Article

Urban Traffic Congestion State Recognition Supporting Algorithm Research on Vehicle Wireless Positioning in Vehicle–Road Cooperative Environment

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Abstract: Vehicle–road cooperative technology applies wireless communication and a new generation of internet technology to urban traffic management, providing an effective way to solve urban traffic congestion and improve traffic efficiency. This article researches the vehicle wireless positioning fusion algorithm, suitable for the actual vehicle–road collaborative environment, which is an important step of urban traffic congestion state recognition. First, based on the error correction of existing wireless positioning algorithms, a weighting indicator considering distance and positioning compound errors is designed, and a vehicle wireless positioning fusion algorithm based on error weighting to eliminate line-of-sight (LOS) and non-line-of-sight (NLOS) error is proposed. Secondly, the wireless positioning fusion algorithm is verified based on accuracy evaluation indicators such as root mean square error (RMSE), Cramer Rao lower bound (CRLB), geometric differentiation of precision (GDOP), and cumulative distribution probability (CDP), and the sensitivity of the distance propagation model parameters to the positioning error is analyzed. The verification results show that the local vehicle wireless positioning fusion algorithm proposed in this article could be useful to locate vehicles in an actual vehicle–road collaborative environment. The positioning accuracy could reach 46.31 m with 67% probability, while the positioning accuracy could reach 122.53 m with 95% probability. The average positioning accuracy could reach 39.97 m. Compared with the two types of wireless positioning methods based on ranging and non-ranging methods, the positioning accuracy is improved by 7.74% and 17.69%. The algorithm can either use the roadside base stations to carry out the individual vehicle positioning or cooperate with GPS positioning and trilateral positioning to make up for the positioning blind spots caused by the lack of signal, interference, or base station overload in the urban complex road environment and, furthermore, improves the robustness of vehicle positioning. The results could assist in all-day real-time traffic congestion state recognition and other actual scenarios.

Keywords: vehicle–road cooperative; vehicle positioning; weighted fusion algorithm

1. Introduction

At present, urban traffic congestion has become a severe problem that many cities need to solve, and the recognition of the congestion state is the cornerstone of solving the congestion problem. The complete recognition of the urban traffic congestion state requires the support of a series of related algorithms, including vehicle positioning, vehicle speed determination, and map matching. This article intends to research and improve the vehicle positioning algorithm.

Vehicle wireless positioning technology is an important part of vehicle–road cooperative technology. Through the wireless sensor network that is densely arranged on the roadside, vehicle–road communication is used for real-time information interaction
and sharing to realize the acquisition of the real-time position of vehicles. At present, Global Positioning System (GPS) is a commonly used wireless positioning method for vehicles, but there are problems such as signal loss or interference under complex urban road environmental conditions, which can cause positioning blind spots. Due to the sparse layout of base stations on some urban roads, when there is a large flow of people and vehicles in the morning and evening peaks, a single base station might be overloaded, which would cause a positioning drift or the target vehicle to receive fewer than three base station signals. Thus, a low-cost and easy-to-layout local vehicle positioning method is required to eliminate positioning blind spots in complex road environments and improve the robustness of vehicle positioning. With the rapid construction of smart cities, many wireless sensor networks will be deployed on the side of urban roads to provide a sensor network environment for realizing the wireless positioning of vehicles.

This article discusses the wireless positioning method of vehicles in a vehicle–road collaborative environment as a supplementary positioning method for the failure of the conventional positioning method and adapts measured data to conduct an empirical analysis of the proposed wireless positioning algorithm for vehicles. Based on reviews of related research, the article elaborates on the related theoretical methods of vehicle wireless positioning. A wireless vehicle positioning fusion algorithm that uses error weighting to eliminate LOS and NLOS errors is proposed. This article uses the experimental data in the outfield vehicle–road collaborative environment to compare and verify the positioning accuracy of the positioning fusion algorithm and analyzes the sensitivity of the distance propagation model parameters to the positioning error of the fusion algorithm.

The research can make up for the short-term vehicle position loss caused by unstable vehicle environments and positioning conditions, help to realize the effective monitoring of the traffic flow operation state, and improve vehicle operation efficiency and safety. In further applications, it will play an important role in all-day real-time traffic congestion state recognition and provide a decision-making basis and technical support for improving traffic congestion in large and medium-sized cities.

2. Literature Review

Scholars have conducted much research on vehicle positioning technology. Based on GPS data and fuzzy rules, Jagadeesh used map matching to realize vehicle positioning [1]. Prinsloo researched the method of using radio frequency identification (RFID) technology to locate vehicles when triangulation cannot work [2]. Kodavati applied the combination of GPS and the global system for mobile communications (GSM) to improve the accuracy of vehicle positioning [3]. Hörcher estimated the congestion level of rail transit based on smart card data and vehicle location data [4]. Wang exploited the Vehicular Ad Hoc Network (VANET) paired with unmanned aerial vehicles (UAVs) to carry out real-time positioning research on vehicles without fixed base stations [5]. Tseng designed a wireless sensor network to locate terminals. Once the target was close to a sensor in the network, the target could be located [6]. Barber utilized fixed-wing UAVs to visually recognize the vehicle and locate the vehicle accordingly [7]. Lin employed mileage data and a visual assistance system to locate the vehicle without using external sensor signals [8]. Arias proposed a location method based on the noise location of base station data [9]. Anisetti researched related positioning algorithms based on the signal strength data of the GSM/3G network [10]. Hata proposed a method of using the strength of the mobile signal to locate the mobile terminal [11]. Spirito evaluated the accuracy of mobile location data based on mobile signals [12]. Lin suggested a mobile positioning method based on the attenuation difference of base station signals and verified the method [13]. Zhao presented that mobile positioning data has important application value for intelligent transportation systems [14]. Tseng implied a terminal positioning method based on dynamic mobile positioning [15]. Cong proposed a positioning method based on code division multiple access data [16]. In the latest research, Liu predicted the vehicle location through the prediction method; his research locates the vehicle by combining short-term accurate
vehicle trajectory prediction and long-term rough vehicle trajectory prediction [17]. In a situation of conventional positioning methods fail in vehicle positioning, Bai proposed a method that uses inertial navigation as a positioning supplement. The vehicle location can be estimated by combining the vehicle’s motion state with GPS positioning [18]. Chen transformed the vehicle positioning problem to a Direction-Of-Arrival (DOA) estimation and proposed a non-convex algorithm to solve the optimization problem [19].

There are also many related types of research concerning the improvement of positioning accuracy. Wang designed and verified a set of mobile location adaptive update solutions [20]. Wang illustrated an NLOS positioning method to improve positioning accuracy [21]. Liu combined the positioning methods of time difference of arrival (TDOA) and angle of arrival (AOA) and proposed a more accurate positioning method [22]. Liao adapted the Kalman filter to process positioning data and obtained a better processing result [23]. Wang distinguished and optimized the near-field positioning algorithm and the far-field positioning algorithm [24]. Jia reduced the errors in positioning and improved positioning accuracy through the weighted least-squares method [25]. Zhao explained the method of choosing a suitable sensor to measure the moving position [26]. Noroozi improved the accuracy of location data acquisition through a weighting matrix [27]. Zhang suggested a two-stage method that combines calibrating the sensor and acquiring position data, which improved the accuracy of the positioning [28]. Li conducted further research on the use of the least-squares method to eliminate position error [29]. Kwon researched methods to eliminate the delay of positioning information and improve the accuracy of the positioning [30]. Imani proposed a location determination method in a scenario that does not use the comprehensive search [31]. Tian used multi-target signal source matrix data to determine and correct position data [32]. Li used the Maximization–minimization method to deal with the positioning problem when only two base stations are available [33].

The collected positioning data could be used in the research of many transportation fields. For instance, Comert estimated the length of a vehicle queuing at the intersection through the change of vehicle location information to analyze the road traffic state [34]. Lovell proposed a method of collecting the moving speed of vehicles using cellular data positioning [35]. Barabino researched the processing methods of the raw data of public transportation vehicle positioning [36]. Huang used vehicle positioning data to analyze the performance of public transportation lines [37]. To analyze the service of public transportation, Ma introduced vehicle positioning data as a basis [38]. Liu used public transportation vehicle positioning data to control traffic lights to achieve the purpose of public transportation priority [39]. Mahadevan perfected the positioning method that combines GPS and GSM methods from the perspective of hardware design and planned to apply the positioning module to locate public vehicles [40].

Furthermore, there are also many scholars concerned about the privacy protection of positioning data and information security. Pan devised a method to protect the privacy of location data [41]. Zheng proposed a cache-based mobile positioning data storage and post-processing method [42]. To ensure the safety of positioning data, Xu proposed a positioning data transmission strategy [43]. Asuquo summarized relevant research results on vehicle positioning data security and privacy [44].

With the continuous development of modern urban road construction to three-dimensional structures, when vehicles are driving under tunnels and viaducts, the upper space of the vehicle will be attenuated due to the relatively heavy building structure, which will cause positioning failure. For vehicles using trilateration positioning, since the accuracy of the positioning method is directly related to the base station, when one or more of the required multiple base stations appear to be overloaded or the signal attenuation is excessive due to building interference, this makes the positioning results inaccurate. Most of the existing research is based on the data collected by ideal GPS positioning or multi-base station positioning, and there are few discussions or studies concerning the data collection environments that are relatively harsh. Therefore, it is necessary to design a supplementary positioning method for when the conventional positioning method fails.
3. Materials and Methods
3.1. Position Algorithm Calculation

This article proposes a received signal strength indication (RSSI)-weighted fusion algorithm (WF). Based on the data that can be obtained in the experiment, the algorithm selects the trilateral positioning method and the least-squares positioning method, together with the dead reckoning positioning method and the two stations ranging plane positioning method from the classic ranging positioning methods; the centroid positioning method is selected from the classic non-ranging positioning methods. Then, the weights based on error distance are assigned to the positioning results of trilateral positioning, least-squares positioning, and centroid positioning to constitute a fusion positioning algorithm.

The algorithm is suitable for vehicle wireless positioning in a vehicle-road collaborative environment. The antennas arranged on the roadside base station and the vehicle are used to send and receive signals to obtain positioning data. The algorithm is less interfered with by signal transmission and can compensate for GPS positioning and trilateral positioning due to the positioning failure caused by unstable vehicle environment and location conditions. The algorithm is a phased experimental result of this research, and the purpose of the experiment is to verify the positioning accuracy of the algorithm. Therefore, the experiment assumes that the GPS coordinates are real coordinates to verify the accuracy of the algorithm. If it is applied in the actual urban traffic state recognition, it is necessary to conduct a more detailed study on the weight calculation in the algorithm.

The calculation process of the fusion location algorithm is as follows.

3.1.1. Step 1: Calibrated Logarithmic Propagation Model

The RSSI location is a common method in the process of wireless location [45]. The RSSI varies with distance, so the distance can be estimated according to signal attenuation, which is a direct and simple ranging method. The main concern in RSSI positioning is the distance propagation model. The path loss in the process of signal propagation directly affects the ranging results, which then affects the positioning accuracy. Therefore, a reasonable communication model could be crucial. In this article, the logarithmic distance propagation model is selected as the distance propagation model; it has been widely used in vehicle wireless positioning. The distance between nodes, calculated by this model, is more consistent with the distance between real nodes, which can effectively improve the accuracy of vehicle positioning.

The logarithmic propagation model refers to the logarithmic attenuation trend of the average received signal power with the increase in distance when the wireless signal propagates indoors or outdoors. In the model, the distance $d$ between the RSSI and the nodes varies logarithmically, so the path loss $PL$ meets the following requirements:

$$ PL = PL(d_0) + 10n\lg\left(d/d_0\right) - \delta $$  \hspace{1cm} (1)

where $PL(d_0)$ indicates the signal strength value received by the vehicle at the reference distance $d_0$, unit: dBm, $d_0 = 1$ m; $PL$ indicates the signal strength received by the vehicle when the distance between points is $d$, unit: dBm; $n$ indicates the path loss coefficient, generally 2–9; and $\delta$ indicates the Gaussian random distribution with the mean value of 0 and the variance of $\mu$ (generally 4–10).

In this article, the experimental data in the field vehicle road coordination environment are selected to calibrate the model. When the experimental vehicle travels around the fixed base station, the signals transmitted by the base station are collected and received by the vehicle when driving. The experiment received information that included RSSI and GPS longitude and latitude. The GPS positioning data in the experimental data have high accuracy and are complete data. Therefore, the GPS positioning track is used as the real driving track of the vehicle to calibrate the model. The GPS data and corresponding RSSI are selected at a certain time, the real distance between nodes is calculated, and the model
is calibrated. The logarithmic curve of the formula above is fitted by MATLAB software, and the fitting result is obtained:

\[ PR(\text{dBm}) = 180.6135 - 10 \times 8.192 \lg d \]  

(2)

The model fitting formula-related parameters are shown in Table 1:

| Model Parameter               | Calibration Results |
|-------------------------------|---------------------|
| Environmental factor (A)      | 180.61              |
| Path loss coefficient (n)     | 8.19                |
| Related coefficient (R)       | 0.94                |

According to the calibrated distance propagation model, when the RSSI is known, the absolute distance between the vehicle and the base station sending the signal at the current time can be calculated. Select the appropriate positioning method for position estimation and, finally, get the vehicle position.

3.1.2. Step 2: Positioning Process

1. The dead reckoning positioning method is used to locate the moving point of the vehicle with the information of only one base station [46]. The positioning principle calculates the vehicle position at the next time based on the vehicle location, driving direction, and vehicle speed at the previous time. Since the position and direction at the previous moment determine the position at the current moment, positioning errors may continue to accumulate as the positioning updates.

When the dead reckoning positioning method is adopted, the initial coordinate is known as \((x_0, y_0)\) and the initial azimuth is \(\theta_0\), and the dead reckoning positioning coordinates \((x_a, y_a)\) can be calculated by:

\[
\begin{align*}
x_a &= x_0 + S_0 \sin \theta_0 \\
y_a &= y_0 + S_0 \cos \theta_0 \\
S_0 &= v_0 t
\end{align*}
\]  

(3)

(4)

where \(S_0\) indicates the real-time measurement of vehicle travel distance, unit: m; \(t\) indicates the vehicle movement time, \(t = 1\) s; and \(\theta\) indicates the included angle between the vehicle driving direction and the horizontal direction.

2. The plane positioning method calculates the vehicle position for the data group that receives two base station signals in one second [47]. The positioning principle is to measure the linear distance between the target and the two base stations with known positions. Under the condition of no measurement error, the target vehicle will be located at the intersection point of the circle, with each base station as the center and the signal propagation distance as the radius. If two circles intersect and there are two intersections, the intersection close to the vehicle position at the previous time is judged as the estimated vehicle position. If there is only one intersection point between two circles, the intersection point is the estimated vehicle position. If two circles intersect without intersection, it is considered that the data at that time cannot be located.

When the plane positioning method is adopted, the positioning coordinate \((x_b, y_b)\) can be obtained by:

\[
\min \sqrt{(x_b - x_0)^2 + (y_b - y_0)^2} \quad \text{s.t.} \quad \begin{cases} (x_b - x_1)^2 + (y_b - y_1)^2 = d_1^2 \\ (x_b - x_2)^2 + (y_b - y_2)^2 = d_2^2 \end{cases}
\]  

(5)
3. The trilateration method is the most used node positioning method in wireless positioning [48]. Taking the distance obtained by the distance propagation model as the radius and the base station coordinates as the center of the circle, the intersection of the circles or the centroid of the intersecting area is the vehicle position. In practical applications, if the three circles cannot intersect at one point due to errors, the position of the target to be measured may not be located.

When the trilateral measurement positioning method is adopted, the vehicle receives signals from three or more base stations, the base station coordinates are represented by 

\[(x_1, y_1), (x_2, y_2), (x_3, y_3)\],

and the positioning coordinate \((x_c, y_c)\) can be obtained by:

\[
\begin{align*}
(x_c - x_1)^2 + (y_c - y_1)^2 &= d_1^2 \\
(x_c - x_2)^2 + (y_c - y_2)^2 &= d_2^2 \\
(x_c - x_3)^2 + (y_c - y_3)^2 &= d_3^2
\end{align*}
\]  

(6)

4. The least-squares method establishes the corresponding characteristic equation according to the positioning distance and obtains the vehicle position by solving the minimum value of the error square sum [25].

When the least-squares positioning method is adopted, the vehicle receives signals from three or more base stations, and the vehicle coordinates can be calculated by establishing a set of equations of multiple equations.

\[Ax = b \]

(7)

Suppose \((x_d, y_d)\) is the vehicle positioning coordinate. The optimal estimation obtained by least-squares positioning is:

\[A = \begin{bmatrix} x_d \\ y_d \end{bmatrix} \]

(8)

where, the matrix forms of \(A\) and \(b\) are:

\[A = \begin{bmatrix} (x_1 - x_k) & (y_1 - y_k) \\ \vdots & \vdots \\ (x_{k-1} - x_k) & (y_{k-1} - y_k) \end{bmatrix} \]

(9)

\[b = \begin{bmatrix} x_1^2 - x_k^2 + y_1^2 - y_k^2 + d_1^2 - d_k^2 \\ \vdots \\ x_{k-1}^2 - x_k^2 + y_{k-1}^2 - y_k^2 + d_{k-1}^2 - d_k^2 \end{bmatrix} \]

(10)

The sum of squares of errors is minimized by:

\[f(X) = (AX - b)^2 = (AX - b)^T(AX - b) \]

(11)

where \(r = Ax - b\) indicates the error vector. The minimum value of \(f(x)\) can then be obtained:

\[x^* = \left(A^T A\right)^{-1}A^T b \]

(12)

where \(x^*\) indicates the estimation of \(x\).

5. The centroid algorithm is one of the typical non-ranging positioning methods [49]. Its positioning principle continuously broadcasts its ID through multiple anchor nodes deployed in the area; the undetermined node receives the ID packet and uses its signal data to measure its position in combination with the position of the anchor node. The centroid algorithm indicates its advantages with the straightforward process and economic deployment.
When the centroid algorithm positioning method is adopted, the vehicle coordinates \((x_e, y_e)\) can be obtained by:
\[
\begin{align*}
    x_e &= \frac{x_1 + x_2 + \cdots + x_n}{n} \\
    y_e &= \frac{y_1 + y_2 + \cdots + y_n}{n}
\end{align*}
\] (13)

3.1.3. Step 3: Error Correction

The random error in the experiment can be converged by the wavelet theory. The present article uses the wavelet threshold denoising method, sets the wavelet coefficients outside the range \(\delta\) and \(\delta\) as noise, compresses the noise, and re-obtains the value. The thresholding can delete small amplitude noises or undesired signal data and obtain the required data through inverse wavelet transform. In the threshold denoising process, the \(n\)-layer wavelet decomposition is processed in the first step, and the decomposed scale coefficients and wavelet coefficients form a coefficient vector, \(W\); \(\delta\) is used to transform vector \(W\) to obtain a new vector, \(W_\delta\); and wavelet reconstruction is executed on vector \(W_\delta\) to obtain the denoising signal.

The most typical wavelet in the wavelet denoising method is the Haar wavelet. Set \(\varphi(x)\) and \(\psi(x)\) as the Haar scale function and the wavelet function; then, scale space \(V_j\) and wavelet function \(W_j\) are respectively generated by Formulas (14) and (15).

\[
V_j = \left\{ 2^j \varphi(2^j x - k) \right\}_{k \in \mathbb{Z}, j = N - 1, \ldots, N - M} 
\] (14)

\[
W_j = \left\{ 2^j \psi(2^j x - k) \right\}_{k \in \mathbb{Z}, j = N - 1, \ldots, N - M} 
\] (15)

The wavelet decomposition refers to the stepwise decomposition from \(f_N\) to \(f_{N-M}\) and \(g_i\) is as in Formula (16).

\[
f_n = g_{N-1} + g_{N-2} + \cdots + g_{n-m} + f_{N-M}
\] (16)

where \(g_i \in \{V_j\}; f_{N-M} \in \{W_j\};\) and \(j \in \mathbb{Z}.

Traditional threshold functions mainly include a hard threshold function and a soft threshold function. The selection rule of threshold adopts unbiased likelihood estimation. The soft threshold method is easy to handle, the result obtained is smoother, and the denoising effect is better. However, the hard threshold method can better retain the edge information and be closer to the actual situation. The two methods have their characteristics. In contrast, the soft threshold method has a better denoising effect. Therefore, the soft threshold method is selected in the present article to denoise the data. The soft threshold is shown in Formula (17).

\[
\omega_i = \begin{cases} 
    \text{sgn}(W)(|W| - \delta), & |W| \geq \delta \\
    0, & |W| < \delta 
\end{cases}
\] (17)

Correcting the positioning error, the error distance comparison chart can be obtained, as shown in the figure below.

It can be seen from Figure 1 that the distance error of the positioning data corrected by wavelet denoising has changed significantly. For the coordinate points with an error of more than 100 m, the error distance has obvious convergence, and for the coordinate points with an error distance of less than 100 m, the fluctuation of the error change is reduced and the change tends to become smooth. After wavelet denoising processing, the random error of the distance between nodes effectively converges according to the threshold standard, indicating that the error correction method is effective.
3.1.4. Step 4: Weight Calculation

There are obvious errors caused by various reasons in the process of positioning measurement or position estimation. The distance error calculated by the ranging model and the positioning error of the positioning result will result in low positioning accuracy, affecting the performance of the localization algorithm. Therefore, after the vehicle position is preliminarily estimated, the obviously abnormal coordinate data need to be corrected to reduce the error.

When the vehicle receives signals from three or more base stations, a weighted calculation is designed for the coordinates of trilateral positioning, least-squares positioning, and centroid positioning. Here, \((x_c, y_c), (x_d, y_d), \) and \((x_r, y_r)\) are the location estimation coordinates of the trilateral location, the least-squares location, and the centroid location, respectively. Considering the distance error \(d\) and the positioning error of coordinate \((x, y)\), the weighting factor of each positioning result is \(w_i\).

\[
W_i = \frac{1}{\sqrt{\Delta x_i^2 + \Delta y_i^2 + d_i^2}} \quad i = 1, 2, \ldots, n
\]  

(18)

where \(i\) indicates the positioning coordinate serial number; \(\Delta x_i\) indicates the X-axis error of the \(i\)th coordinate, unit: m; \(\Delta y_i\) indicates the Y-axis error of the \(i\)th coordinate, unit: m; and \(d_i\) indicates the \(i\)th coordinate distance error, unit: m.

3.1.5. Step 5: Positioning Scheme Formulation

According to the above weighting matrix, the two errors are taken as the main basis for determining the weight. It is distributed in multiple positioning methods to reduce the positioning error and improve the accuracy of coordinate positioning. The fusion coordinates are obtained by the following:

\[
\begin{align*}
x &= x_c \frac{w_1}{\sum_{i=1}^{n} w_i} + x_d \frac{w_2}{\sum_{i=1}^{n} w_i} + x_r \frac{w_3}{\sum_{i=1}^{n} w_i}, \quad i = 1, 2, \ldots, n \\
y &= y_c \frac{w_1}{\sum_{i=1}^{n} w_i} + y_d \frac{w_2}{\sum_{i=1}^{n} w_i} + y_r \frac{w_3}{\sum_{i=1}^{n} w_i}
\end{align*}
\]  

(19)

This article proposes the following three fusion positioning schemes based on the ranging positioning method, the non-ranging positioning method, and the ranging and non-ranging fusion positioning method.

1. Comparison scheme 1: fusion positioning based on the ranging method

In this scheme, trilateral measurement positioning and least-squares positioning are fused with dead reckoning positioning and plane positioning to obtain fusion positioning.
algorithm A (WFA). According to the wireless location fusion algorithm formula, the algorithm formula of the WFA scheme can be obtained as follows:

\[
\begin{align*}
x &= x_c \frac{w_1}{w_1 + w_2 + w_3} + x_d \frac{w_2}{w_1 + w_2 + w_3} + x_e \frac{w_3}{w_1 + w_2 + w_3} \\
y &= y_c \frac{w_1}{w_1 + w_2 + w_3} + y_d \frac{w_2}{w_1 + w_2 + w_3} + y_e \frac{w_3}{w_1 + w_2 + w_3} \\
d &= \sqrt{(x - x_0)^2 + (y - y_0)^2}
\end{align*}
\] (20)

where \((x_c, y_c)\) and \((x_d, y_d)\) are the vehicle positioning coordinates located by the trilateral measurement method and the least-squares method, and \(w_1, w_2\) are the weighting factors of the trilateral measurement method and the least-squares method. It can be obtained that the positioning coordinate of the WFA fusion positioning scheme is \((x, y)\). Furthermore, \(d\) indicates the positioning error distance, and \((x_0, y_0)\) indicates the real vehicle position.

2. Comparison scheme 2: fusion location based on the non-ranging method

In this scheme, centroid positioning, dead reckoning positioning, and plane positioning are selected to obtain the fusion positioning algorithm B (WFB). The algorithm formula of the WFB scheme can be obtained as follows:

\[
\begin{align*}
x &= x_c \cdot w_3 \\
y &= y_c \cdot w_3 \\
d &= \sqrt{(x - x_0)^2 + (y - y_0)^2}
\end{align*}
\] (21)

where \((x_c, y_c)\) is the vehicle positioning coordinates of the centroid algorithm, and \(w_3\) is the weighting factor of centroid positioning. It can be obtained that the positioning coordinate of the WFB fusion positioning scheme is \((x, y)\).

3. Fusion scheme: fusion location based on ranging and non-ranging methods

Based on scheme (1) and scheme (2), considering the fusion of ranging-based and non-ranging-based positioning methods, the fusion positioning algorithm C (WFC) is obtained. The algorithm formula of the WFC scheme can be obtained as follows:

\[
\begin{align*}
x &= x_c \frac{w_1}{w_1 + w_2 + w_3} + x_d \frac{w_2}{w_1 + w_2 + w_3} + x_e \frac{w_3}{w_1 + w_2 + w_3} \\
y &= y_c \frac{w_1}{w_1 + w_2 + w_3} + y_d \frac{w_2}{w_1 + w_2 + w_3} + y_e \frac{w_3}{w_1 + w_2 + w_3}, \quad i = 1, 2, 3 \\
d &= \sqrt{(x - x_0)^2 + (y - y_0)^2}
\end{align*}
\] (22)

where \((x_c, y_c), (x_d, y_d),\) and \((x_e, y_e)\) are the vehicle positioning coordinates of the trilateration, least squares, and centroid algorithms, and \(w_1, w_2, w_3\) are the weighting factor of the trilateration, least squares, and centroid positioning. It can be obtained that the positioning coordinate of the WFC fusion positioning scheme is \((x, y)\).

3.2. Empirical Data and Preprocessing

3.2.1. Raw Data

In this article, the data comes from the experiment of “data set collection based on Wi-Fi connectivity between vehicles and base stations in an urban environment” done by Microsoft Corporation in the United States. The experiment was completed in the Microsoft Experimental Park in Redmond, Washington. Using the experimental results of vehicle wireless locations in the vehicle road cooperative environment, the algorithm verification of this article is completed. There are 11 Wi-Fi fixed base stations set in the experimental park to transmit wireless signals; the red mark in Figure 2 below marks the base station setting.
When the vehicle is driving along the road in the park covered by the wireless sensor network, it receives the wireless signal from each base station. The experiment is completed by collecting Wi-Fi signal data within the vehicle communication range, its own vehicle driving data, and GPS data during vehicle driving.

The experiment uses the deployed fixed base station to obtain Wi-Fi signal data and analyzes the basic characteristics of the data between the base station and the vehicle. The experimental data package includes GPS data field information, Wi-Fi data field information, and vehicle data field information.

1. GPS data fields

The data names and data samples contained in the GPS data package can be found in Table 2.

Table 2. GPS data fields.

| Number | Data Name                     | Data Sample                      |
|--------|-------------------------------|----------------------------------|
| 1      | Machine time                  | T06:47:57.3593750-08:00         |
| 2      | UTC time                      | T14:47:15.0000000               |
| 3      | Latitude in degrees, followed by N | 47.644565 N                      |
| 4      | Longitude in degrees, following by W | 122.13342 W                   |
| 5      | Speed in knots (1 knot = 1.852 Kmph) | 0.13                          |
| 6      | Direction of motion           | 157                              |
| 7      | Percent                       | 2.9                              |
| 8      | Horizontal                    | 1                                |
| 9      | Vertical dilution of precision| 2.7                              |

2. Wi-Fi data fields

The data names and data samples contained in the Wi-Fi data package can be found in Table 3.
Table 3. Wi-Fi data fields.

| Number | Data Name                                      | Data Sample                                                                 |
|--------|-----------------------------------------------|------------------------------------------------------------------------------|
| 1      | Timestamp                                     | T06:47:45.4062500-08:00                                                      |
| 2      | Upper 32 bits of the hardware timestamp       | 471                                                                         |
| 3      | Lower 32 bits of the hardware timestamp       | 2566571334                                                                  |
| 4      | Frequency of the logged packet                | 2412                                                                        |
| 5      | Status of this packet. 0 means a packet has been received |                                                                                  |
| 6      | 102 means packet sent                         |                                                                              |
| 7      | Other values are ignored                      |                                                                              |
| 8      | RSSI                                          | 9                                                                            |
| 9      | Transmission rate of the packet               | 1000                                                                        |
| 10     | Packet size                                   | 89                                                                           |
| 11     | Retry                                         | MGMT, BEACON F                                                              |
| 12     | Source MAC address                            | 00:02:6F:3E:1D:77                                                           |
| 13     | Destination MAC address                       | FF:FF:FF:FF:FF:FF                                                           |
| 14     | BSSID                                          | 02:03:04:05:06:07                                                           |
| 15     | DS field values; FromDS:ToDS                  | Ds:00                                                                      |

3. Vehicle data fields

The data names and data samples contained in the Vehicle data package can be found in Table 4.

Table 4. Vehicle data fields.

| Number | Data Name                                      | Data Sample                                                                 |
|--------|-----------------------------------------------|------------------------------------------------------------------------------|
| 1      | S/R: packets status                           | S is the packet sent by the base station R is the data packet received by the vehicle |
| 2      | Timestamp when the packet was logged          | T06:48:18.5156250-08:00                                                      |
| 3      | Interface IP addresses of the packet source   | 10.198.17.02                                                                |
| 4      | Experiment ID of the packet sourcing application | 1                                                                          |
| 5      | Source-specific sequence number of the packet | 309                                                                         |
| 6      | Transmission rate (in Kbps)                   | 1000                                                                        |

3.2.2. Data Preprocessing

Wireless signal data is the basis of the vehicle wireless positioning experiment. To improve the accuracy of the experimental results, the data need to be preprocessed first by extracting and integrating the signal data in the data packet. Using the longitude and latitude of the vehicle at each time in the GPS data, its motion trajectory can be obtained, as shown in Figure 3. The vehicle running track basically follows the road direction. Therefore, the vehicle position positioned by GPS can be regarded as the real driving track of the vehicle because of the high GPS positioning accuracy in the experiment.

By integrating the three kinds of data with timestamp data, the GPS data, base station data, and vehicle data at each time can be obtained, where the complete data information can be sorted according to the timestamp. A total of 1190 groups of data were extracted from the period of 7:40:54–7:46:13. The base station IP number is 1–11. An experimental motion coordinate system is established for the GPS coordinates of the vehicle and the base station, which is used in the verification of the fusion positioning algorithm.
The sorted data fields are presented in Table 5.

Table 5. Integration of data fields.

| Number | Data Name     | Data Sample                  |
|--------|---------------|------------------------------|
| 1      | ID            | 2                            |
| 2      | Time          | 7:41:07                      |
| 3      | Time-s        | 0.59375                      |
| 4      | RSSI          | 9                            |
| 5      | Base station IP | 2                  |
| 6      | GPS-s         | 0.359375                     |
| 7      | Speed         | 12.42 (1 knot = 1.852 k)     |
| 8      | Angle         | 94.58                        |
| 9      | Actual veh GPS | (65573.45175, 5279031.715)  |
| 10     | Base station GPS | (65705.26914, 5278991.382) |
The WFA fusion positioning is a positioning scheme based on range trilateral positioning and least-squares positioning fusion. Figure 4 shows the comparison between the WFA fusion scheme vehicle positioning trajectory and the vehicle driving trajectory.

There is a continuous large error in the middle of the positioning trajectory, and only some vehicles’ trajectory results are suitable. From the positioning result calculated by formula (20), the positioning accuracy analysis diagram of the WFA fusion method can be obtained, as shown in Figure 5.

In Figure 5, the WFA fusion positioning scheme analyzes the accuracy of the mean positioning error, RMSE, and CRLB. The positioning error of the WFA scheme is basically controlled within 100 m. Firstly, compared with the three RMSE values, the RMSE of WFA is better than the RMSE of trilateral positioning, which is close to the least-squares result, and the accuracy is improved. Secondly, among the three positioning methods, the positioning error of WFA fusion positioning is the closest to CRLB. From the perspective of CRLB, the positioning accuracy of the fusion scheme is relatively good. The reason why the error distance of individual points is lower than CRLB is that it is assumed that the error in CRLB estimation follows Gaussian distribution, and the error in the experiment is
biased to a certain extent, so some individual errors may exceed the lower limit of CRLB. The quantitative comparison of positioning accuracy is shown in Table 6.

Table 6. Positioning accuracy evaluation index.

| Programme          | Trilateration Algorithm | Least-Squares Algorithm | WFA Fusion Location Algorithm |
|--------------------|-------------------------|-------------------------|------------------------------|
| Mean value (m)     | 88.40                   | 72.91                   | 43.32                        |
| RMSE (m)           | 53.88                   | 43.45                   | 45.94                        |
| CRLB (m)           | -                       | -                       | 11.25                        |
| GDOP               | 1.18                    | 1.27                    | 1.29                         |

From the comparison of the accuracy evaluation indicators in Table 6, the positioning accuracies of the three positioning schemes are evaluated and compared from the four aspects of error distance average, RMSE, CRLB, and GDOP. The results show that the WFA fusion algorithm is better than the least-squares method and the trilateral localization algorithm. In terms of mean error, the mean error of WFA fusion positioning is 43.32 m, which is significantly improved compared with 88.40 m for trilateral positioning and 72.91 m for least-squares positioning, and the average positioning error is reduced by 51.00% and 40.58%, respectively. In terms of RMSE, the RMSE of the WFA fusion location is 45.94 m, which is 14.74% higher than 53.88 m for the trilateral location. Compared with 43.45 m of least-squares positioning, the positioning accuracy is improved by 5.73%. In terms of the GDOP, the GDOP of trilateral positioning is 1.18, which is better than the other two positioning methods. The result of 1.29 for the WFA fusion positioning is similar to that of 1.27 for least-squares positioning.

Figure 6 shows the CDP function diagram of the WFA fusion positioning scheme. It can be seen from the figure that the positioning error of the WFA fusion scheme is more concentrated in the range of 0–60 m. From the CDP, 67% of the positioning accuracy is within 46.70 m, and 95% of the positioning accuracy is within 123.69 m.

The comparison of various indicators shows that the positioning accuracy of the WFA fusion scheme has a certain improvement effect. The positioning accuracy of RMSE and CRLB is better than the results of trilateral measurement positioning and least-squares positioning, where only GDOP does not show a better result.
2. Analysis of WFB Fusion Positioning Accuracy

The WFB fusion positioning is a positioning scheme based on non-range centroid positioning fusion. Figure 7 shows the comparison between the WFB fusion scheme vehicle positioning trajectory and the vehicle driving trajectory.

Figure 7. WFB fusion method trajectory.

There are many large error coordinates in the positioning track. From the positioning result calculated by Formula (21), the positioning accuracy analysis diagram of the WFB fusion method can be obtained, as shown in Figure 8.

Figure 8. WFB fusion method analysis of the positioning accuracy.

In Figure 8, the accuracy analysis of the average positioning error, the RMSE, and the CRLB lower limit of the WFB fusion positioning scheme is carried out. Compared with the positioning error of centroid positioning, the error distance of the WFB scheme is partially reduced to within 50 m, indicating that the positioning accuracy of the WFB fusion positioning scheme has been significantly improved. The positioning error value of the WFB
fusion positioning is closer to the CRLB lower limit, indicating that the positioning accuracy is better. The quantitative comparison of positioning accuracy is presented in Table 7.

Table 7. Positioning accuracy evaluation index.

| Programme              | Centroiding | WFB Fusion Location Algorithm |
|------------------------|-------------|-------------------------------|
| Mean value (m)         | 189.65      | 48.56                         |
| RMSE (m)               | 89.10       | 45.87                         |
| CRLB (m)               | -           | 1.65                          |
| GDOP                   | 1.91        | 2.62                          |

From the comparison of the accuracy evaluation indicators in Table 7, the positioning accuracies of the two positioning schemes are evaluated and compared from the four aspects of error distance average, RMSE, CRLB, and GDOP. From the positioning results, the improvement of the WFB fusion positioning scheme is more obvious. The mean RMSE of the fusion positioning error is 48.56 m. Compared with the 189.65 m of the centroid algorithm, the average positioning error is reduced by 74.39%. The RMSE of the WFB fusion positioning is 45.87 m, which has a 48.52% improvement over the 89.10 m of the centroid algorithm. In terms of GDOP, the GDOP of fusion positioning is 2.62, which is 37.17% worse than the result of single positioning.

Figure 9 is the CDP function diagram of the WFB fusion positioning scheme. It can be seen from the figure that the positioning error of the WFB fusion scheme is 0–70 m and that it is relatively concentrated in this range. From the CDP, 67% of the positioning accuracy is within 57.08 m, and 95% of the positioning accuracy is within 127.55 m.

Figure 9. WFB cumulative distribution probability.

Comprehensive consideration of the WFB fusion scheme has a significant improvement effect on positioning accuracy. The positioning accuracy of fusion positioning is significantly improved compared to the positioning accuracy of single positioning from the mean error, CRLB, and GDOP, but a large positioning error in the results of the WFB fusion algorithm scheme still exists.

3. Analysis of WFC Fusion Positioning Accuracy

The WFC fusion positioning is a positioning scheme based on range-based trilateral measurement positioning, least-squares positioning, and non-range-based centroid positioning fusion. Figure 10 shows the comparison between the WFC fusion scheme vehicle positioning trajectory and the vehicle driving trajectory.
3. Analysis of WFC Fusion Positioning Accuracy

The WFC fusion positioning is a positioning scheme based on range-based trilateral measurement positioning, least-squares positioning, and non-range-based centroid positioning fusion. Figure 10 shows the comparison between the WFC fusion scheme vehicle positioning trajectory and the vehicle driving trajectory.

![Figure 10. WFC fusion method trajectory.](image)

It can be seen from Figure 10 that the positioning trajectory presents a similar result to that of WFA, and the overall positioning accuracy is suitable. According to the positioning result calculated by Formula (22), the positioning accuracy analysis diagram of the WFC fusion method is obtained, as shown in Figure 11.

![Figure 11. WFC fusion method analysis of the positioning accuracy.](image)

In Figure 11, the accuracy analysis of the average positioning error, the RMSE, and the CRLB lower limit of the WFC fusion positioning scheme is carried out. Comparing the WFC scheme with the least-squares positioning result with relatively good positioning results, the WFC fusion algorithm is better than the least-squares method. Compared with least-squares positioning, the positioning precision of the WFC scheme is significantly improved, and the distance of the coordinate error with a large error is obviously converged. Compared to the RMSE of the two methods, the RMSE of the WFC scheme is slightly lower than the least-squares positioning result. The WFC fusion has better positioning accuracy than least-squares positioning. Secondly, the positioning error of WFC fusion positioning is closest to CRLB, which shows that the positioning accuracy of the WFC fusion scheme is relatively better. The quantitative comparison of positioning accuracy is shown in Table 8.
Table 8. Positioning accuracy evaluation index.

| Programme         | Trilateration Algorithm | Least-Squares Algorithm | Centroiding | WFC Fusion Location Algorithm |
|------------------|-------------------------|-------------------------|-------------|-------------------------------|
| Mean value (m)   | 88.40                   | 72.91                   | 189.65      | 39.97                         |
| RMSE (m)         | 53.88                   | 43.45                   | 89.10       | 41.63                         |
| CRLB (m)         | -                       | -                       | -           | 13.03                         |
| GDOP             | 1.18                    | 1.27                    | 1.91        | 0.99                          |

Through the accuracy evaluation indicators in Table 8, the positioning accuracy of the four positioning schemes is evaluated and compared from the four aspects of error distance, RMSE, CRLB, and GDOP. The result is that the WFC fusion algorithm is better than the least-squares method, the trilateral positioning algorithm, and centroid positioning. In terms of the average error value, the average error of WFC fusion positioning is 39.97 m. By comparing this value to the 88.40 m for trilateral positioning, 2.91 m for least-squares positioning, and 189.65 m for centroid positioning, the average positioning error is reduced by 54.79%, 45.18%, and 78.92%, showing that the positioning effect is significantly improved. In terms of the RMSE, the RMSE of the WFC scheme is 41.63 m compared to the 53.88 m for trilateral positioning, 43.45 m for least-squares positioning, and 89.10 m for centroid positioning, where the average positioning error is reduced by 22.74%, 4.19%, and 53.28%. In terms of the GDOP, the GDOP of the WFC fusion scheme is 0.99, which is better than the 1.18 of trilateral positioning, the 1.27 of least-squares, and the 1.91 of the centroid algorithm.

Figure 12 is the CDP function diagram of the WFC fusion positioning scheme. It can be seen from the figure that the positioning error of the WFC fusion scheme is relatively concentrated in the range of 0–40 m. From the CDP, 67% of the positioning accuracy is within 46.31 m, and 95% of the positioning accuracy is within 122.53 m.

In summary, the WFC fusion scheme has the most significant improvement effect on positioning accuracy. From the mean error, RMSE, CRLB, and GDOP, the positioning accuracy of the fusion algorithm is much higher than the positioning results of the centroid algorithm, the trilateral measurement positioning, and the least-squares.

3.3.2. Comparison of Fusion Positioning Schemes

Comparing the positioning results of the three fusion positioning schemes—WFA, WFB, and WFC, Figure 13 shows the comparison of the accuracy evaluation indexes of
the three positioning schemes. The figure shows the comparison results of the positioning error, RMSE, and CRLB of the three fusion positioning schemes.

Figure 14 shows the positioning trajectory diagrams of the three fusion positioning schemes. It can be seen from the figure that the positioning trajectory of the WFC fusion positioning scheme is the closest to the real driving trajectory of the vehicle, and the positioning accuracy is the highest.

In summary, the WFC fusion scheme has the most significant improvement effect on positioning accuracy. From the mean error, RMSE, CRLB, and GDOP, the positioning accuracy of the fusion algorithm is much higher than the positioning results of the centroid algorithm, the trilateral measurement positioning, and the least-squares.

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Figure 14 shows the positioning trajectory diagrams of the three fusion positioning schemes. It can be seen from the figure that the positioning trajectory of the WFC fusion positioning scheme is the closest to the real driving trajectory of the vehicle, and the positioning accuracy is the highest.

Among the three positioning schemes in Table 9, the WFC fusion positioning scheme has the best positioning effect, the WFA fusion positioning scheme is in second place, and the WFB fusion positioning scheme has the lowest positioning accuracy. The positioning accuracy of the WFC fusion positioning scheme can reach 39.97 m, and the positioning accuracy of the WFA and WFB fusion schemes can also reach 43.32 and 48.56 m, respectively.

Table 9. Positioning accuracy evaluation index.

| Programme | WFA | WFB | WFC | Accuracy Improvement |
|-----------|-----|-----|-----|----------------------|
| Mean value (m) | 43.32 | 48.56 | 39.97 | 7.74% ↑ |
| RMSE (m) | 42.88 | 45.87 | 41.63 | 2.92% ↑ |
| CRLB (m) | 11.25 | 1.65 | 13.03 | 15.82% ↑ |
| GDOP | 1.29 | 2.62 | 0.99 | 23.26% ↑ |
| 67% CDP (m) | 46.70 | 57.08 | 46.31 | 0.84% ↑ |
| 95% CDP (m) | 123.69 | 127.55 | 122.53 | 0.94% ↑ |

In summary, the WFC fusion positioning scheme, based on ranging and non-ranging integration, has the best positioning effect. From the comparison of the mean error and RMSE, the positioning accuracy of the WFC fusion scheme is significantly improved.
Compared with the better schemes in the WFA and WFB schemes, the WFC scheme is significantly improved in terms of mean, CRLB lower limit, GDOP, and CDP, proving the positioning superiority of the WFC scheme. Among them, the average positioning error is improved by 7.74%. The RMSE dropped by 2.92%, indicating that the error convergence of WFC is the best. The CRLB increased by 15.82%, indicating that the standard deviation of the WFC scheme is closer to the CRLB lower limit, and the positioning error is smaller. The GDOP decreased by 23.26%, indicating that the influence of the relative location between the vehicle and the base station on the positioning accuracy is reduced. In the WFC fusion positioning scheme, 67% of the positioning accuracy reached 46.31 m, and 95% of the positioning accuracy reached 122.53 m.

Table 9. Positioning accuracy evaluation index.

| Programme | WFA Algorithm | WFB Algorithm | WFC Algorithm | Accuracy Improvement |
|-----------|---------------|---------------|---------------|----------------------|
| Mean value (m) | 43.32 | 48.56 | 39.97 | 7.74%↑ |
| RMSE (m) | 42.88 | 45.87 | 41.63 | 2.92%↑ |
| CRLB (m) | 11.25 | 1.65 | 13.03 | 15.82%↑ |
| GDOP | 1.29 | 2.62 | 0.99 | 23.26%↑ |
| 67% CDP (m) | 46.70 | 57.08 | 46.31 | 0.84%↑ |
| 95% CDP (m) | 123.69 | 127.55 | 122.53 | 0.94%↑ |

In summary, the WFC fusion positioning scheme, based on ranging and non-ranging integration, has the best positioning effect. From the comparison of the mean error and RMSE, the positioning accuracy of the WFC fusion scheme is significantly improved. From the comparison of CRLB and GDOP, the variability of the positioning error of the WFC fusion scheme is the smallest, and the error distribution is the most uniform.

4. Discussion

The distance propagation model locates the node position according to wireless signal strength. The positioning method, based on ranging, determines the quantitative relationship between the signal strength and the node spacing, according to the model. The node spacing is the calculated distance between the base station coordinates and the vehicle coordinates. The fitting results of the model have a great impact on the accuracy of positioning.

Based on the WFC fusion positioning scheme based on the optimal positioning result, the environmental impact indicator $A$ and the path loss coefficient $n$ in the model are taken as different values, and the positioning errors are respectively calculated for comparison. The original data of the same period are selected and calculated according to the positioning method in the WFC fusion positioning scheme.

The environmental impact indicators are respectively selected ($A = 178.6135$, $A = 184.6135$, and $A = 180.6135$) in the fitting result to obtain the effect of the positioning error, as shown in Figure 15.

It can be seen from Figure 15 that compared with the positioning results of the fitted model, the positioning error of the calculation with different environmental impact indicators is significantly increased, indicating that the accuracy of the positioning effect cannot meet the requirements.

Analyze the path loss indicator. Select $n = 7.892$, $n = 8.492$, and $n = 8.192$ in the fitting result, respectively, to obtain the effect diagram of the positioning error, as shown in Figure 16.

It can be seen from Figure 16 that compared with the positioning results of the fitting model, the positioning error of calculating the position with different path loss coefficients is significantly increased, indicating that the accuracy of the positioning effect cannot meet the requirements.
The changes in the environmental impact factor and the path loss coefficient have a negative impact on positioning accuracy, making the positioning error much higher than that of the WFC scheme. This indicates that the WFC fusion scheme is relatively better in the fusion positioning method based on ranging. Table 10 shows the comparison of positioning accuracy indicators when different parameters are selected for the model.

Table 10. Positioning accuracy evaluation index.

| Parameter Selection | A = 180.6135 | A = 178.6135 | A = 184.6135 | A = 180.6135 | A = 180.6135 |
|---------------------|--------------|--------------|--------------|--------------|--------------|
|                     | n = 8.192    | n = 8.192    | n = 8.192    | n = 7.892    | n = 8.492    |
| Mean value (m)      | 39.97        | 134.51       | 147.12       | 163.52       | 129.62       |
| Root mean square error (m) | 41.63      | 75.95        | 82.34        | 86.95        | 73.68        |
| Positioning effect  | -            | 86.98%↓      | 102.71%↓     | 114.06%↓     | 81.39%↓      |

It can be summarized from Table 10 that the selection of model parameters has a great influence on the error of the positioning results. A reasonable curve fitting can greatly reduce the error between the calculated distance and the true distance to obtain more accurate positioning results. The RMSE of the WFC fusion scheme, obtained according to the fitted distance propagation model, is 40.62 m, and the change of model parameters causes the positioning accuracy to decrease with varying degrees. The positioning effect of the four reference positioning schemes drops between 81.39% to 114.06%, and the average value of positioning error is above 100 m. According to the change of the selected model parameters, it can be explained that the change of the model parameters will have a negative impact on the positioning results and reduce the positioning accuracy of the vehicle. The positioning accuracy shows a downward trend with the change of the distance propagation model parameters, which is caused by the model parameters having reasonable calibration values, which makes the most accurate calculation.
5. Conclusions

First, the logarithmic distance propagation model was calibrated. The classical location methods based on ranging and non-ranging were integrated so that a vehicle wireless location fusion algorithm based on error weighting could be proposed. Then, based on the algorithm, a vehicle wireless positioning fusion method weighted by distance error and positioning error was proposed. Finally, the positioning accuracy of the fusion algorithm was verified by using the actual field measurement data.

The article shows that the results of the different fusion location methods are different. The fusion positioning scheme based on the integration of ranging and non-ranging positioning methods has the highest positioning accuracy and is better than the other two comparison schemes. The positioning effect of the other two fusion schemes is also significantly improved compared with the single positioning results. The model parameters have reasonable calibration values, which makes the positioning accuracy of the fusion algorithm optimal.

The main contributions of this study can be summarized as follows:

1. This article innovatively proposes a local vehicle positioning method as a supplement to GPS and trilateral positioning methods when the vehicle environment and positioning conditions are unstable; the method improves the robustness of vehicle wireless positioning.
2. Based on the data samples in the field experiment, the logarithmic propagation model is used to fit the distance propagation model of the node spacing in the positioning calculation. The model calibrates the environmental impact factor $A$ and path loss coefficient $n$.
3. A vehicle wireless location fusion algorithm using error weighting to eliminate line-of-sight and non-line-of-sight errors is proposed.
4. The positioning accuracy of the fusion algorithm is compared and verified using data samples, and the sensitivity of the influencing factors in the distance propagation model to the positioning error of the fusion algorithm is analyzed.
5. It assists in the all-day real-time recognition of regional traffic congestion status and makes up for the inaccurate traffic status recognition caused by the traditional vehicle positioning method due to the short-term position loss.

In further research, we will further discuss the applied research of the algorithm and optimize the algorithm to improve positioning accuracy. Starting from the calculation of improved weights, we will simulate and calculate the positioning information that can obtain the accurate position through GPS positioning within the service range of the base station and obtain the corresponding weight values of these points as the target weight reference value set. According to the space–time distance between the position obtained by each weight reference value and the target position (signal loss coordinate point), the weight reference value set is comprehensively processed to obtain the analog weight value of the target position. At the same time, more vehicle driving information, such as vehicle speed and vehicle loading rate, can be considered with the location algorithm to make it more suitable for the complex urban road environment and to solve the increasingly serious traffic congestion. According to the work of this article, we can continue to research other supporting algorithms of urban traffic congestion recognition. For example, the algorithm of vehicle speed can be based on the research result of this research. After completing the construction of all supporting algorithm systems, a complete set of urban traffic congestion recognition methods can be obtained, and, in cooperation with urban traffic managers, they can be applied to actual urban traffic management scenarios.

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