conclusion

Although the real-time location tracking algorithm of intelligent logistics cold chain transport vehicle based on wireless sensor network proposed in this paper improves the accuracy of target tracking to a certain extent, it also has the following deficiencies:

In the real-time tracking algorithm of wireless sensor networks, due to the dependence on the initial solution proposed by coarse positioning, it is necessary to select the appropriate fitness function and parameters to make the algorithm converge quickly and find the optimal solution accurately. The next goal of real-time tracking algorithm of wireless sensor network is to use the existing limited resources, reduce the system energy consumption, improve the tracking accuracy and robustness of the algorithm. The research in three-dimensional space still needs to be strengthened. The location node tracking algorithm of intelligent logistics cold chain transport vehicles needs to be further improved to optimize the tracking efficiency.

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