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Urban Road Traffic State Identification Algorithm Based On Particle Filter and Fuzzy Discrimination

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Abstract

Urban road traffic state identification is a key link to realize the intelligent transportation based on the Internet of Vehicles, and accurately positioning vehicles is the foundation to realize the traffic state identification. Aiming at the problem that GPS has signal blind area in positioning vehicles, a vehicle positioning algorithm based on particle filter was proposed, it could improve the traditional algorithm on degradation and large amount of calculations; Based on vehicle positioning, an urban road traffic state identification algorithm based on fuzzy discrimination was proposed, it could comprehensively consider multiple factors' influence on traffic state. The experiment results show that the improved particle filter algorithm's mean squared error has increased about 55.437% compared with GPS method, and the traffic state identification algorithm can accurately identify the traffic state of the study area, it can prove that the urban road traffic state identification algorithm based on particle filter and fuzzy discrimination is feasible and effective.

Keywords: *Traffic state identification, Particle filter, Fuzzy discrimination, TDOA, RSSI*

1. Introduction

The explosive increase of vehicles has brought enormous pressures for urban road traffic, and traffic congestion has become a key obstacle to city development. With the rapid development of the Internet of Things, the intelligent transportation system (ITS) based on the Internet of Vehicles has become more and more important for alleviating traffic burden [1], and how to intelligently identify the road traffic state is a key link in ITS, it can provide fast and reliable traffic guidance information for traffic participants and managers, and then achieve the goal of alleviating traffic burden [2-3].

There are different kinds of urban road traffic state identification methods in present, among them, road traffic state identification model based on GPS is widely used [4-5], these kinds of models are built on road traffic parameters, such as travel time, average travel speed, traffic flow density, queue length, etc., different traffic parameters constitute the different road traffic state identification algorithms. But these algorithms mainly have two problems as follows:

(1) Although GPS has many advantages, such as simple deployment, economy, etc., cities always have GPS signal blind areas, therefore, GPS signal is not stable, which may

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decrease the accuracy in collecting data and positioning vehicles, finally, it can affect the traffic state identification precision.

(2) Road traffic state is usually influenced by many factors, such as road conditions, vehicle types, weather conditions, etc., and different factor's influence on traffic state has different degree [6], therefore, the changes of traffic states have large uncertainties, and usually these uncertainties can not be described by an absolutely accurate model.

Therefore, based on a wireless sensor network system oriented to urban road traffic data collection, we collect position and velocity information of moving vehicles, and then use TDOA and particle filter to positioning vehicles, finally, use fuzzy discrimination method to intelligently identify the traffic state. Simulation experiments show that the urban road traffic state identification algorithm based on particle filter and fuzzy discrimination is feasible, and the traffic state identification results are accurate.

2. Vehicle Positioning Algorithm Based On Improved Particle Filter

The algorithm is based on a wireless sensor network oriented to urban road traffic data collection, it needs to install sensor nodes on road sides and crossroads, and each vehicle also needs to install on-board sensor nodes. Among them, the road sensor nodes are responsible for broadcasting their own coordinates in the wireless sensor network, while the on-board sensor nodes are responsible for receiving the coordinates of the nearby road sensor nodes, and then positioning the corresponding vehicle by using the following methods.

2.1. Vehicle Coordinates Calculation Based on TDOA

When positioning signal source by using TDOA [6-7], refer to the time difference that signal arrives at different nodes, namely TDOA measure value, TDOA value is one-to-one corresponding to a hyperbola [8], multiple hyperbolas' intersection point is the location of the signal source. The principle of vehicle coordinates' calculation based on TDOA [9] is shown in Figure 1.

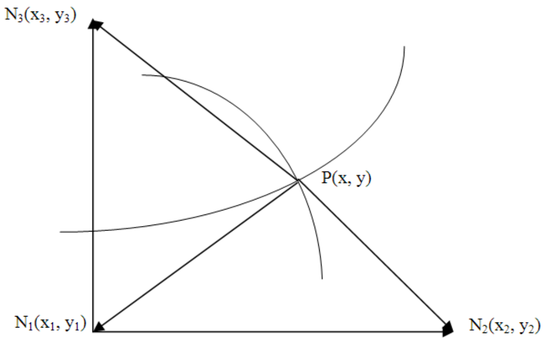

Figure 1. The Principle of Vehicle Coordinates' Calculation Based on TDOA

Among which $P(x, y)$ is the coordinates of vehicle to be positioned. $N_1(x_1, y_1)$ 、$N_2(x_2, y_2)$ 、 $N_3(x_3, y_3)$ are respectively the coordinates of three road sensor nodes with known coordinates, then:

$$d_{12} = \sqrt{(x - x_1)^2 + (y - y_1)^2} - \sqrt{(x - x_2)^2 + (y - y_2)^2} \qquad (1)$$

$$d_{13} = \sqrt{(x - x_1)^2 + (y - y_1)^2} - \sqrt{(x - x_3)^2 + (y - y_3)^2} \qquad (2)$$

Among which d_{12} is the distance difference between P to N_1 and P to N_2 ; d_{12} is the distance difference between P to N_1 and P to N_3 , usually, set N_1 as the reference coordinates, namely $N_1(0,0)$. As the collection of different road sensor nodes' coordinates have time difference, then:

$$d_{12} = ct_{12} \tag{3}$$

$$d_{13} = ct_{13} \tag{4}$$

Among which $c = 3 \times 10^8$ is the propagation velocity of electromagnetic waves, t_{12} 、 t_{13} are respectively the time difference of N_1 、 N_2 and N_1 、 N_3 .

Combine with formula (1)-(4), use the least squares estimation method, we can preliminarily estimate the coordinates of a moving vehicle. However, there are many groups of road sensors which can be used for vehicles positioning, therefore, we can get a vehicles positioning coordinates set $P = \{p_1, p_2, ..., p_n\}$, in order to reduce the overall error, according to a pre-set proportion, eliminate $p_i (i = 1,2,..., n)$ with larger error from P , and the elimination method is described as follows:

$$p_{mean} = \frac{1}{n} \sum_{i=1}^{n} p_i \tag{5}$$

$$i = \arg \max_{i} \left| p_i - p_{mean} \right| \tag{6}$$

Among which p_{mean} is the mean value of all calculated coordinates; i is the coordinate which has the maximum difference with p_{mean} , namely, i is the coordinate with maximum error.

Set the eliminating proportion as 40%, circularly calculate formula (6), eliminate coordinates with larger errors, and use the coordinates set $PR = \{p_1, p_2, ..., p_m\}$ constituted by the residual 60% coordinates to conduct the subsequent calculations.

2.2. Weighted Coordinates Calculation Based on RSSI

Considering that different positions of road sensor nodes have influences on calculating vehicle coordinates, use RSSI (Received Signal Strength Indicator) to adjust the coordinates calculated by different road sensor nodes, which can get the weighted positioning coordinates [9-10]. This paper uses logarithmic normal model as the RSSI propagation model, its formula is:

$$PL(d) = \overline{PL}(d_0) + 10\rho \lg(\frac{d}{d_0}) + Z_\sigma \tag{7}$$

Among which $PL(d)$ is the received signal strength as the propagation distance is d miles; $\overline{PL}(d_0)$ is the distance between the reference point and the signal source; d is the distance between the signal source and the vehicle to be positioned; d_0 is the low earth reference distance which is set as 1m; ρ is the path loss exponent which is set as 3; Z_σ is the Gaussian background noise which obeys $(0, \sigma^2)$.

According to different road sensor nodes' signal strength received by on-board sensor nodes, calculate the weight as follows:

$$W_{ij} = \frac{RSSI_i + RSSI_j}{\sum_{i=1}^{l} \sum_{j=1, j \neq i}^{l} (RSSI_i + RSSI_j)} \tag{8}$$

Among which W_{ij} is the received signal strength weight of two road sensor node i and j ; $RSSI_i$ 、 $RSSI_j$ are respectively the received signal strength of road sensor node i and j received by on-board sensor nodes to be positioned. The weighted coordinates of vehicles to be positioned can be calculated as:

$$p = \sum_{i=1}^{m} p_i w_i \tag{9}$$

Among which p is the weighted coordinates; $p_i \in PR$ ； w_i is the received signal strength weight of road sensor nodes corresponding to p_i .

2.3. Vehicle Positioning Algorithm Based On Improved Particle Filter

The basic principle of particle filter is to describe probability distribution by a random sample, through adjusting the weight and position of particles to approach the events probability, and use sample mean value as the state, at which the system estimate value has the minimum variance, it uses MC theory to extract particles in order to approximate posterior probability. However, classic particle filter algorithm has degeneration defect, and Bayes sampling method has large calculation defect, therefore, this paper improves the probability density function and the sampling method, and implements a vehicle positioning algorithm based on improved particle filter.

Assume that $q(x_{0:k} \mid y_{1:k})$ is the importance probability density function; X_0 is the weighted coordinates calculated by TDOA and RSSI; $x_{0:k} = \{x_i = i = 1,2,.., k\}$ is the unknown variables list at time k ; $x_{0:k}(i)$ is one item of $x_{0:k} = \{x_i = i = 1,2,.., k\}$; $y_{1:k} = \{y_i = i = 1,2,.., k\}$ is the observational variables list at time k ; $y_{1:k}(i)$ is one item of $y_{1:k} = \{y_i = i = 1,2,.., k\}$; $p(y_k \mid x_k)$ is the observation likelihood probability density; $p(x_k \mid x_{k-1})$ is the system state transition probability density; V_0 is the threshold of particle effective sampling size. The vehicle positioning algorithm based on improved particle filter is described as follows:

(1) Set $k = 0$, sample from $q(x_{0:k} \mid y_{1:k})$ and extract n samples $\{x_{0:k}(i), i = 1,2,.., n\}$ as particles, they need to obey the probability distribution $P(X_0)$, set the weight of each $x_{0:k}(i)$ as $w_k(x_{0:k}(i)) = \frac{1}{n}$;

(2) Set $k = k + 1$, sample from $q(x_k \mid x_{0:k-1}(i), y_{1:k})$ and extract n samples $\{x_k(i), i = 1,2,.., n\}$, add them into old samples $x_{0:k-1}(i) \sim q(x_{0:k-1} \mid y_{1:k-1})$;

(3) According to $w_k(x_{0:k}(i)) = w_{k-1}(x_{0:k-1}(i)) \frac{p(y_k \mid x_k) p(x_k \mid x_{k-1})}{q(x_k \mid x_{0:k-1}, y_{1:k})}$, update the weight of particle $x_{0:k}(i)$ at time k ;

(4) According to $w_k(x_{0:k}(i))' = \frac{w_k(x_{0:k}(i))}{\sum_{i=1}^{n} w_k(x_{0:k}(i))}$, normalize the weight of particle $x_{0:k}(i)$ at time k ;

(5) According to $V = \frac{n}{1 + \mathrm{var}(w_k(x_{0:k}(i))')}$, calculate the particle effective sampling size, if $V < V_{initial}$, then sample again;

(6) According to $X_k = \sum_{i=1}^{n} w_k(x_{0:k}(i))' x_{0:k}(i)$, estimate the coordinates of vehicle to be positioned at time k ;

(7) Repeat procedure （2）-（5）, if X_k does not change or calculations reach the maximum iteration times, end the algorithm.

3. Road Traffic State Identification Algorithm Based On Fuzzy Discrimination

Urban road traffic state is determined by multiple factors, which not only include the objective factors, such as road conditions, weather, but also include the subjective factors from drivers and passengers, therefore, it is difficult to evaluate the traffic by using an absolutely accurate model. However, fuzzy discrimination is a system evaluation method, it is useful to evaluate a system which is influenced by varies of factors, we can get a clear evaluation results through calculating the fuzzy relation between factors and evaluation results [11-12]. This paper proposes a fuzzy road traffic state identification algorithm based on fuzzy discrimination.

3.1. Traffic States and Evaluation Factors

3.1.1. Define The Traffic States: In 《evaluation index system of urban road traffic management (2007)》 issued by China, the classification of main road traffic state is primarily based on two parameters, they are the average schedule delays and the average speed of main road at peak time, aiming at different types of cities, road traffic states can be divided to 5 levels, and companies providing real-time traffic information in China usually divide the traffic states into 3 or 4 levels.

Considering traffic state quo of the study area and the above standards, this paper divides the traffic states into 4 levels, they are the flow, mild congestion, severe congestion and congestion.

3.1.2. Define The Traffic State Evaluation Factors: Road traffic state is usually influenced by varies of factors, some of them affect more while some of them affect litter, and they are likely to be connected with each other, therefore, we should choose the typical impact factors to evaluate the traffic state. The commonly used parameters include road average speed, traffic density, driving freedom, travel time and so on, according to principles of accuracy, convenience and sensitivity, this paper selects road average speed $\overline{V_i}$ and speed variation coefficient K_i of every vehicle in study area as the evaluation factors, the calculation method is described as follows:

$$\overline{V_i} = \frac{L}{\Delta t} \tag{10}$$

$$K_i = \frac{\sqrt{\frac{1}{n}\sum_{j=1}^{n}(V_{ij} - \overline{V_i})^2}}{\overline{V_i}} \tag{11}$$

Among which $\overline{V_i}$ is the average speed of vehicle i; L is the driving miles of vehicle i; Δt is the travel time of vehicle i; K_i is the speed variation coefficient of vehicle i; V_{ij} is the speed rate of vehicle i at every moment.

3.2. Subordinate Function and Weight

3.2.1. Define the Subordinate Function: The determination of subordinate function is the basis to do fuzzy arithmetic [13]. This paper uses linear analysis method to determine the subordinate function between evaluation factors and traffic states [13]. Assume that x is a evaluation factor, and $A(x)$ is the subordinate function between factor x and traffic state, k_1、k_2、k_3、k_4、k_5、k_6 are respectively the boundary data points chosen in liner analysis method. Then, the subordinate function can be described as follows:

$$A_1(x) = \begin{cases} 1 & x < k_1 \\ \frac{k_2 - x}{k_2 - k_1} & k_1 \le x < k_2 \\ 0 & x \ge k_2 \end{cases} \tag{12}$$

$$A_2(x) = \begin{cases} 0 & x < k_1 \\ \frac{x - k_2}{k_2 - k_1} & k_1 \le x < k_2 \\ 1 & k_2 \le x < k_3 \\ \frac{k_4 - x}{k_4 - k_3} & k_3 \le x < k_4 \\ 0 & x \ge k_4 \end{cases} \tag{13}$$

$$A_3(x) = \begin{cases} 0 & x < k_3 \\ \frac{x - k_3}{k_4 - k_3} & k_3 \le x < k_4 \\ 1 & k_4 \le x < k_5 \\ \frac{k_6 - x}{k_6 - k_5} & k_5 \le x < k_6 \\ 0 & x \ge k_6 \end{cases} \tag{14}$$

$$A_4(x)=\begin{cases}0 & x<k_5\\ \dfrac{x-k_5}{k_6-k_5} & k_5\le x<k_6\\ 1 & x\ge k_6\end{cases} \tag{15}$$

To $\overline{V_i}$, we set $k_1=10$, $k_2=15$, $k_3=20$, $k_4=25$, $k_5=30$, $k_6=35$; To K_i , we set $k_1=0.1$, $k_2=0.3$, $k_3=0.5$, $k_4=0.7$, $k_5=0.9$, $k_6=1.1$ 。

3.2.2. Define the Weight of Evaluation Factors: Different evaluation factors influence the traffic state in different degrees, therefore, use weight to value the influence degree, if a factor has a bigger influence on traffic state, and then the factor has a greater weight. When identifying the traffic state, if calculating each factor with weight, then we can get a more reasonable traffic state evaluation result.

The commonly used methods for determining the weight are expert experience and hierarchy analytic process, according to the predecessors' researches, this paper respectively sets the weight of $\overline{V_i}$ and K_i to be 0.68 and 0.32.

3.3. Road Traffic State Identification Algorithm Based On Fuzzy Discrimination

As urban road has varies kinds of uncontrollable factors, in order to avoid the abnormal vehicle driving state which may be caused by drivers or other factors, use data of all the vehicles driving in the study area, based on the position and velocity information of all the vehicles, combine with the vehicle positioning algorithm above, we can get the required data through a series of calculations.

Assume that there are n vehicles in the study area, $x_m\,(m=1,2)$ is the evaluation factor, r_{imp} is the subordinate degree between x_m of vehicle i and traffic state $p\,(p=1,2,3,4)$; $\circ$ is the inner product of two vectors. Road traffic state fuzzy discrimination algorithm can be described as follows:

(1) According to formula (12)-(15), calculate the evaluation matrix $R_i=\begin{bmatrix} r_{i11} & r_{i12} & r_{i13} & r_{i14}\\ r_{i21} & r_{i22} & r_{i23} & r_{i24}\end{bmatrix}$ of vehicle i ;

(2) Calculate the comprehensive evaluation result matrix $B_i=\begin{bmatrix} b_{i1} & b_{i2} & b_{i3} & b_{i4}\end{bmatrix}=(x_1 \quad x_2)\circ\begin{bmatrix} r_{i11} & r_{i12} & r_{i13} & r_{i14}\\ r_{i21} & r_{i22} & r_{i23} & r_{i24}\end{bmatrix}$;

(3) Use weighted average model, calculate the evaluation result $b_{ip}=\min(1,\sum_{m=1}^{k}x_m r_{imp})$ of vehicle i on level p ;

(4) calculate the subordinate degree $Y_p=\frac{1}{n}\sum_{i=1}^{n}b_{ip}$ of the entire road on level p ;

(5) The level p corresponding to $Y'=\max\{Y_p\}$ is the fuzzy discrimination result.

4. Simulation Experiment and Analysis

4.1. Simulation Experiment and Analysis of the Vehicle Positioning Algorithm

Choose the road between Campus West Road and Campus East Road crossing with Xiaxin Road of Northeast Forestry University as the study area, its width is 8m and its length is 250m, install 30 road sensor nodes around the road sides and two crossroads, these nodes' coordinates are all known before.

At initial time, choose 5 nodes to first position a vehicle, these nodes are nearest to the moving vehicle, and then use the vehicle positioning algorithm based on improved particle filter to calculate the coordinates on x axis and y axis, finally, comprehensively calculate the mean positioning error of x axis and y axis.

According to the calculated positioning result, comparing with the predecessors' research based on GPS positioning method on mean square error (MSE) and mean maximum error (MME), the comparison results are respectively shown in Figure 2 and Figure 3.

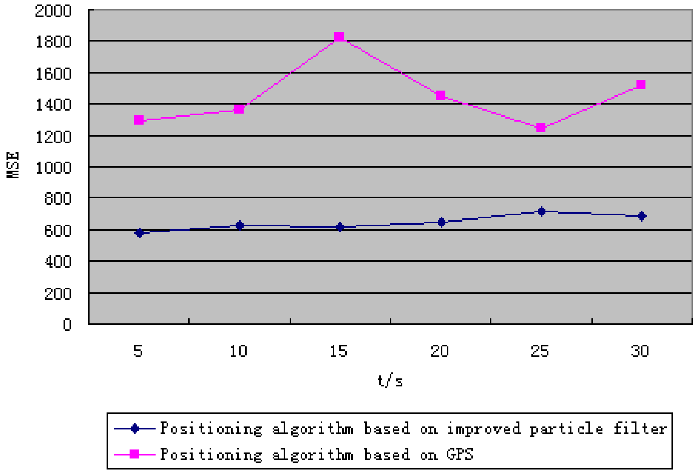

Figure 2. MSE Comparison Result of the Two Positioning Methods

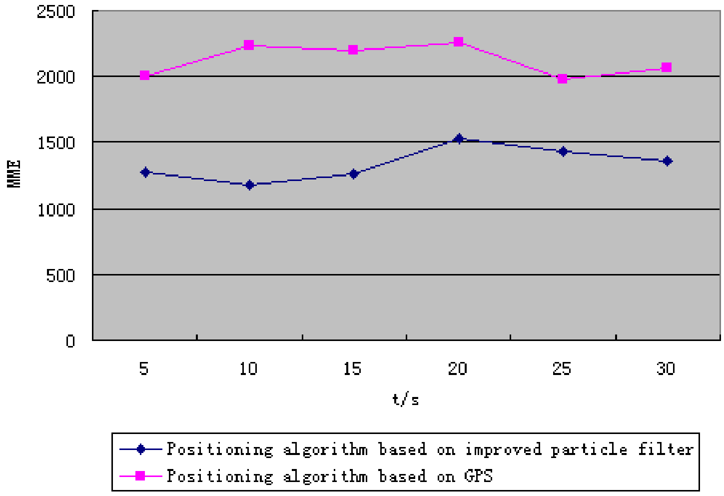

Figure 3. MME Comparison Result of the Two Positioning Methods

It can be seen from the figures that the vehicle positioning algorithm based on the improved particle filter is obviously better than the traditional GPS method on MSE and

MME, the MSE of the improved algorithm is 646.9cm while the traditional GPS method is 1451.66cm, he MSE of the improved algorithm has reduced about 55.437%.

4.2. Simulation Experiment and Analysis of Traffic State Identification

On the basis of the vehicle positioning algorithm based on improved particle filter, choose the road between Zhengyi Road and Haping Road crossing with Hexing Road of Harbin as the study area, its width is 20m and its length is 920m, install 70 road sensor nodes around road sides and two crossroads, these nodes' coordinates are all known before. Data collection intervals are respectively 13:38:30~14:12:44 and 16:00:13~16:25:48; driving speeds of each vehicle in the study area can be collected by the on-board sensor nodes.

Based on the collected coordinates and speeds data, first, positioning the vehicles using the above positioning algorithm, then calculate the membership degree matrix using traffic state identification algorithm; finally, evaluate the road traffic state according to the maximum subordinate degree principle.

Through a series of calculation, this paper gets the subordinate degree matrixes are respectively $Y = [0 \quad 0 \quad 0.2631 \quad 0.5264\ ]$ and $Y = [0 \quad 0.2466 \quad 0.7762 \quad 0.5832\ ]$, among which the traffic state level corresponding to the maximum value are flow and mild congestion. The identification results are agreed with the usual traffic state of the study area, it can prove that the algorithm can correctly identify the traffic state.

5. Conclusions

Aiming at the roundedness of GPS vehicle positioning method, considering the defects of traditional particle filter algorithm, this paper proposes an improved particle filter algorithm based on TDOA and RSSI to positioning vehicles, and based on the accurately vehicle positioning, an urban road traffic state identification algorithm based on fuzzy discrimination is proposed, this paper has got several conclusions as follows:

(1) The improved particle filter algorithm based on TDOA and RSSI can correctly positioning the moving vehicles, comparing with the GPS method, the MSE of the improved algorithm has reduced about 55.437%.

(2) Use fuzzy discrimination method to identify the traffic state can comprehensively consider different factors' influence on traffic state, and it can describe the traffic state more accurately.

As equipments are limited, this paper only chose one road to do the traffic state identification experiments, although data of different interval can prove the feasibility and accuracy of the improved algorithm, different roads lack the comparability, therefore, we should choose more roads to do the comparable experiments in order to further prove the significance of the algorithm.

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