Research on train fingerprint positioning based on LTE-R signal strength

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Abstract. Being aimed at improving the low accuracy when using WKNN location fingerprint based on LTE-R signal strength value, CPSO algorithm, for its advantage, is applied to optimize the weight. CPSO_WKNN location fingerprint positioning algorithm is proposed to solve the train position coordinates. Through verification by cases, WKNN weight optimized by CPSO algorithm and PSO algorithm are separately analyzed and compared, which proves that CPSO optimizes the weight of WKNN algorithm with faster convergence speed. By fingerprint spacing every 25m, 50m, and 100m, the positions of the train in tunnel environment are solved separately by CPSO_WKNN location fingerprint positioning, PSO_WKNN location fingerprint positioning and WKNN location fingerprint positioning. The simulation results show that the positioning accuracy increases with the decrease of the fingerprint spacing for any of the three positioning methods. Under the same fingerprint spacing and the same accuracy demand, the accuracy level of CPSO_WKNN location fingerprint positioning is the highest. When fingerprint spacing is 25m and CPSO_WKNN location fingerprint is applied, the probability of positioning error less than 10m is 87.8%, and the probability of positioning error less than 25m is 96%, which can meet the demand of high-precision positioning in tunnel environment.

1. Preface
With the rapid development of high-speed railway system, the operational problems of multiple tunnels need to be solved urgently when trains are actually running through them. The current GPS (Global Positioning System), GNSS (Global Navigation Satellite System), BDS (Beidou Navigation Satellite System) and other positioning methods can meet the demand of precise continuous positioning of trains in open plains[1-2], but they are not suitable for high-precision continuous positioning in tunnel environments. In response, some scholars have proposed using BDS / GSM-R (Global System for Mobile Communications_Railway) train positioning method to achieve continuous accurate positioning of a train by fitting the train's driving route through neural networks[3-4]. But, GSM-R cannot be used to set up a base station in a tunnel, and when GSM-R is used to locate the train, it needs to rely on the installation of leaky coaxial cables. Furthermore, GSM-R is increasingly unable to meet the positioning needs of high-speed trains in terms of transmission delay and throughput. Some other scholars proposed to directly use LTE-R (Long term Evolution_Railway), a new mobile communication system for railway, to locate trains. Trains receive the signals in the LTE-R downlink channel containing the positioning reference signal PRS (Positioning Reference Signal) and take TDOA (Time Differences of Arrival) to achieve vehicle positioning[5], but this method requires at least 3 different fixed base stations, and due to the railway...
operating environment, especially in a tunnel environment, the multipath effect on the measurement time will cause a large error. To reduce the error, the complexity of the algorithm will increase or the large-scale additional equipment must be installed. On the contrary, location fingerprint positioning only needs one base station to complete positioning, by using instead of eliminating the errors caused by multipath effect[6,7].

This article applies a location fingerprint positioning method based on LTE-R signal strength characteristics to determine the train position. Based on LTE-R signal strength, the information characteristics of location fingerprints are used to construct a fingerprint space, and WKNN(Weighted k-Nearest Neighborhood) algorithm calculates the train position, but when the train is running at high speed in a tunnel, it is easily affected by the multipath effect, and the measured RSS(Received Singnal Strength) value will change greatly and affect positioning accuracy. The weight of WKNN algorithm is optimized, and a CPSO_WKNN algorithm is used to solve the train position information, which can effectively solve the problem of low positioning accuracy when performing location fingerprint positioning of trains based on signal strength.

2. Principle of location fingerprint positioning based on LTE-R signal strength

LF(Location fingerprint) is an RSS-based positioning technology, and its solution method for positioning is essentially a DCM (Database correlation algorithm) or a PM (pattern matching) algorithm[8-9]. The multipath propagation of wireless signals greatly depend on its environment. So the wireless signals are unique to each other at any location. Location fingerprinting technology is actually a combination of wireless signal characteristics and location information that forms a fingerprint strip, and a fingerprint database is established. Then the signal characteristics collected in real time on the mobile end are matched with the existing fingerprint database, and the position information of the target to be located is finally obtained. This positioning method is quite suitable for trains in a railway tunnel environment. This article applies signal feature values based on LTE-R to locate trains in a tunnel environment by using location fingerprints. Its principle is shown in Figure 1.

Location fingerprint positioning is based on the signal strength values of LTE-R. Before applying location fingerprint to positioning, a channel model of LTE-R is to be set up firstly, and then, a simulation scenario of LTE-R location fingerprint in tunnel environment is set up,too. Obtaining the RSS values of the train mainly includes two phases when performing location fingerprint positioning. First, in the offline phase, the RSS values of different AP (access points) obtained at a known reference point PR are collected to establish an offline fingerprint database; second, the real-time RSS values of the train is obtained in the established simulation scenario, and the train position is solved by using CPSO_WKNN (Chaotic Particle Swarm Optimization_Weighted k-Nearest Neighborhood) algorithm.

Figure 1. Principle of location fingerprint train positioning based on LTE-R signal strength.
3. LTE-R channel modeling and scene construction

3.1. LTE-R channel modeling

Reference [10] has fully proved that SPM (Super Position Model) model is more suitable for LTE systems. SPM model can accurately calculate the path loss difference for various environments in which trains are actually operated (plains, tunnels, or stations). Therefore, this article also draws on the model. SPM model is shown in Equation (1).

\[
L(d) = \lambda_1 + \lambda_2 \lg(d) + \lambda_3 \lg(h_{te}) + \lambda_4 \text{Diff} \\
+ \lambda_5 \lg(d) \lg(h_{te}) + \lambda_6 (h_{te})
\]  

(1)

\(\lambda_1\) is an offset constant with a value of 69.55; \(\lambda_2\) is a correction factor related to distance \(d\), which is generally 26.1; \(\lambda_3\) defaults to 5.83, which indicates the correlation factor of the effective height of the base station; \(\lambda_4\) is the correction factor for diffraction during the signal transmission process, taking 0.2 in the high-speed rail tunnel environment; \(\lambda_5\) is the correction factor for \(\lg(d) \lg(h_{te})\), the default value is -6.55; The default value of \(\lambda_6\) is 0, indicating the correction factor of the effective height of the train; \(d\) is the three-dimensional straight distance from the transmitting point to the receiving point, in km; \(h_{te}\) is the effective height of the base station transmitting antenna, in m; \(h_{re}\) is the train's effective height in m; \(\text{Diff}\) is the diffraction loss during signal transmission.

Since the model given by (1) is a general model, this article also needs to combine the operating characteristics of the high-speed railway tunnel to make it closer to the real scene. References [11, 12] have demonstrated that the reception intensity will not cause too much distortion and the actual cabin loss is 15-20dBm if train speed keeps under 500km/h. However, due to the complexity of the train operating environment, in addition to the speed affection on the channel model, other factors such as the environment needs to be added for correction. By considering the actual operating environment, this article improves the general SPM model in equation (1).

Added correction factors are speed correction factor \(\delta_1\) (\(\delta_1 = 0\) when speed is less than 200 km/h; \(\delta_1 = 1\) when speed is greater than 200 km/h; and \(\delta_1 = 3\) when speed is greater than 300 km/h), LTE-R network correction factor \(\delta_2\) (suburban \(\delta_2 = 5\); plain \(\delta_2 = 20\); mountain \(\delta_2 = 15\); tunnel \(\delta_2 = -15\)), Environmental correction factor \(\delta_3\) which obeys \(n \sim (0,2)\) normal distribution, and Width correction factor \(L_3 = \lg(d/2), 0 < a < 20, d^* = 8\), it is the distance from the mobile end to the leaked cable). The final improved SPM loss model is:

\[
L(d) = \begin{cases} 
10n, \lg(d) + p_i + 20 + \delta_1 + \delta_2 + \delta_3 + L_3 & d \leq 1000m \\
69.55 + 26.1\lg(d/1000) + 5.83\lg(h_{te}) + 0.2\text{Diff} & \\
-6.55\lg(d/1000)\lg(h_{te}) + 20 + \delta_1 + \delta_2 + \delta_3 + L_3 & d \geq 1000m
\end{cases}
\]  

(2)

3.2. Set up location fingerprint positioning scene

The simulation scenario of high-speed train location fingerprint positioning constructed in this article is shown in Figure 2. The length of the tunnel area is 20km, the base station antenna gain is 18dBi, the train antenna gain is 0dBi, and the circle along the railway line indicates the collection point of the location fingerprint positioning during the offline phase. Formula (2) is adopted as the channel transmission model of LTE-R in the tunnel environment, and formula (3) is to calculate the power of the received signal at any collection point in the tunnel area.

\[P_r = P_i + AP_{power} + FP_{power} - L(d) - \sigma\]  

(3)

\(P_r\) is the strength of received signal; \(P_i\) is the signal strength transmitted by a base station, which is set to 43dBm; \(AP_{power}\) is base station antenna gain; \(FP_{power}\) is the mobile station antenna gain; \(L(d)\) is the path loss value in the channel propagation model; \(\sigma\) is Gaussian noise, the average value of which is 0, and the standard deviation in the tunnel environment is 6.
4. Train positioning algorithm based on CPSO_WKNN location fingerprint

4.1. Offline phase
Location fingerprint positioning is designed to establish a fingerprint database in the offline positioning phase. In this article, the channel values given by equations (2) and (3) are used to calculate the RSS values from the surrounding APs, which are received by collection points. The RSS values are combined with the coordinates of the sampling points, obtained through the track circuit, to complete the establishment of the fingerprint database. This article sets up three types of distances (25m, 50m, and 100m) during simulation, because location fingerprint distance is an important index that affects the accuracy of train positioning.

4.2. Online Phase
The online positioning phase of location fingerprint positioning is actually a matching process between the RSS values obtained by the mobile terminal and the existing fingerprints in the fingerprint database. Generally, the final position is determined by calculating the Euclidean distance \( D_{ri} \) between the fingerprint to be located and the fingerprint in the database. It can be calculated by equation (4) [13].

\[
D_{ri} = \left( \sum_{j=1}^{n} \left| (ss_i - S_{ij}) \right|^r \right)^{1/r} \tag{4}
\]

In the equation, \( ss_i \) is the RSS vector corresponding to the \( i \)-th fingerprint currently tested, and \( S_{ij} \) is the RSS vector from fingerprint \( i \) located in the database to the base station \( j \). When \( r = 1 \), \( D_{ri} \) is Manhattan distance; when \( r = 2 \), \( D_{ri} \) is Euclidean distance.

WKNN algorithm is to select database vectors of \( k \) (\( k \geq 2 \)) closest target fingerprints, and multiply the coordinates corresponding to each database vector by a weighting coefficient as the estimated position [14,15] to obtain the position of the target train, as shown in Equation (5).

\[
f(\hat{x}, \hat{y}) = \sum_{i=1}^{K} \frac{1}{D_{ri} + \varepsilon} \times (x_i, y_i) \sum_{i=1}^{K} \frac{1}{D_{ri} + \varepsilon} \tag{5}
\]

In Equation (5), \((x_i, y_i)\) are the coordinates corresponding to the \( i \)-th fingerprint in the fingerprint database; \( \varepsilon \) is a small positive real number. Figure 3 shows how the position is obtained by WKNN.

![Figure 2. Simulation scene of LTE-R location fingerprint positioning in tunnel environment.](image1)

![Figure 3. Schematic diagram of WKNN positioning.](image2)

As can be seen from the above, the standard WKNN algorithm mainly relies on Euclidean distance to estimate the position of the target point. The calculation accuracy of the Euclidean distance is the key that can reflect the difference between the signal intensity vectors from different APs. Ideally, the closer the locations are, the smaller the vector difference between RSS is, and the higher the positioning accuracy will be. However, distance is not the only factor that determines the difference in signal strength. The fluctuation of the signal strength itself can easily cause the received signal strength vector RSS and the distance \( D_{ri} \) in the database to wrongly reflect the actual physical position.
difference. Therefore, this article applies CPSO algorithm to the optimization of the weights in WKNN algorithm before estimating the position points of the target train. So, the final positioning accuracy is improved. The algorithm flowchart of CPSO_WKNN location fingerprint train positioning is shown in Figure 4.

![CPSO_WKNN location fingerprint train positioning algorithm flow chart.](image)

The optimization process is as follows:

1. First, consider any weight of WKNN as a particle, which flies at a certain speed in the N-dimensional search space, and then map the particles from chaotic space to solution space. And form an initial particle group by Logistic chaotic operation with Equation (6). [13]

\[
X_{n+1} = L(\mu, X_n) = \mu X_n(1-X_n) \quad n=0,1,2,\ldots
\]  

In Equation (6), \(X_n \in [0,1] ; \mu \in [0,4]\) is the control parameter. When \(\mu = 4\) and \(X_n\) is not equal to 0.25, 0.5, 0.75, the Logistic mapping is a chaotic invariant set. After chaotic operation, the flying speed of a few particles can be ergodic and random. These particles do not easily fall into a local optimum, and they will not converge prematurely during the evolution process. Finally, the global optimal value of the particles is obtained. [14]

2. Throughout the evolution of the particle swarm, in addition to updating the speed and position of the particles [15-17] by equations (7) and (8), the optimal position of each particle and all particles in the swarm need to be stored. The optimal position of a single particle is compared with the optimal position of the particle swarm, and then the particles are moved to the global optimal point of the particle swarm, so that the optimal solution of WKNN weights can be obtained.

\[
v_{(i+1),j} = \omega v_{i,j} + c_1 \text{rand}((p\text{Best} - x_{i,j}) + c_2 \text{rand}((g\text{Best} - x_{i,j})
\]

\[
x_{(i+1),j} = x_{i,j} + v_{(i+1),j}
\]

Here "i" represents particle i, "j" represents the j-th dimension of the particle, \(t\) represents the t-th generation particle, pBest represents the optimal position of the i-th particle in the evolution process, and gBest represents the optimal position experienced by all the particles in the particle group, while \(c_1, c_2\) are the self-learning factor of the particles and the learning factor of the particle swarm, ranging from 0 to 2. Rand() is a random number in (0,1); \(\omega\) is Inertia weight. If the algorithm is expected to
contain good global convergence ability, \( \omega \) takes a larger value; if it is expected to contain good local convergence ability, \( \omega \) takes a smaller value. In actual values, a linear decreasing method can be used to adjust the weight factor and improve the optimization ability of the algorithm as shown in equation (9).

\[
\omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{t_{\text{max}}} \cdot t
\]

In the equation, \( t_{\text{max}} \) is the maximum number of iterations, \( \omega \in [\omega_{\text{min}}, \omega_{\text{max}}] \). According to experts’ experience, \( \omega_{\text{min}} \) is taken as 0.4, and \( \omega_{\text{max}} \) is taken as 0.9.

(3) When using the CPSO_WKNN location fingerprint positioning algorithm to determine train position, it is necessary to determine the fitness function when optimizing the weight of WKNN. According to the previous analysis, it can be seen that the target train position is to be located by the coordinates closest to it in the fingerprint database. The smaller the inverse of equation (4) is, the higher the positioning accuracy will be. The fitness function \( f \) when the CPSO algorithm is used to optimize WKNN is shown in equation (10).

\[
\text{fitness} (f) = \min \left[ \frac{1}{f(\hat{x}, \hat{y})} \right]
\]

5. Experimental simulation and results analysis

In order to test the superiority of WKNN location fingerprint positioning algorithm optimized by CPSO, this article conducts a simulation based on actual line data, comparing the accuracy of WKNN algorithm and CPSO_WKNN algorithm for positioning at 25m, 50m, and 100m. The standard deviation of Gaussian noise is taken as 6, and LTE-R simulation parameter settings are shown in Table 1.

| Parameter name | Value |
|----------------|-------|
| \( f_c \) MHz | 450   |
| \( h_o \) m   | 35    |
| \( h_y \) m   | 4.5   |
| \( d \) km    | 0.05~5|
| \( n \)       | 3.5/3/-15 |
| \( l_3 \)     | N-(0,2)22 dBm |
| \( K \)       | 20    |
| \( l_3 \)     | 500 m(tunnel) |
| \( l_3 \)     | 43 dBm |
| \( l_3 \)     | 12 dBm |
| \( l_3 \)     | 2 dBm |

When CPSO is used to optimize the weight of WKNN, the parameters are set as follows: the initial number of particles is 50, and the number of iterations of chaotic mapping is \( N \). The number of iterations of particle swarm evolution is taken as 200, the inertia weight \( \omega \) is linearly decremented from 0.8 to 0.6, and learning factor \( c_1 = c_2 = 2 \). When optimizing WKNN weights, the fitness value is to be calculated according to formula (10), and the calculation ends when its value is less than 0.0001. As shown in Figure 5, the CPSO and PSO algorithms are separately used to optimize the fitness curve of WKNN weights.

It can be seen from Figure 5 that CPSO algorithm can optimize WKNN weights with faster convergence and better results. After 9 iterations, the algorithm has converged well, and the fitness value is less than 0.0001, while PSO algorithm converges well after 23 iterations. In order to verify the positioning accuracy of WKNN location fingerprint positioning algorithm, it is optimized by CPSO, CPSO_WKNN, PSO_WKNN, and WKNN algorithms at 25m, 50m, and 100m. Figure 6 shows the comparison of the accuracy of the three ways to solve the train position. As can be seen from Figure 6, when using the CPSO_WKNN location fingerprint positioning, PSO_WKNN location fingerprint positioning, and WKNN location fingerprint positioning to locate the train, the positioning errors increase with the increase of the fingerprint spacing. when the weight of WKNN is optimized by the algorithms, the positioning error is significantly reduced, and it can be seen that the accuracy of CPSO_WKNN location fingerprint positioning is much higher than that of PSO_WKNN location.
fingerprint positioning. As a result, it is verified that the CPSO algorithm has a good correction effect on the positioning results of WKNN algorithm.

![Fitness curve.](image1)

**Figure 5.** Fitness curve.

![CDF (different distance).](image2)

**Figure 6.** CPSO_WKNN, PSO_WKNN, and WKNN location fingerprint train positioning error side-by-side to save space. Justify the caption.

Table 2 shows the positioning results of the three different algorithms at fingerprint spacing 25m, 50m, and 100m. It can be seen from the diagram that the probability of positioning error less than 10m is 87.8%, and the probability of positioning error less than 25m is 96% when fingerprint spacing is 25m and CPSO_WKNN location fingerprint is applied, while the probability of positioning error less than 10m is merely 40.3% with PSO_WKNN location fingerprint, and 10.9% with WKNN location fingerprint. When the fingerprint spacing is 50m or 100m, the probability of positioning error less than 10m and less than 25m under the CPSO_WKNN location fingerprint positioning method is significantly higher than that of PSO_WKNN location fingerprint positioning and WKNN location fingerprint positioning. As far as real trains are concerned, CPSO_WKNN location fingerprint positioning based on LTE_R can be applied at an interval of 25m for fingerprint collection, so that the probability of positioning error less than 10m is more than 87%, which can meet the demand of high-precision positioning.

| Train position solution method | Fingerprint pitch | Pitch |
|-------------------------------|------------------|-------|
|                              | 25m              | 50m   | 100m |
| CPSO_WKNN Positioning probability error<10m | 87.8% | 80.4% | 73.3% |
| CPSO_WKNN Positioning probability error<25m | 96.0% | 87.6% | 84.5% |
| PSO_WKNN Positioning probability error<10m | 40.3% | 25.9% | 18.2% |
| PSO_WKNN Positioning probability error<25m | 60.3% | 38.4% | 24.3% |
| WKNN Positioning probability error<10m | 10.9% | 3.1%  | 2.0% |
| WKNN Positioning probability error<25m | 19.8% | 4.1%  | 3.1% |

**6. Conclusion**

Based on the characteristic values of LTE-R signal strength considered as WKNN location fingerprints, this article firstly discusses CPSO algorithm for the optimization of the weight of WKNN, and then applies CPSO_WKNN location fingerprint positioning algorithm to train position coordinates
solving. The results of simulation show that the accuracy of WKNN location fingerprint positioning is very low. When the fingerprint spacing is 25m, the probability of its positioning error less than 10m is merely 10.9%. If PSO algorithm is used to optimize the weight of WKNN, the probability under the condition can be increased to 40.3%, but it still cannot meet the demand of high-precision positioning, for PSO algorithm tends to premature. CPSO_WKNN location fingerprint positioning algorithm proposed in this article successfully increases the probability of positioning error less than 10m to 87.8% when fingerprint distance is 25m. It is verified that CPSO converges faster than PSO algorithm when optimizing WKNN weights; it can converge to the best state by step 11. Therefore, CPSO_WKNN location fingerprint positioning algorithm can meet the demand of high-precision positioning of trains. Also, location fingerprint positioning discussed in this article is based on the characteristic values of LTE-R signal strength, and it makes full use of existing equipment to complete high-precision positioning in the blind zones of GPS / BDS under a tunnel environment. In addition, it may bring more applications with LTE.

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