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Vehicle Wireless Location Fusion Algorithm in Highway Vehicle Road Collaborative Environment

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Abstract: As the core technology for the development of intelligent transportation systems, vehicle-road collaboration technology also plays a key role in improving the safety of people and vehicles in the transportation system. This paper mainly studies the fusion algorithm of wireless positioning of vehicles in the coordinated environment of highway vehicles and roads. In the experiment, the model is adjusted using experimental data in a coordinated environment between vehicles and roads. By analyzing the applicability of the wireless positioning method in the coordinated environment of vehicles and roads, a wireless positioning method suitable for vehicle positioning research is selected. Then, select the appropriate positioning performance evaluation index to evaluate the positioning accuracy. The input and output of the simulation system are determined by analyzing the requirements of the simulation platform based on the functions of the Internet of Vehicles environment BRT simulation platform and the system engineering perspective. First, acquire a video image, perform grayscale and noise removal processing on the image, and perform an image histogram operation. Experimental data shows that the proposed vehicle wireless positioning fusion algorithm can locate vehicles in the actual road environment. When the accuracy rate is 67%, the accuracy is 46.31m; when the accuracy rate is 95%, the accuracy is 122.53m. The results show that the vehicle positioning algorithm can improve traffic efficiency and safety to a certain extent, and can delay traffic congestion when the vehicle density is oversaturated.

1. Introduction

Under the background that the traffic conditions of urban roads are deteriorating day by day, the operation status of expressway system has also received great negative impact. At present, GPS, Beidou, base station, WiFi and other mature positioning technologies are common. However, with the development of electronic chips, embedded systems, micro communication systems and sensors, wireless sensor network (WSN) gradually occupies an important position in the field of data perception and data acquisition with its advantages of low cost, simple implementation, strong stability and self construction.

For most of its applications, how to obtain accurate, stable and continuous vehicle position information is an important prerequisite for its function. Therefore, the research of vehicle location technology is very important to the development of intelligent transportation system (ITS), and is one of the basic key technologies. Vehicle wireless positioning technology can effectively promote the construction of LBS based traveler service information in China's its field, and provide more comfortable and convenient information service for travelers in the complex urban traffic environment. It has important practical significance to improve the traffic support of large and medium-sized cities in China.

Ismail A H uses fingerprint technology in the indoor wireless positioning system for mobile robots. The realization process is divided into two stages: offline that is, collecting the reference data of the database; and online, that is, matching the unknown data with the data in the database. He introduced the Signal Propagation Modified Shepard Method (SP-MSM), which constructs a database by interpolating missing wireless data (used in mobile robot applications). He can determine the reference position and build a database by introducing the selection probability. Although his research is more accurate, it is not very maneuverable [1]. Gikas V proposes a relatively low-cost indoor parking facility management system, which is a combined solution of RFID/WiFi and MEMS IMU monitoring solutions. He proposed the RFID positioning module in the form of a virtual door. To define such a virtual door, he can place an RFID tag or reader in a known location throughout the area of interest. He also proposed CoO technology to determine the location of vehicles in multi-storey parking lots. WiFi is used to monitor passing vehicles and reduce the distance until the tag can detect the user reader again. Therefore, a combined positioning solution of RFID and WiFi is realized. As a complement to the proposed RFID/WiFi system, he examined the potential and limitations of MEMS IMU sensors (ie accelerometers, gyroscopes and barometers) commonly found in modern smartphones. Although his research is relatively comprehensive, there are still many flaws [2]. Chen L believes that digital television (DTV) signal has been recognized as a promising signal for navigation and positioning. However, due to the single frequency network (SFN) transmission in the European standard digital video broadcasting terrestrial (DVB-T) system, transmitter confusion occurs in navigation and positioning, resulting in the receiver unable to know which transmitter received the signal. Considering the problem of transmitter confusion in DVB-T SFN network, he proposed a joint radio location and emitter identification algorithm based on expectation maximization method. In the case of receiving signals from three to five transmitters, he tested the proposed algorithm. His research lacks necessary experimental data [3].

Aiming at the error types of distance measurement based on signal strength, corresponding distance error diagnosis methods and correction methods are proposed respectively. By analyzing the accuracy of two types of wireless positioning methods based on ranging and non-ranging, a vehicle wireless positioning fusion algorithm that uses error weighting to eliminate line-of-sight and non-line-of-sight errors is proposed. Using the experimental data in the outfield vehicle-road collaborative environment, the positioning accuracy of the positioning fusion algorithm was compared and verified, and the sensitivity of the distance propagation model parameters to the positioning error of the fusion algorithm was analyzed.

2. Vehicle Wireless Positioning Fusion Algorithm

2.1 Vehicle-Road Cooperation System

Assuming that the traffic control center can predict the trigger time of all bus signal priority and the time interval of bus arrival at the intersection in the same cycle, the single-phase multi-conflict signal priority problem is modeled as a dynamic programming model. Simulation experiments show that, compared with the first-come-first-served model, the dynamic programming model can serve more TSP requests, improve the punctuality of public transport vehicles and reduce the negative impact on social vehicles [4]. The vehicle-to-vehicle communication link is realized by dynamic networking in a wireless network. Use a network composed of vehicle-mounted units in a small area to exchange traffic information between the networks, or you can also use this network to expand information on the Internet. The OBU carried by the vehicle can complete its own dynamic information transmission, such as position, vehicle speed, steering and braking status. The transmission of this information can effectively provide reliable data support for subsequent active safety and intelligent driving [5]. The vehicle-to-road communication link is the key data exchange link of CVIS. Vehicle-vehicle can form a dynamic wireless network through each OBU, and RSU is also an organic part of the vehicle-vehicle dynamic network. That is, the dynamic network is a wireless network system covering a certain range, and the OBU or RSU in this range is a part of the dynamic network. The vehicle-to-road communication link mainly realizes the collection of vehicle information and the transmission of traffic control information by the RSU, and the OBU receives traffic control information from the RSU [6].

2.2 Internet of Things and Virtual Reality

The Internet of things involves all sectors of society. How to realize the transmission and sharing of information among these industries requires a unified interface, communication specifications and guidelines. Therefore, standardization is one of the key issues in the Internet of things, and the standardization process will greatly affect the degree of application of the Internet of things in social production and life. No matter how the Internet of things technology develops, sensor technology and network communication technology are the most critical technologies, because they represent the most basic functions, including data acquisition and transmission. The network communication technology in the Internet of things mainly realizes the information transmission of sensor nodes and the transmission and sharing of data in a large range [7].

The structure of IOT is generally divided into three layers: perception layer, network layer and application layer. Among them, the perception layer includes WSN, camera, RFID, sensor, etc, which can perceive, identify and collect information. The network layer mainly includes radio and television network, Internet, telecommunication network and various private networks, which can process and transfer the information obtained by the perception layer. The application layer is to realize intelligent application in smart home, medical care, military war and other fields through the combination of actual demand and Internet of things technology. In the field of intelligent transportation, many services are based on the collection of vehicle real-time location information, mainly through the installation of GPS receiver on the vehicle to achieve positioning, tracking, and provide navigation services. In addition, it can collect traffic information in real time and transmit it to vehicle users, so that users can bypass the traffic jam section and choose a smooth route [8-9].

When a traffic accident occurs, it can be handled and rescued timely according to the location information of the vehicle, so as to reduce the death rate of the traffic accident. As the nodes need to communicate, calculate and store when positioning in the Internet of things, it will cause energy consumption. The energy efficiency of the node will reduce the service life in the case of high-power consumption. Once the nodes fail due to energy depletion, the accuracy of communication and positioning between nodes will be affected. Therefore, it is necessary to reduce the power consumption as far as possible while ensuring the positioning accuracy [10]. For the ideal virtual reality technology should have all the perceptual characteristics of human body. However, due to the limitations of related technologies, especially the limitations of biosensor technology, the perception function of virtual reality technology is only simple perception of hearing, touch, vision, motion perception and so on. Positioning in virtual reality also needs hardware implementation and expression in the computing scene. Among the technologies that can be used in the Internet of things, UWB technology can obtain the highest theoretical positioning accuracy. Ultra-wideband signal has the advantages of extremely short pulse duration and high time resolution, which is very suitable for precise ranging and positioning [11].

2.3 Wireless Positioning Fusion Algorithm

The router is mainly used as a transfer station for data transmission. When the ZigBee network is used for sensor data collection, both the router and the terminal node are counted as the underlying module. The sum of the number of routers and the number of terminal nodes is less than the carrying capacity of the network, although router nodes can also be carried Sensors collect data, but this will consume more power. Therefore, the use of routers in a network should be selected according to actual needs. If the coverage area of the network is not high, a small number of routers and multiple terminal nodes can be used. If you need to cover a larger area, you can choose the mode that the router is also equipped with sensors [12]. When the ZigBee network is used for wireless sensor network positioning, the router node is generally used as a beacon node and is fixedly placed in the positioning area to form a positioning network. The mesh network consists of a coordinator and multiple terminal nodes. Unlike the star network, each terminal node in the mesh network can be used as a routing node, so the mesh network needs to have a cluster head election algorithm. The node with higher energy is selected as the cluster head node. The cluster head node not only collects sensor data but also forwards the data forwarding of the terminal nodes in the cluster, and the cluster head nodes can forward data to each other, such as close to the coordinator. The farther cluster head can transmit data to the coordinator through the forwarding of other cluster head nodes. The advantage of this method is to ensure that every node in the network can collect data and ensure the coverage area of the network. The disadvantage is that frequent elections of cluster heads will cause unnecessary energy waste and increase the communication burden of cluster head nodes. This leads to a reduction in the battery life of the cluster head node [13-14].

Assume that N incoherent narrowband signals are projected onto a uniform linear array composed of M array elements. The covariance matrix of the received signal can be expressed as:

$$R_x = E[X(t)X^H(t)] = AE[SS^H]A^H + AE[SN^H] = E[NS^H]A^H + E[NN^H] \tag{1}$$

Assuming that the signal and noise are independent, and the noise is Gaussian white noise with zero mean and variance σ^2, that is, $E[NN^H] = \sigma^2 I$, the above equation can be simplified as:

$$R_x = AR_sA^H + \sigma^2 I \tag{2}$$

Where R_s is the covariance matrix of the incident signal. TDOA is a technology derived from TOA. Its main advantage is to overcome the problem of electronic clock time synchronization, that is, it does not require a strictly synchronized electronic clock [15]. Assuming there are two signals with different propagation speeds, the calculation formula for distance R is as follows:

$$R = \left|(T_4 - T_3) - (T_2 - T_1)\right| \times \frac{V_2 - V_1}{V_2 \times V_1} \tag{3}$$

In the formula, V1 and V2 are the propagation speeds of the two signals respectively.

Because only the connectivity of the network needs to be obtained, the convex programming method has low requirements for node hardware, and does not need to consume too much cost for the provision of high-performance measurement components. Generally, the convex programming method requires a large density of known nodes in the experiment. When the density of known nodes in the network reaches about 20%, the positioning accuracy of the algorithm can reach 85%. In order to ensure that all unknown nodes in the network can enter the public convex set formed by known nodes, it is necessary to arrange more known nodes at the edge of the reward network in order to obtain higher positioning accuracy. The positioning server, sensors, and target nodes together constitute an infrared positioning system [16]. The target tag can emit infrared rays at regular intervals, and the infrared signal carries the unique identification number of the target node. The sensor receives the infrared signal of the target node and transmits the collected information to the server. The nearest neighbor algorithm is used to estimate the position of the target node. The position of the sensor that can receive the infrared signal is the position of the target signal, that is, the positions of the two are considered to be coincident. Display the location of the target node in the application of the positioning server [17].

3.4 Formalization of Vehicle-Road Collaborative Environment

(1) Definition of objective function

The objective function f of this article is to maximize the number of passengers (that is, minimize the number of unsuccessful vehicles), minimize the total cost of the vehicle, minimize the total time of vehicle operation, and minimize the probability of sudden accidents on the vehicle driving route. The weights α , β , γ , and δ are the relative importance coefficients of the four components.

$$f = \min \alpha(n - ar) + \beta \sum_{j \in F} Cost_j + \gamma \sum_{j \in F} Duration_j + \delta Accident_j \tag{4}$$

(1) Definition of constraints

1) Vehicle capacity constraints

When the vehicle is running, the number of passengers on board cannot exceed the limit of the carrying capacity of the vehicle, then:

$$p_x^j = initp_j, x \in F^+, j \in F \tag{5}$$

$$p_x^j = initp_j, x \in F^-, j \in F \tag{6}$$

$$p_x^j \leq P_j, x \in P, j \in F \tag{7}$$

Where formula (5) represents the initial number of passengers carried by vehicle j when it departs from the starting point, and formula (6) represents that when the vehicle reaches the end point, after all passengers have got off, the number of passengers carried by the vehicle is the same as at the starting point, $initp_j$ is The initial number of passengers; formula (7) indicates that the total number of passengers in the vehicle cannot exceed the upper limit of the vehicle capacity.

2) Constraint on service times

For a passenger who can only be served by one car, that is, only one car can be carried, then:

$$\sum_{j \in F} \sum_{y \in U} X_{x,y}^j \leq 1, x \in N \tag{8}$$

$$\sum_{j \in F} \sum_{x \in U} X_{x,y}^j \leq 1, y \in N \tag{9}$$

Equation (8) indicates that the in-degree of the passenger's starting point x and the initial degree of the end point y are both maximum 1, that is, the maximum number of times the passenger's getting on and off point is served is 1.

3) Time constraints

The passenger's boarding time must be earlier than the passenger's getting off the bus, and the passenger's getting off the bus must be earlier than the upper limit of the time window of the getting off point.

$$TC_x^j + RT_x \le TC_{m+n+x}^j, x \in N^+, j \in F \tag{10}$$

To ensure that passengers are successfully carried, passengers must be allowed to board at the pick-up point, and they must get off at the drop-off point, that is, the vehicle must pass both the passenger's boarding point and the drop-off point.

$$\sum_{y_1 \in U \setminus \{x\}} X_{x,y_1}^j - \sum_{y_2 \in U \setminus \{m+n+x\}} X_{y_2,m+n+x}^j = 0, x \in P^+, j \in F \tag{11}$$

The time when the vehicle arrives at the point where passengers get on and off must be within the time window of the corresponding vehicle's point of getting on and off, otherwise the loading fails, namely:

$$e_x \le TC_x^j \le I_x, x \in N, j \in F \tag{12}$$

In reality, the time when the vehicle arrives at the passenger boarding point can be earlier than the lower limit of the time window of the passenger boarding point. However, in this case, the vehicle must wait for a certain period of time, and the constraint condition (Equation 12) can be modified as :

$$TC_x^j \le I_x, x \in N, j \in F \tag{13}$$

In the driving route of the vehicle, the starting point and ending point of the vehicle cannot be changed, and it must be ensured that the vehicle departs from the starting point to the end point.

$$\sum_{y \in p^+} X_{d_j^+,y}^j = 1, j \in F, d_j^+ \in F^+ \tag{14}$$

$$\sum_{y \in p^-} X_{x,d_j^-}^j = 1, j \in F, d_j^- \in F^- \tag{15}$$

The formula (14) guarantees that the vehicle must start from the starting point, and the formula (15) guarantees that the vehicle must reach its destination.

3. Simulation Experiment of Vehicle Wireless Positioning Fusion Algorithm in a Vehicle-Road Collaborative Environment

3.1 Model Parameters

The model in the experiment is adjusted using experimental data in a coordinated environment of field vehicles and roads. When the experimental vehicle is driving around a fixed base station, the base station sends the signals received by the collected vehicle during operation. The signal contains information such as RSSI value, GPS latitude and longitude. The GPS positioning data of the experimental data has high accuracy, so the GPS positioning track is used to adjust the model. Select the RSSI value corresponding to the GPS data at a specific time, calculate the actual distance between the nodes, and complete the recalibration of the model. The relevant parameters of the model fitting formula are shown in Table 1. The logarithmic distance propagation model is used, and the absolute distance between nodes is calculated based on the RSSI value. Choose the wireless positioning method of the suitable vehicle to determine the vehicle [18-19].

Table 1: Model related parameters

Model parameters	Calibration result
Environmental factor A	180.61
Path loss factor n	8.19
Correlation coefficient R2	0.94

3.2 Experimental Platform

Using VISSIM micro-simulation software, combined with the Visual Studio 2010 software compilation platform, and based on the VISSIM COM secondary development interface, a BRT simulation platform under the car networking environment is constructed. This platform can repeatedly test, evaluate and optimize the BRT collaborative control model [20].

3.3 Vehicle Inspection

(1) Haar feature analysis

First of all, Haar features intelligently describe some simple gray structures in specific directions (such as horizontal, diagonal, and vertical), but facial features are often not represented by Haar features in these simple and specific directions; secondly, Haar features can well describe some symmetrical faces, and cannot well represent faces with a certain angle [21].

(2) Adaboost algorithm

The Boosting algorithm can combine multiple classifiers with weaker classification effects into a strong classifier with good classification effects in some way. This method can transform a rule with weak classification accuracy into a high-precision classification rule. The final strong classifier is performed through a voting mechanism through multiple weaker classifiers [22-23]. The specific algorithm is as follows:

1) A weak classifier h1 is obtained by training on N samples.

2) Add the misclassified samples in h1 and other sample sets to obtain a sample set containing N samples and obtain another weak classifier h2 through training.

3) Combine the misclassified samples in h1 and h2 with other samples into another sample set containing N samples and obtain the third weak classifier h3 through training.

In the process of vehicle detection, because the vehicle pictures in each direction are very different, if the sample pictures in each direction are uniformly trained to obtain a classifier, the classifier can be used to detect the pictures in the video image sequence. In the process of the experiment, it will be found that the training time of training a unified classifier is increased. When the vehicle is detected with the classifier obtained by this training, the detection time of the vehicle will also increase, and it will also cause vehicle detection. There have been many false positives and false negatives. On the other hand, for each specific haar feature, it cannot be well matched to vehicles traveling in each direction, so according to the different driving angles of the vehicle, different haar features are used for training to obtain different detection classifiers [24-25].

3.4 Data Extraction

In the first stage of data association, the application layer data and vehicle WIFI record data are associated. The key of association is to correspond to the IP address of roadside node in the application layer data and the MAC physical address of the source roadside node in the vehicle WIFI record data. In the second stage of data association, the matched time and signal strength data are filtered. In order to increase the accuracy of positioning, the data used in this study is based on the requirements of traditional RSS positioning data, only considering the points that receive three or more roadside node signals at the same time. Because the original Microsoft data receives less signals at the same time, the data processing in this study considers increasing the time interval of 1 second, that is, taking seconds as the unit. The signal strength of each roadside node received in each second is counted. If more than one signal strength is received in the same second, the average value is taken. The third stage of data association is the association between the data obtained in the first stage and the GPS record data. The purpose of this step of association is to establish the corresponding relationship between WIFI signal strength data and real-time position coordinates of mobile nodes. The key data of association is time data [26-27].

4. Application Analysis of Vehicle Wireless Positioning Fusion Algorithm

4.1 Sensitivity Analysis of Model Parameters

POA transmits signals with the same frequency, pure sinusoidal signal and zero compensation phases, and estimates the distance between the receiving and receiving devices through the phase or phase difference of the carrier signal. Like AOA, POA based methods need to be carried out within the scope of LOS conditions, which can hardly be satisfied in indoor environment. However, POA is easier to obtain than AOA in signal propagation, but it will cause phase ambiguity due to phase winding. For location algorithm, on the one hand, it needs to provide other modules or subsystems in the system with interfaces to obtain location information, such as object identification, location-based routing, and so on. These subsystems or modules need to implement location-based basic services. Therefore, it is necessary to define a good interface for other modules to call. On the other hand, location algorithm can be used as a part of the framework of location-based services, abstracting the whole service process into a general framework, so as to provide more intelligent and personalized services. Therefore, how to define a good benign location-based service structure, efficient use of location technology, and provide flexible system construction is a challenging task. The development of Internet of things technology provides a rare opportunity and application platform for location-based services, because it links mobile terminal manufacturers, positioning technology, communication network and content providers together to support the rational and efficient use of location information. The results obtained according to the calculation statistics are shown in Table 2.

Table 2: The relationship between A change and distance

Distance	1	2	3	4	5	6	7	8	9
A=170.61	120	94	99	100	106	100	98	100	97
A=175.61	205	198	200	220	280	230	190	208	218
A=180.61	340	340	305	400	400	381	321	310	350
A=185.61	456	462	423	508	510	500	476	410	480
A=190.61	590	599	586	620	689	657	601	556	600

The relationship between RSSI and distance when A changes is shown in Figure 1. It can be seen from the figure that the signal propagation distance d becomes smaller and smaller as the environmental impact factor A increases; under the same propagation distance condition, the smaller A is, the stronger the RSSI. Compared with the theoretical curve, the closer A is to the theoretical fitting value, the closer the distance d is to the true value. In the process of wireless signal propagation, the distance d has a negative correlation with RSSI. The closer you are to the base station, the faster the signal attenuation speed; as the distance increases, the attenuation speed gradually slows down. After a certain distance, the signal tends to attenuate linearly, and the signal propagation distance is related to the selected transmission power. In the signal propagation environment, the weaker the signal strength, it means that it has experienced more non-line-of-sight propagation loss and multipath fading in the propagation environment. According to the analysis, the environmental impact factor A mainly depends on the signal propagation environmental impact, that is, complex interference such as attenuation, reflection, and multipath effects in the air. When A=180.6135, the environmental impact best meets the experimental conditions.

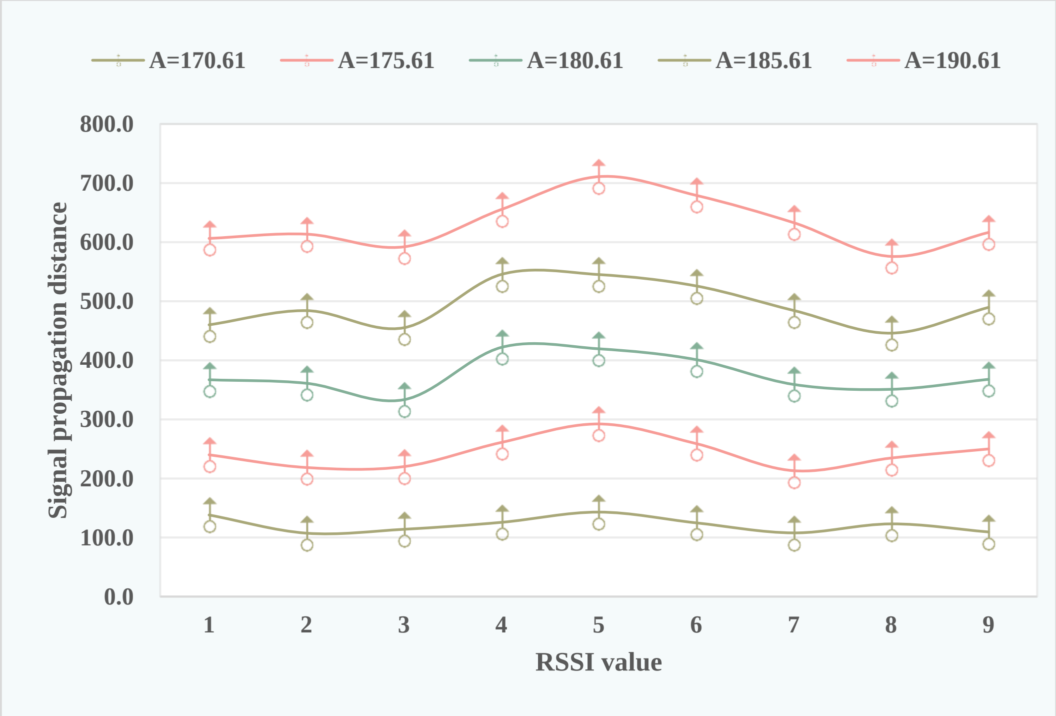

Figure 1: The relationship between RSSI and distance when A changes

4.2 Fusion Positioning Simulation and Performance Analysis

The strength of the wireless signal is inversely proportional to the propagation distance of the wireless signal. The closer the target node (receiver) and the reference node (transmitter) are, the stronger the signal strength received by the target node; conversely, the stronger the signal strength received by the target node. The positioning principle is: the received power is measured by the target node, and the distance between the reference node and the target node can be calculated according to the propagation loss model. The distance between the target node and other reference nodes is measured, and the position coordinates of the target node can be calculated using the H-angle positioning theory. This method has the advantages of simple principle, easy implementation, and low price. It does not need the support of other hardware devices. However, the positioning accuracy and anti-interference ability are poor. The results of the ranging experiment are shown in Table 3.

Table 3: Ranging experiment results

	Maximum distance error (m)	Distance average error (m)	X axis average error (m)	Y axis average error (m)
OSS-TWR	11.44	2.86	1.83	1.69
EOSS-TWR	8.95	2.16	0.99	1.05
Non-collision	4.37	141	0.84	0.75

In order to observe the data comparison more intuitively, the table is drawn as a picture, as shown in Figure 2.

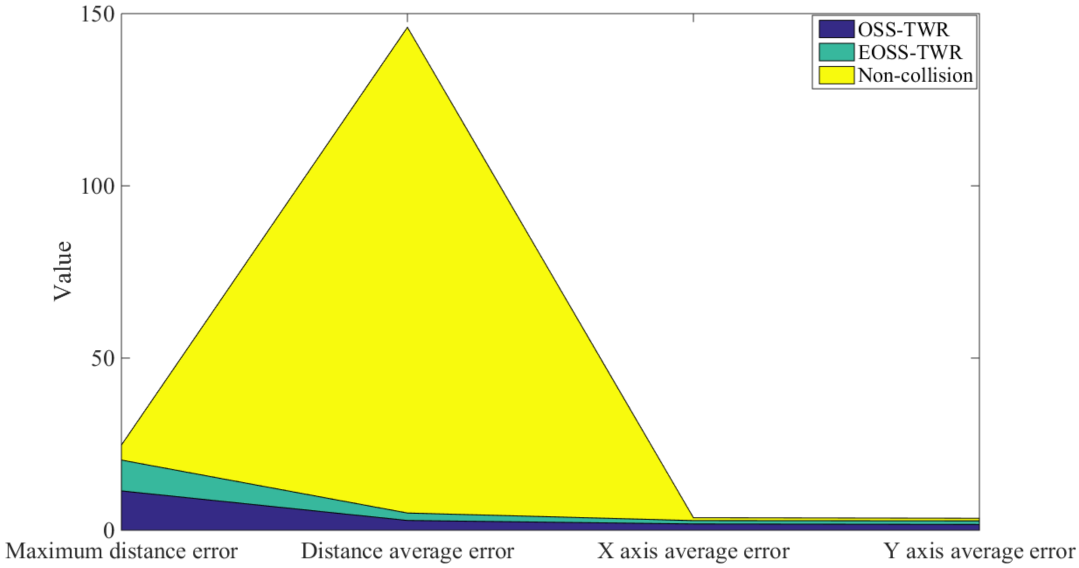

Figure 2: Test distance experiment comparison

As can be seen from the table, the maximum error distance shows that OSS-TWR is affected by network collisions. The maximum error is 11.44 meters, and the average error is 2.85 meters. Although EOSS-TWR is also affected by network collisions, the impact is small. The positioning accuracy is higher than OSS-TWR, the maximum distance error is 8.95 meters, the average distance error is 2.16 meters; non-collision's positioning algorithm has the highest accuracy.

In actual WSN, the motion model of the target object can basically be obtained, and the motion state of the target is continuous, so the problem becomes to use a series of noise-containing measurement values on the system to estimate the system state over time. The state estimate obtained by such an estimation algorithm is itself fused, the state estimate at the previous moment, the noise-containing measurement value at the current moment, and the error of all states at the previous moment, without additional storage of historical information of observations and estimates: recursive state Estimation means that the received data can be processed in real time without the need to store the complete data set; in the worst case, even if there is no reliable measurement value, the estimated value at the previous time can be used for inference. The proposed vehicle wireless positioning fusion algorithm can locate the vehicles in the actual vehicle-road collaborative environment. The positioning accuracy can reach 46.31m with a 67% probability, and the positioning accuracy can reach 122.53m with a 95% probability. Assuming that the model is provided in the form of probability, the state space equation in the form of probability and the requirement of updating the state through the measured value are very suitable for the Bayesian method, which provides a general framework for this kind of recursive estimation method. Using

Bayesian tracking framework to track and locate moving objects is, fundamentally speaking, to estimate the state of mobile nodes recursively. When the state equation about the mobile node's state transition is known, the measured value about the mobile node can be obtained by other measurement methods, and the state equation and measurement equation can be combined to estimate the state of the mobile node at every moment.

Because there are inevitably errors in distance measurement, the impact of measurement errors on positioning accuracy is an important factor in evaluating the performance of positioning algorithms. Five anchor nodes are randomly and uniformly distributed in the simulation area, other simulation conditions remain unchanged, and the variance of the distance measurement error is changed. The results obtained through analysis and calculation are shown in Table 4.

Table 4: Algorithm error statistics

Distance	1	2	3	4	5	6
Trilateral measurement	17	15	12	7	16	9
Positioning algorithm	7	13	13	9	6	14
Algorithm combination	15	16	13	11	9	16
CRLB	15	8	12	13	16	6

The curve of the positioning error of the three algorithms with the variance of the measurement error and its CRLB curve are shown in Figure 3. It can be seen from the figure that the positioning errors of the three algorithms all increase with the increase of the measurement error variance, but the positioning error of the new algorithm is significantly smaller than the other two algorithms, and it is close to the lower bound of CRLB. This is because the multivariate Taylor series expansion model considers the distance information between unknown nodes more than the traditional Taylor series expansion model, and increases the constraint condition of the position between nodes, which further improves the positioning accuracy. In addition, as the distance measurement error changes, the positioning error slope of the new algorithm is smaller than that of the other two algorithms, indicating that the algorithm can effectively reduce the influence of measurement error on positioning error.

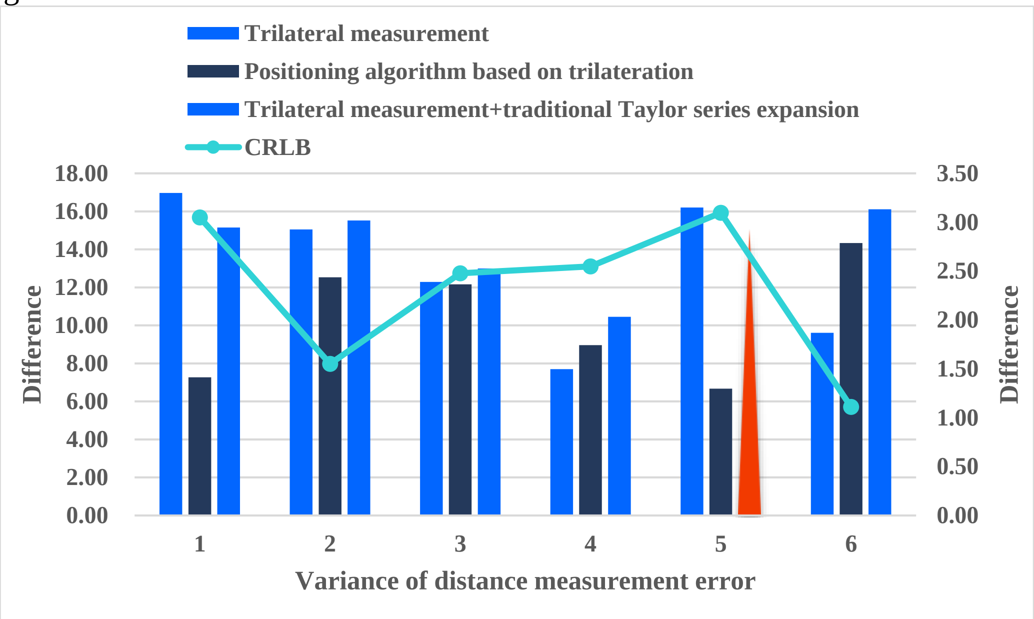

Figure 3: The positioning error of the three algorithms varies with the variance of the measurement error and its CRLB curve

4.3 Simulation Analysis of Wireless Positioning Algorithm

In order to verify the efficiency of the signal coordination control method at the main line intersection, three different scenarios are simulated for many times. The simulation results are shown in Table 5 and Figure 4. Under the maxband coordinated control, the average delay is reduced by 30.5% compared with the timing control, and the average delay is reduced by 48.2% under the condition of DSDS vehicle road coordinated control. Under maxband coordinated control, the average number of stops decreased by 45.1% compared with the timing control, and the average number of stops decreased by 64.6% under the condition of DSDS vehicle road coordinated control. Under the coordinated control of maxband, the average travel time of the trunk line is decreased by 27.8% compared with the timing control, and the average travel time of the trunk line is reduced by 29.7% under the condition of DSDS vehicle road cooperative control. Under the coordinated control of maxband, the average travel time of the trunk line is reduced by 39.6% compared with the timing control, and the average travel time of the trunk line is reduced by 30.6% under the condition of DSDS vehicle road cooperative control. The average delay, average number of stops, average stopping time, up and down travel time of trunk line coordinated control method are better than timing control. The main reason is that the method proposed in this paper is to form trunk line coordinated control of intersections, and there are vehicle road cooperative communication facilities to guide the dynamic speed of vehicles. Vehicles can form a good fleet, maintain a stable headway, and can drive on the trunk line according to the system green wave band speed. Therefore, the average delay and average number of stops of vehicles have been reduced to a certain extent.

Table 5: Simulation results

Simulation scene	Timing control	MAXBAND coordinated control	DSDS vehicle-road coordinated control
Average delay (s)	174	120.9	90.1
Average parking time (s)	114	62.6	40.3
Average number of stops (times)	3.7	2.6	1.6
Average travel time on trunk lines (s)	187.8	135.5	132.1
Average travel time down the trunk line (s)	234.0	141.3	162.4

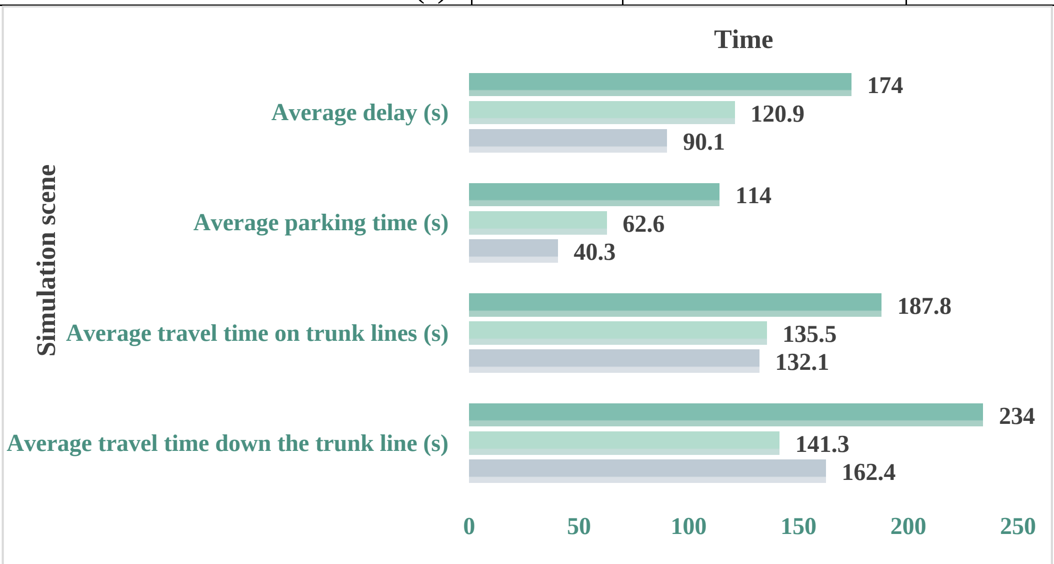

Figure 4: Simulation results

4.4 Sensitivity Analysis

The benefit comparison of RCTSP/NTSP is shown in Figure 5. The improvement degree of RCTSP to intersection per capita delay time decreases with the increase of saturation. When the saturation is 0.5, compared with NTSP and CTSP, RCTSP can reduce the per capita delay time by about 60% and 50%, respectively. When the intersection is close to saturation, the benefits of RCTSP and CTSP are very close, which can reduce the delay time per person by about 5%. Generally speaking, taking the per capita delay time at the intersection as the evaluation index, the benefit of the RCTSP control strategy is higher than the benefit of the CTSP control strategy. The main reason for vehicle misdetection is that the distance between vehicles is too close, which conceals the characteristics of the vehicle lights. This situation generally occurs when the road is congested. In a rainy environment, the algorithm can also detect vehicles better, but because of the reflection of lights on the road in the rainy day, the road has misdetected. Generally speaking, the false detection rate of the algorithm is relatively low, and the adaptability to weather conditions is relatively strong. The video in this experiment was shot on a real-time highway, which can basically meet the requirements of real-time vehicle monitoring. The specific results are shown in Table 6:

Table 6: Benefit comparison between different algorithms

Argorithm	LS	Chan	Taybor	Chan-Tayor	FCL
0	3	2	3	5	8
5	5	12	5	1	9
10	1	3	2	13	7
15	5	5	3	7	1

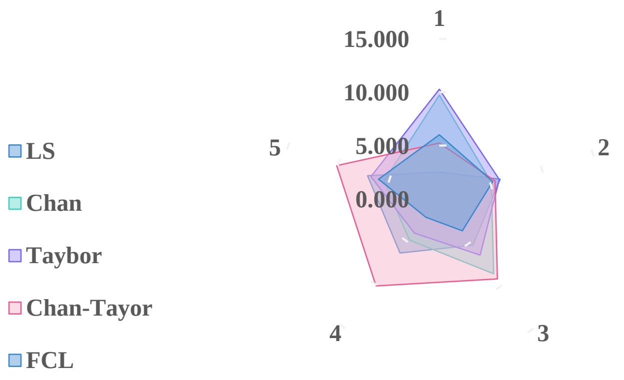

Figure 5: Benefit comparison of RCTSP/NTSP

It can be seen from the figure that in the LOS environment, the positioning performance of the algorithm improves to varying degrees with the increase of the signal-to-noise ratio, but when the signal-to-noise ratio is greater than 2dB, the positioning accuracy tends to be stable. Among traditional positioning algorithms, Taylor algorithm has the best positioning effect, Chan algorithm is more affected by noise, and LS algorithm gives a sub-optimal solution, and the positioning effect is not ideal. The improved FCL algorithm has significantly improved the positioning accuracy. The positioning algorithm based on model fusion has the best positioning effect under low signal-to-noise ratio, reducing the RMSE of a single model during position prediction, and the algorithm is finally stable near 9cm, which meets the requirements of vehicle positioning accuracy are improved. It can be seen that for the same signal-to-noise ratio, the positioning accuracy of different positioning algorithms differs greatly. For the same positioning algorithm, the continuous increase of the signal-to-noise ratio has a smaller impact on the positioning accuracy. Therefore, in the actual environment, a moderate increase in the signal-to-noise ratio can improve the positioning accuracy, but the appropriate positioning algorithm should be selected according to the environment.

4.5 Fusion Location Algorithm

In order to evaluate the positioning performance of the algorithm, three indicators of Root Mean Square Error (RMSE), Geometric Dilution of Precision (GDOP), and Cumulative Distribution Probability (CDP) are selected for the fusion positioning algorithm Effectiveness is evaluated.

Figure 6 shows the comparison between the positioning trajectory of the fusion positioning algorithm and the real trajectory of the vehicle.

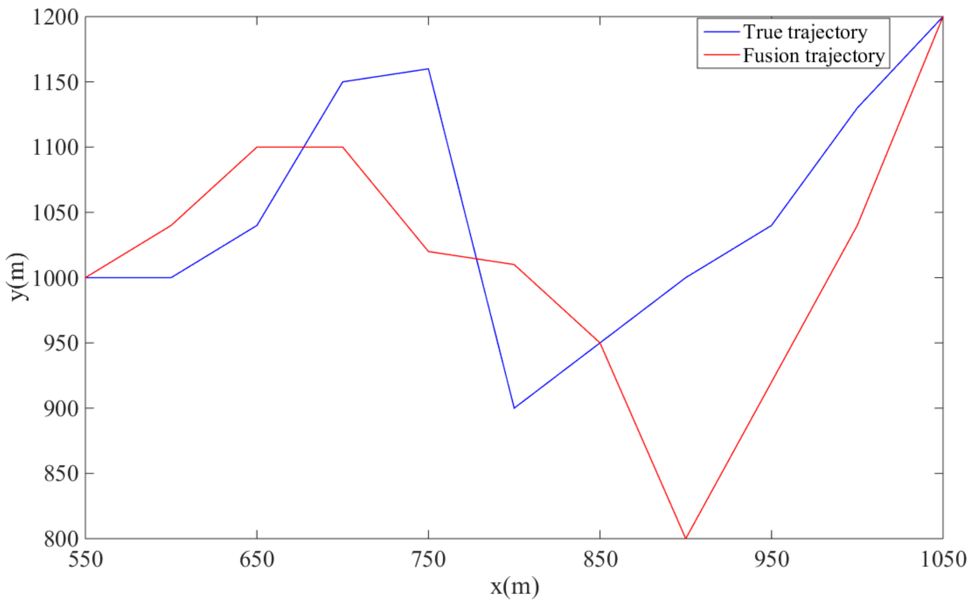

Figure 6: Comparison of trajectories of different algorithms

It can be seen from Figure 6 that the trajectory of the fusion positioning algorithm is distributed around the real trajectory of the vehicle, which can realize the position tracking of the vehicle. Table 7 shows the comparison of evaluation indexes of the four positioning algorithms.

Table 7: Comparison of four positioning algorithm rating indicators

Algorithm index	Trilateral positioning method	Least squares method	Centroid	Fusion positioning algorithm
RMSE(m)	53.9	43.5	89.4	41.6
GDOP	1.2	1.3	1.9	0.1

It can be seen from the data in the table that the fusion positioning algorithm is better than the other three positioning algorithms on the whole. Compared with the trilateration method, the least square positioning method and the centroid method, the RMSE of the fusion positioning algorithm is reduced by 29.51%, 4.28% and 112.03%, respectively. From the GDOP results, the fusion positioning algorithm GDOP is 0.99, which is better than other positioning algorithms. Figure 7 shows the cumulative distribution probability of the positioning error of the fusion positioning algorithm.

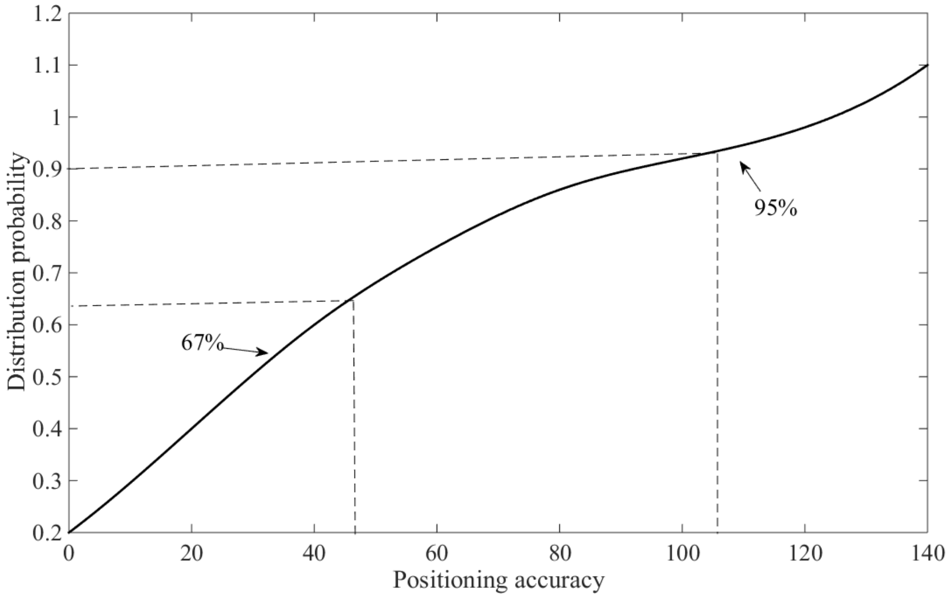

Figure 7: Cumulative distribution of fusion positioning algorithm

From the data analysis in the figure, it can be seen that the positioning error of the fusion positioning algorithm is relatively concentrated in the range of 0-40m, 67% of the track points have a positioning accuracy of less than 46 meters, and 95% of the track points have a positioning accuracy of less than 123 m.

5. Conclusions

This paper mainly studies the fusion algorithm of wireless positioning of vehicles in the coordinated environment of highway vehicles and roads. By analyzing the applicability of the wireless positioning method in the coordinated environment of vehicles and roads, a wireless positioning method suitable for vehicle positioning research is selected. Then, select the appropriate positioning performance evaluation index to evaluate the positioning accuracy. In the wireless positioning of vehicles, three traditional wireless positioning algorithms based on ranging and non-ranging are selected respectively. Contrary to the sensitivity of traditional algorithms to the initial coordinates, the vehicle position estimation problem is transformed into an unconstrained nonlinear programming problem, and the external penalty function method and the proportional algorithm are combined to obtain free coordinates that do not depend on precise initial coordinates.

This paper proposes a positioning algorithm and simulates the performance of all positioning algorithms. The simulation results show that the FCL algorithm can perform position estimation under random coordinates, which relieves the traditional algorithm’s dependence on the accuracy of the initial coordinates; the residual weight is used to introduce the model fusion positioning algorithm, and multiple improved positioning algorithms with good positioning performance are incorporated. Fusion avoids accidental errors caused by a single model. The algorithm meets the premise that a single base station can be located in the MANET network. When multiple base stations are available, multi-data fusion based on the principle of minimum MSE can achieve higher-precision positioning through multi-point coordination.

With the rapid development of intelligent transportation and Internet of vehicles, the application of inter vehicle communication is more and more widely based on vehicle road communication. It plays an important role in active safety, traffic management and so on to establish the connection between vehicles and roads, to exchange information between vehicles and roads and to locate vehicles. Through the weighted fusion of multi information, the accuracy of single satellite positioning system not only makes full use of the estimated value of each subsystem, but also effectively suppresses the impact of local large noise on the overall accuracy. Therefore, it is theoretically proved that the weighted fusion method can further improve the positioning performance of the system, and the positioning error of the system is analyzed theoretically. Finally, the feasibility of the algorithm is verified by the actual garage test.

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