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Research Article

Fuzzy-Based Hybrid Location Algorithm for Vehicle Position in VANETs via Fuzzy Kalman Filtering Approach

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Location information is very critical to VANETs such as navigation, routing, network management, and road congestion. In this paper, the vehicle location problem under urban road conditions is investigated by employing the GPS, WiFi, and Cellular Network (CN) positioning systems and by developing neighbor vehicle utilization in VANETs. Since GPS is possibly affected by satellite signal in real urban environment, while WiFi is only suitable for urban and CN is affected by the number of Base Stations (BSs) and signal strength, then a fuzzy-based hybrid location algorithm is developed. The algorithm has some advantages that it can enhance these positioning features by establishing a new fuzzy-weighting location mechanism (FLM) and also can adjust dynamically the measurement noise covariance by making use of a novel fuzzy Kalman filtering method. Finally, experiment results are given to show effectiveness and merit of the proposed approach.

1. Introduction

1.1. Motivation. VANETs are considered to be a special application of Mobile Ad Hoc Networks. It provides communications among moving vehicles and roadside infrastructures that are in close proximity to each other. Using vehicle-to-vehicle (V2V) communication, urgent messages can be transmitted among vehicles to support intelligent transport systems. Besides, vehicles can access Internet through the access points (APs) by using vehicle-to-infrastructure communication. Therefore, VANET has become an active area of research because it can be utilized for a broad range of safety and nonsafety applications [1–3]. All of these applications require or can take advantage of some sort of location information [4–8]. The different accurate localization information adapts for different applications [9]. It is significant to conduct investigations on localization problem in VANETs.

There have been works on vehicle location. GPS or differential GPS (DGPS) [10] is the most common technology providing LBS. However, the multipath error, low update rate, and shadowing effects limit its application in vehicle positioning systems. To improve the positioning performance with GPS/DGPS, a common choice is to integrate it with the INS [11]. Literature review shows that the GPS/INS integration filter is typically some form of a KF [12]. During the last decades, the filtering problem has attracted many researchers to study through various methodologies; see, for example, [12–14] and the references therein, in which these methods mostly consist of two main approaches, namely, the KF approach [12] and the H∞ filtering approach [13]. However, it is well known that the measurement noise covariance may decrease its filtering accuracy when keeping constant value in KF. In [15], a fuzzy estimator is used to compensate for the changing biases in measurement source, but these satellites do not tell the whole story about the bias in GPS noise.

In recent years positioning techniques in network-based methods such as CN and WiFi are available. The CN positioning method [16] determined a position by using Time Difference of Arrival (TDOA) measurements between a set of BSs and a targeted mobile station. To solve the navigation problem in the case that the number of visible GPS satellites is not sufficient, an integration method of GPS and TDOA from pilot signal of BSs [17] was introduced. This research is suitable for larger areas of positioning, but it ignores the CN method when the number of visible GPS satellites is more than three. The WiFi positioning method [18] used signal indication strength to determine user position by

establishing a radio map of WiFi signal strength, but only the error distance or the variance calculation of error distance considered.

Communication-based positioning technologies, fusing data from different sources, can be used to improve the performance of vehicle positioning in VANETs [19–21]. In [22], a distributed localization algorithm has been proposed to assist GPS-unequipped vehicles in estimating their positions based on nearby GPS-equipped vehicles. The proposed algorithm can successfully estimate the position of vehicles that not equipped with GPS, but it is hard to identify situations in which vehicles have network cards to communicate with other vehicles but have no GPS equipment.

Based on the above discussion, many positioning technologies and methods have been proposed for vehicle location, but each technology has its own drawbacks [20]. To the best of our knowledge, the hybrid vehicle positioning problem in VANETs has not been investigated by combining both multiple location technologies and KF method based on fuzzy control approaches, and it motivates the present work.

1.2. Our Contributions. With the rapid growing of wireless communications technology, combination of multiple localization technologies system which can compensate and overcome the weaknesses in single location technology has become a popular proposal [21]. Fuzzy logic control is an adequate methodology for designing controllers to certain nonlinear systems [23] and has found numerous applications in a wide range of real engineering problems [24, 25]. To overcome their individual limitations, by combining with GPS, WiFi, and CN positioning technology, a novel FLM is firstly proposed to enhance their individual positioning features. In detail, the FLM considers the outlier rating and absolute error as factors that affect the importance degree of each positioning method (GPS, WiFi, and CN). And, since the outlier rating and absolute error have a stronger nonlinear relationship with the importance degree [24], we integrate these two factors to obtain the corresponding importance degree by employing fuzzy theory.

Furthermore, it is well known that the KF is an optimal estimator and shows an optimal estimation of the system state by using the state space concept and system error model [26], while the measurement noise covariance in KF keeping constant decreases its filtering accuracy [25]. To solve this point, a fuzzy Kalman filter (FKF) is proposed to further enhance estimation precision for the concerned positioning model with perturbation, which is realized by dynamically adjusting its measurement noise covariance.

Based on the above discussion, we deal with the problems of the hybrid vehicle positioning technologies and the measurement noise covariance facts for vehicle location system in urban transportation area. The major contributions of this paper are summarized as follows:

(i) A FLM is proposed to distribute the weights of positioning technologies rationally with the assistance of nearby vehicles' location information, which is to overcome the limitations in each positioning technology.

(ii) A FKF is designed to dynamically adjust its measurement noise covariance by utilizing another fuzzy inference mechanism, which is to improve the filtering accuracy.

(iii) Experiment results are presented which could clearly show the effectiveness of the present results. Therefore, the main purpose of this paper is to make the first attempt to deal with the listed contributions.

The remainder of this paper is organized as follows: Section 2 presents the system architecture and situations. Section 3 details the FLM and the FKF is described in Section 4. Section 5 presents the hybrid location algorithm. In Section 6, experiment results show the performance of the proposed scheme. Section 7 concludes this paper.

2. System Architecture and Situations

2.1. System Architecture. Under specified circumstances and requirements from applications in VANETs, independent technologies were proposed and optimized. Among the most used technologies there are GPS, WiFi, CN, and other methods based on RFID, camera, accelerometer, and so forth. It is worth noting that the proposed system does not depend on any specific localization technologies but is built to be an open platform so that multiple heterogeneous localization technologies can be integrated into. In this paper, we just utilize several common positioning methods (GPS, WiFi, and CN) to illustrate the proposed system.

Though more technologies applied means more information to improve precision as well as availableness, each positioning technology has its own drawbacks. For example, GPS is not good with shelter or when the number of visible satellites is reduced, WiFi is only suitable for urban areas and the positioning performance of CN method is also affected by the number of BSs and signal strength. If we can combine them and determine which method is to be trust more in real-time, then the localization results can be more credible and reliable. In addition, the location information of neighboring vehicles can be useful for locating a vehicle [27].

Based on the above analysis, we make the following assumptions:

(i) All vehicles in VANETs can communicate with each other by using V2V communication and access Internet through the APs.

(ii) All vehicles in VANETs are equipped with GPS, WiFi, and CN positioning systems and can obtain the corresponding data.

(iii) The exact distance between one vehicle and its neighbor can be measured by using ultrasonic ranging technology [28].

Due to those requirements, the proposed positioning system in this research can be split into two parts: FLM and FKF. In FLM part, the target vehicle collects the location coordinates from GPS, WiFi, CN positioning systems, and the corresponding data of neighboring vehicles. These data are used for calculating the outlier rating and absolute error,

which are integrated by the method of fuzzy theory and obtain the importance degree of each positioning method. Then, the composite position can be calculated by using the weighted average method. In FKF part, the composite position is used as the measurement value, and the importance degree of the three positioning method is applied to adjust the measurement noise covariance dynamically. The system architecture of the proposed scheme is shown in Figure 1.

2.2. Situations. Since that the urban road conditions and vehicle location are essentially complicated case for vehicle driving environment, the two following situations are selected to better understand the proposed scheme.

(i) Situation 1. Suppose that there is an optimal situation when GPS, WiFi, and CN have the same localization coordinates. Then, (1) in Section 3.1 will become illegal. In this case, the importance degree of each positioning method must be set to 1.

(ii) Situation 2. Suppose that there is one positioning method extremely unreliable. Then, the positions out by this method should be excluded. For instance, if the importance degree of GPS is less than the set threshold (denoted by *th*, in this paper, *th* is set to 0.3), then the importance degree of GPS must be set to 0.

3. The FLM Method

3.1. Calculation of the Outlier Rating and Absolute Error. The outlier rating is one of the two factors that have effect on the importance degree of each positioning method, which indicates the deviation between the localization coordinates of one positioning method and the others'. Let $GPS(X, Y)$, $WiFi(X, Y)$, and $CN(X, Y)$ denote the localization coordinates given by GPS, WiFi, and CN devices on the target vehicle. Then, the outlier rating (denoted by s) of each positioning method can be defined as

$$\begin{aligned} s_{GPS} &= \frac{(d_{GW} + d_{GC})}{(d_{GW} + d_{GC} + d_{WC})} \\ s_{WiFi} &= \frac{(d_{GW} + d_{WC})}{(d_{GW} + d_{GC} + d_{WC})} \\ s_{CN} &= \frac{(d_{WC} + d_{GC})}{(d_{GW} + d_{GC} + d_{WC})} \end{aligned} \tag{1}$$

where d_{GW} is the Euclidean distance between $GPS(X, Y)$ and $WiFi(X, Y)$; d_{GC} and d_{WC} have the similar format. Obviously, the bigger the outlier rating's value, the smaller the positioning method's credibility. Accordingly, the importance degree of the positioning method should be a smaller value.

However, in some cases the outlier rating would make the wrong judgment. For example, GPS positioning errors will become large when satellite signals are weak. In this situation, if WiFi position happens to be close to GPS position and far away from CN position, which is more accurate than the other two. According to (1), s_{CN} is larger than s_{GPS} and s_{WiFi}, so the importance degree of CN position is smaller. The result is opposed to the hypothesis that the CN position is accurate.

To compensate the wrong judgment of the outlier rating, we adopt the absolute error as another factor that has an impact on the positioning method's importance degree. The absolute error can indirectly reflect the positioning method's localization error. Let $GPS_{nei}(X, Y)$, $WiFi_{nei}(X, Y)$, and $CN_{nei}(X, Y)$ denote the corresponding localization coordinates of the target vehicle' neighbor. And the exact distance between the target vehicle and its neighbor is denoted by D. Then the absolute error (denoted by e) of each positioning method can be defined as

$$\begin{aligned} e_{GPS} &= |D_G - D| \\ e_{WiFi} &= |D_W - D| \\ e_{CN} &= |D_C - D| \end{aligned} \tag{2}$$

where D_G is the Euclidean distance between $GPS(X, Y)$ and $GPS_{nei}(X, Y)$; D_W and D_C have the similar format. It is clear that the absolute error has an inverse relationship with the positioning method's credibility. If the absolute error is a bigger value, then the importance degree of the positioning method should be a smaller value.

3.2. FLM. To integrate the outlier rating and absolute error, we design a novel FLM inference model. The fusion process [29] of the FLM consisted of the following components:

(i) Fuzzification. The outlier rating (s) and absolute error (e) are transformed into fuzzy sets of corresponding domain as input variables and the importance degree (w) is transformed into fuzzy sets of corresponding domain as output variable.

(ii) Interface Engine. Mimicking features of human thought, according to expert knowledge or fuzzy inference rules based on control experiences, output results of FLM were obtained by fuzzy inference.

(iii) Defuzzification. Fuzzy inference results obtained by fuzzy logic reasoning were fuzzy voted into precise volumes.

The inputs and outputs of the FLM are fuzzified and described by their membership function. In order to compromise control accuracy and computational effort, this section sets five fuzzy subsets for input variables. In detail, as shown in Figure 2, the five fuzzy subsets, marked as VS (very small), S (small), M (medium), L (large), and VL (very large), have been chosen to smooth the control action. Meanwhile, triangular, Gaussian, and trapezoidal shapes have been adopted for the membership functions [30].

The FLM is constructed by employing these fuzzy inference rules, and these fuzzy rules can be described in the following rules:

if $s = A_i$ and $e = B_j$ then
$w = C_{ij}$ $(i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m)$

where A_i is fuzzy value of the outlier rating, B_j is fuzzy value of the absolute error, and C_{ij} is fuzzy value of the

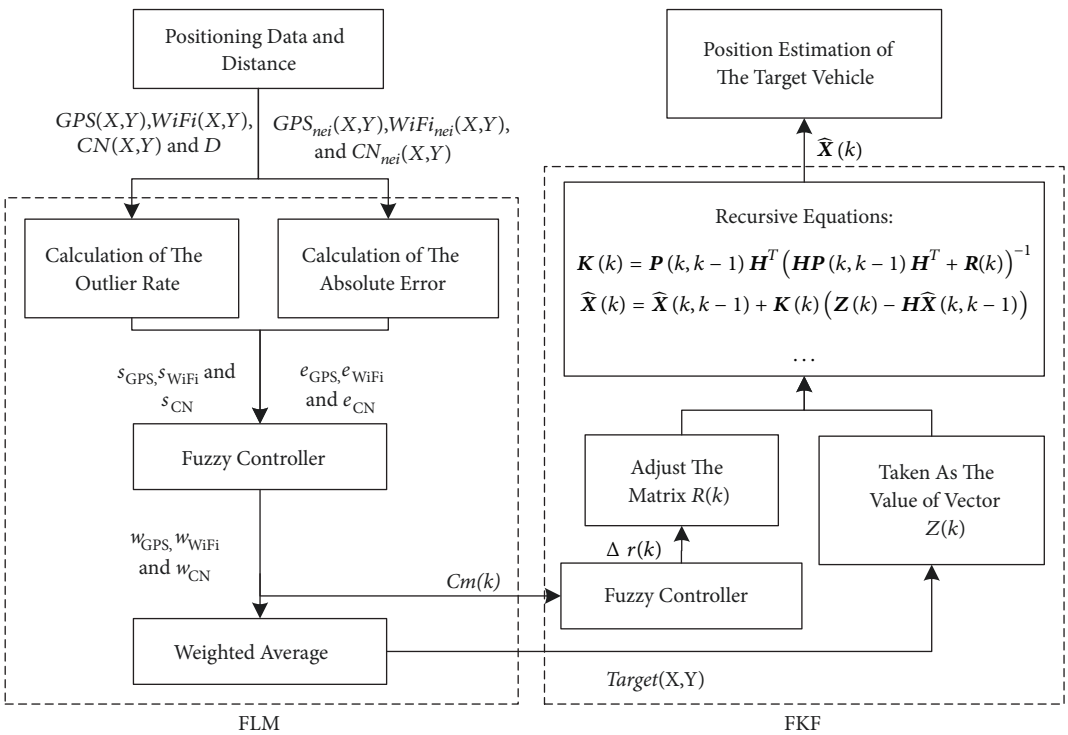

Figure 1: The FLM+FKF positioning system architecture.

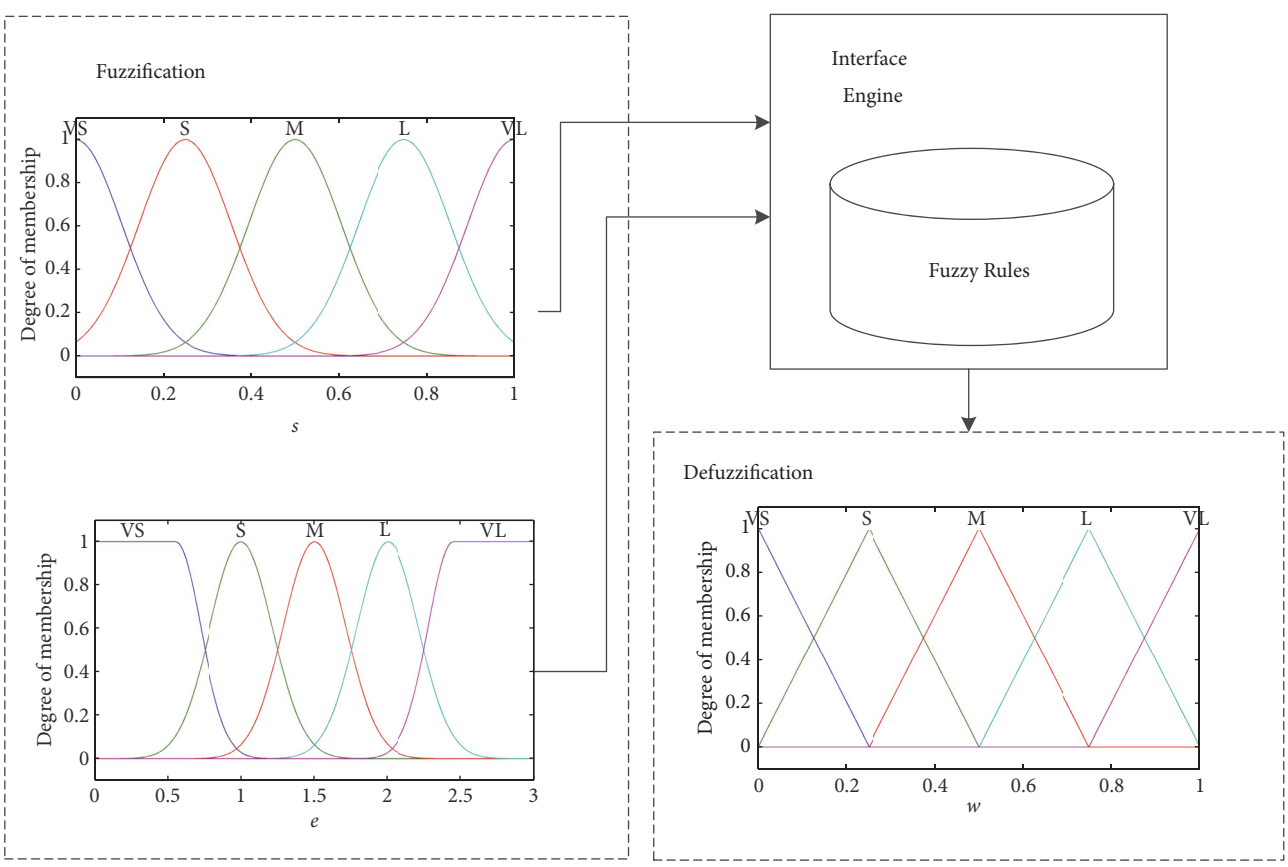

Figure 2: The FLM fuzzy inference model architecture.

Table 1: Fuzzy inference rules.

Importance degree (w)		Outlier rating (s)				
		VS	S	M	L	VL
Absolute error (e)	VS	VL	VL	L	L	M
	S	VL	VL	L	M	M
	M	L	L	M	S	S
	L	M	S	S	VS	VS
	VL	S	S	S	VS	VS

importance degree. Fuzzy rules are obtained from the analysis of the system behavior. For instance, if the outlier rating is very large (s=VL) and the absolute error is also very large (e=VL), then it means that the considered method is highly unreliable, and degree of this method, i.e., the output of controller system, and thus the importance should be a pretty small value (w=VS). These rules are shown in Table 1.

Moreover, the well-known Mamdani's MAX-MIN manner is considered as the inference method, in which there are several methods for interface engine [30], while the center of gravity is used for the defuzzification process [31]. According to the inference machine, the inferred output value (w) correspondence to the input values (s and e) is given as

$$w = \frac{\sum_{l=1}^{n\times m} \alpha_l c_l}{\sum_{l=1}^{n\times m} c_l} \tag{3}$$

where c_l is singleton value of fuzzy output variable using the l-th rule and α_l is the degree of fulfillment of the l-th rule that using the min operator can be expressed as

$$\alpha_l = \min\left\{\mu_{Al}(s), \mu_{Bl}(e)\right\} \tag{4}$$

where Al and Bl are the input fuzzy variables corresponding to the l-th rule.

3.3. Composite Position of the Target Vehicle. Let us put the outlier rating and absolute error of each positioning method into the FLM model, and then we can obtain the importance degree accordingly. To get the composite position, we assume that the importance degree of each positioning method can be denoted by w_{GPS}, w_{WiFi}, and w_{CN}, and then the composite position of the target vehicle by weighted average approach can be obtained as

$$\begin{aligned} Target(X,Y) = {} & GPS(X,Y) * \alpha + WiFi(X,Y) * \beta \\ & + CN(X,Y) * \gamma \end{aligned} \tag{5}$$

where α, β, γ are

$$\begin{aligned} \alpha &= \frac{w_{GPS}}{(w_{GPS} + w_{WiFi} + w_{CN})} \\ \beta &= \frac{w_{WiFi}}{(w_{GPS} + w_{WiFi} + w_{CN})} \\ \gamma &= \frac{w_{CN}}{(w_{GPS} + w_{WiFi} + w_{CN})} \end{aligned} \tag{6}$$

4. The FKF Design

4.1. Description of the Filter Equations. In order to explain the FKF's recursive relations, let us start with state and measurement equations which are the same as KF. State equation is as follows [26, 32]:

$$\boldsymbol{X}(k+1) = \boldsymbol{A}\boldsymbol{X}(k) + \boldsymbol{W}(k) \tag{7}$$

where $\boldsymbol{X}(k)$ is process state vector at the time t_k, $\boldsymbol{X}(k+1)$ is process state vector at the time t_{k+1}, $\boldsymbol{A}$ defines state transition matrix from $\boldsymbol{X}(k)$ to $\boldsymbol{X}(k+1)$, and $\boldsymbol{W}(k)$ defines process error vector (a white sequence with a defined covariance function is presumed). Measurement equation is as follows:

$$\boldsymbol{Z}(k) = \boldsymbol{H}\boldsymbol{X}(k) + \boldsymbol{V}(k) \tag{8}$$

where $\boldsymbol{Z}(k)$ defines measurement vector at time t_k, $\boldsymbol{H}$ is a matrix which defines ideal relation (noiseless) between measurement vector and state vector at t_k, and $\boldsymbol{V}(k)$ defines measurement error vector (it is presumed as a white sequence with a defined covariance and zero correlation with $\boldsymbol{W}(k)$ sequence). Covariance matrix for $\boldsymbol{W}(k)$ and $\boldsymbol{V}(k)$ vectors is defined with the following equations [33]:

$$E\left[\boldsymbol{W}(k)\boldsymbol{W}(i)^T\right] = \begin{cases} \boldsymbol{Q} & i = k \\ 0 & i \neq k \end{cases} \tag{9}$$

$$E\left[\boldsymbol{V}(k)\boldsymbol{V}(i)^T\right] = \begin{cases} \boldsymbol{R} & i = k \\ 0 & i \neq k \end{cases} \tag{10}$$

$$E\left[\boldsymbol{W}(k)\boldsymbol{V}(i)^T\right] = 0 \quad \textit{for all } i \textit{ and } k \tag{11}$$

where $\boldsymbol{Q}$ is the process noise covariance matrix and $\boldsymbol{R}$ is the measurement noise covariance matrix.

As soon as the measurement vector $\boldsymbol{Z}(k)$ is known, then the FKF's recursive equations are as follows:

$$\widehat{\boldsymbol{X}}(k,k-1) = \boldsymbol{A}\widehat{\boldsymbol{X}}(k-1) \tag{12}$$

$$\boldsymbol{P}(k,k-1) = \boldsymbol{A}\boldsymbol{P}(k-1)\boldsymbol{A}^T + \boldsymbol{Q} \tag{13}$$

$$\begin{aligned}\boldsymbol{K}(k) &= \boldsymbol{P}(k,k-1)\boldsymbol{H}^T \\ &\quad * \left(\boldsymbol{H}\boldsymbol{P}(k,k-1)\boldsymbol{H}^T + \boldsymbol{R}(\mathrm{k})\right)^{-1}\end{aligned} \tag{14}$$

$$\begin{aligned}\widehat{\boldsymbol{X}}(k) &= \widehat{\boldsymbol{X}}(k,k-1) \\ &\quad + \boldsymbol{K}(k)\left(\boldsymbol{Z}(k) - \boldsymbol{H}\widehat{\boldsymbol{X}}(k,k-1)\right)\end{aligned} \tag{15}$$

$$\boldsymbol{P}(k) = (\boldsymbol{I} - \boldsymbol{K}(k)\boldsymbol{H})\boldsymbol{P}(k,k-1) \tag{16}$$

where $\widehat{\boldsymbol{X}}(k-1)$ is the a priori estimate of $\boldsymbol{X}(k)$, $\boldsymbol{P}(k\text{-}1)$ is the a priori error covariance matrix, $\boldsymbol{K}(k)$ is the Kalman gain, $\widehat{\boldsymbol{X}}(k)$ is the one-step-ahead estimate, $\boldsymbol{R}(k)$ is the modified measurement noise covariance matrix, and the adjustment process of $\boldsymbol{R}(k)$ will be described in the next subsection.

4.2. Fuzzy Control of the Measurement Noise Covariance. According to (14) and (15), we can easily infer that the smaller value of $\boldsymbol{R}(k)$, the bigger value of $\boldsymbol{K}(k)$, which means that the estimation of $\boldsymbol{X}(k)$ is more reliance on the measurement value and vice versa. In light of this, the value of $\boldsymbol{R}(k)$ plays an important role in the filtering process and has an impact on filtering accuracy. Therefore, the value of $\boldsymbol{R}(k)$ should change along with the credibility of measurement value (denoted by $C_m(k)$) rather than keeping a constant: the bigger value of $C_m(k)$, the smaller value of $\boldsymbol{R}(k)$, and vice versa. In this study, we can use the sum of the three positioning methods' importance degree as the credibility of measurement value.

$$C_m(k) = w_{GPS}(k) + w_{WiFi}(k) + w_{CN}(k) \tag{17}$$

where $w_{GPS}(k)$, $w_{WiFi}(k)$, and $w_{CN}(k)$ are the importance degree of GPS, WiFi, and CN method of positioning at time t_k, respectively.

In order to obtain a robust control of $\boldsymbol{R}(k)$, we adopt another fuzzy inference model whose input variable is $C_m(k)$ and output variable (denoted by $\Delta r(k)$) is used directly in the equation of $\boldsymbol{R}(k)$ adjustment.

$$\boldsymbol{R}(k) = (1 + \Delta r(k))\boldsymbol{R} \tag{18}$$

Considering the above analysis, we can make the fuzzy rules as follows:

(i) Rule 1: if $C_m(k)$ is very small (VS) then $\Delta r(k)$ is positive big (PB).

(ii) Rule 2: if $C_m(k)$ is small (S) then $\Delta r(k)$ is positive small (PS).

(iii) Rule 3: if $C_m(k)$ is medium (M) then $\Delta r(k)$ is zero (Z).

(iv) Rule 4: if $C_m(k)$ is large (L) then $\Delta r(k)$ is negative small (NS).

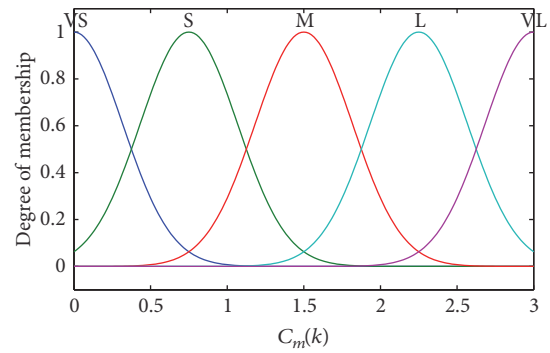

Figure 3: Membership functions for the credibility of measurement.

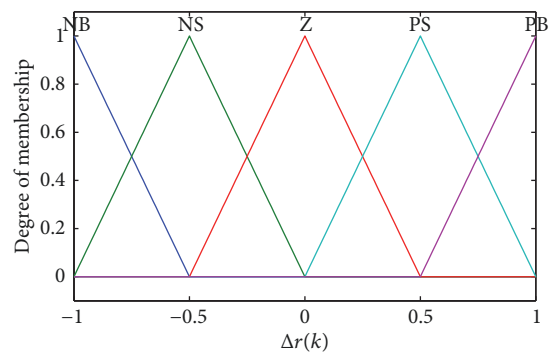

Figure 4: Membership functions for the adjustment value.

(v) Rule 5: if $C_m(k)$ is very large (VL) then $\Delta r(k)$ is negative large (NL).

The membership functions for $C_m(k)$ and $\Delta r(k)$ are shown in Figures 3 and 4, respectively.

According to all these fuzzy rules, we can make out the fuzzy relation matrix as follows:

$$\begin{aligned}RR &= (VS \times PB) + (S \times PS) + (M \times Z) + (L \times NS) \\ &\quad + (VL \times NB)\end{aligned} \tag{19}$$

The defuzzification process is also implemented by the Center of gravity method, which is mentioned in Section 3.2.

4.3. Determination of the Filter Parameters. In this study, the state vector (denoted by $\boldsymbol{X}$) of a vehicle consists of its location, speed, and acceleration. Therefore, the state vector can be defined as

$$\boldsymbol{X} = [\boldsymbol{s}, \boldsymbol{v}, \boldsymbol{a}]^T \tag{20}$$

where $\boldsymbol{s}$, $\boldsymbol{v}$, and $\boldsymbol{a}$ represent the vehicle's location, speed, and acceleration respectively, then we can obtain the state transition matrix $\boldsymbol{A}$ as follows:

$$\boldsymbol{A} = \begin{bmatrix} 1 & T & \dfrac{\left(-1 + \alpha T + e^{-\alpha T}\right)}{\alpha^2} \\ 0 & 1 & \dfrac{\left(1 - e^{-\alpha T}\right)}{\alpha} \\ 0 & 0 & e^{-\alpha T} \end{bmatrix} \tag{21}$$

Table 2: Experiment parameters.

Parameters	Value
Maximum vehicle speed	60km/h
Distance between target vehicle and its neighbor (D)	10m
Simulation time	1000s
Sampling time (T)	1s
Maneuvering frequency (α)	1
Initial position of target vehicle	(0,0)
Maneuvering acceleration variance ($\sigma_a{}^2$)	0
Measurement noise variance ($\delta_G{}^2$, $\delta_W{}^2$ and $\delta_C{}^2$)	1
Initial state ($\boldsymbol{X}(0)$)	$[0\ 0\ 0]^T$
Initial error covariance matrix ($\boldsymbol{P}(0)$)	Diag([1000 1000 1000], 0)

where α is maneuvering frequency which is determined by the driving environment. T is the sampling period of the FKF.

In the measurement update stage, we adjust estimation of the unknown state $\boldsymbol{X}(k)$ based on measurement value $\boldsymbol{Z}(k)$. In this paper, we use the composite position as measurement value. Therefore, the measurement matrix $\boldsymbol{H}$ can be defined as

$$\boldsymbol{H} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \tag{22}$$

The noise covariance matrix $\boldsymbol{Q}$ describes uncertainty in FKF model, in which its goal is to define unknown parameters in time. The value for $\boldsymbol{Q}$ matrix is determined as follows:

$$\boldsymbol{Q} = 2\alpha\sigma_a{}^2 \begin{bmatrix} q_1 & q_2 & q_3 \\ q_2 & q_4 & q_5 \\ q_3 & q_5 & q_6 \end{bmatrix} \tag{23}$$

where $\sigma_a{}^2$ is maneuvering acceleration variance. The value for $\sigma_a{}^2$ and q_x ($x = 1,2,\ldots,6$) is determined as follows [34]:

$$\sigma_a{}^2 = \frac{A_{\max}{}^2}{3}\left(1 + 4P_{\max} - P_0\right) \tag{24}$$

$$q_1 = \frac{1}{2\alpha^5}\left[1 - e^{-2\alpha T} + 2\alpha T + \frac{2\alpha^3 T^3}{3} - 2\alpha^2 T^2 - 4\alpha T e^{-\alpha T}\right] \tag{25}$$

$$q_2 = \frac{1}{2\alpha^4}\left[e^{-2\alpha T} + 1 - 2e^{-\alpha T} - 2\alpha T + 2\alpha T e^{-\alpha T} + \alpha^2 T^2\right] \tag{26}$$

$$q_3 = \frac{1}{2\alpha^3}\left[1 - e^{-2\alpha T} - 2\alpha T e^{-\alpha T}\right] \tag{27}$$

$$q_4 = \frac{1}{2\alpha^3}\left[4e^{-\alpha T} - 3 - e^{-2\alpha T} + 2\alpha T\right] \tag{28}$$

$$q_5 = \frac{1}{2\alpha^2}\left[e^{-2\alpha T} + 1 - 2e^{-\alpha T}\right] \tag{29}$$

$$q_6 = \frac{1}{2\alpha}\left[1 - e^{-2\alpha T}\right] \tag{30}$$

where A_{max} is the max maneuvering acceleration, P_{max} is A_{max}'s probability to occur, and P_0 is the probability of nonmaneuver situation to occur.

The measurement noise covariance matrix $\boldsymbol{R}$ is a diagonal matrix with zero nondiagonal elements [33]. The quantity of elements on the principal diagonal depends on measurement noise variance of the positioning devices. In this study, $\boldsymbol{R}$ is one-dimensional matrix and is determined as follows:

$$\boldsymbol{R} = \left[\frac{\delta_G{}^2\delta_W{}^2\delta_C{}^2}{\delta_W{}^2\delta_C{}^2 + \delta_G{}^2\delta_C{}^2 + \delta_G{}^2\delta_W{}^2}\right] \tag{31}$$

where $\delta_G{}^2$, $\delta_W{}^2$, and $\delta_C{}^2$ represent the measurement noise variance of GPS, WiFi, and CN systems, respectively.

5. Hybrid Location Algorithm

Based on the above system architecture and situations analysis, FLM method, and FKF approach in Sections 2, 3, and 4, the main hybrid location algorithm is addressed in Algorithm 1.

6. Results and Analysis

6.1. Simulation Platform and Parameters. In this section, we carry out an extensive simulation study on MATLAB platform to evaluate the performance of the proposed scheme, in which the communication model is the data direct connection in MATLAB/Simulink. We use a random number generator to produce the location error of each positioning method (GPS, WiFi, and CN). The major experiment parameters used in this paper are listed in Table 2.

6.2. Other Location Schemes. To show the effectiveness of the proposed hybrid location scheme, the other three location schemes are presented for comparison.

(i) Scheme 1 uses an adaptive-weighting locating mechanism in Yeh et al. [18] by using the Current Divider Rule with the variance of the error distance.

(ii) Scheme 2 uses the FLM, which adaptively adjusts the weight of each positioning method in [18] under different circumstances.

```
Input:
  Positioning data of the target vehicle:
     GPS(X, Y), WiFi(X, Y), CN(X, Y);
  Positioning data of its neighbor:
     GPS_nei(X, Y), WiFi_nei(X, Y), CN_nei(X, Y);
  Distance between the target vehicle and its neighbor: D
Output:
   Position estimation of the target vehicle: X̂(k);
Begin
(1)  if the positioning data and distance are available then
(2)     procedure FLM
(3)       if GPS(X, Y) = WiFi(X, Y) = CN(X, Y) then
(4)          set w_GPS = w_WiFi = w_CN = 1;
(5)       else
(6)          compute s as (1);   // the outlier rating
(7)          compute e as (2);     // the absolute error
(8)          if s and e are not null then
(9)             compute w as (3);     // the importance degree
(10)             if w_x is less than th then
(11)               set w_x = 0, //x is GPS, WiFi, and CN;
(12)            end if
(13)         end if
(14)         if w_GPS, w_WiFi, and w_CN are not null then
(15)          compute Target(X, Y) as (5);   // composite position:
(16)         end if
(17)    end procedure
(18) end if
(19) if w and Target(X, Y) are available then
(20)    procedure FKF
          //iterate at each sampling time (T)
(21)      compute C_m(k) as (17);
(22)      compute R(k) as (18) with (31);
(23)      compute Q as (23);
(24)      compute Z(k) as (8);
(25)      compute X̂(k) as (15);
(26)    end procedure
(27) end if.
(28) Return X̂(k)
End
```

Algorithm 1: Hybrid location algorithm.

(iii) Scheme 3 integrates the FLM with a conventional Kalman filter in [14], which keeps the measurement noise covariance matrix as a constant value.

(iv) Scheme 4 integrates the FLM with a FKF in this paper.

We will analyze the positioning performance of each location scheme on the aspects of accumulation error and cumulative distribution function (CDF) in different cases. As shown in Table 3, these cases are described as follows.

Case 1. It means the three positioning methods (GPS, WiFi, and CN) work in normal condition.

Case 2. It means GPS works in bad condition while WiFi and CN work normally.

Case 3. It means WiFi works in bad condition while GPS and CN work normally.

Case 4. It means CN works in bad condition while GPS and WiFi work normally.

6.3. Computation Complexity Analysis. The complexity computation of the proposed method is mainly relied in the fuzzy inference part and the base KF part. In general, the number of fuzzy sets defined in the input and output universes of discourse and the number of fuzzy rules in the fuzzy rule base mainly influence the complexity of a fuzzy system, where complexity includes time complexity and space complexity. These parameters can be viewed as structure parameters of a fuzzy control system. It is worth mentioning that the larger these parameters are, the more complex the fuzzy system is while the higher the expected performance of the fuzzy system is. Therefore, there is always a trade-off between complexity and accuracy in the choice of these parameters, because the accuracy is relatively proportional to

Table 3: Location error and accumulation error of GPS, WiFi, and CN for the first 200 meters.

Cases	Location error (m)			Accumulation error (m)		
	GPS	WiFi	CN	GPS	WiFi	CN
Case 1	10	10	10	102.33	104.16	101.49
Case 2	20	10	10	203.39	119.22	117.68
Case 3	10	20	10	104.88	221.47	109.21
Case 4	10	10	20	105.14	113.64	192.41

Table 4: Accumulation error of the proposed scheme and other location schemes for the first 200 meters.

Cases	Accumulation error (m)			
	Scheme 1	Scheme 2	Scheme 3	Scheme 4
Case 1	75.31	67.94	56.24	48.21
Case 2	94.75	88.91	60.68	50.37
Case 3	93.53	81.23	61.84	50.26
Case 4	91.43	79.25	57.82	49.71

calculation complexity. For the proposed algorithm, the KF part, the computation complexity is constant level while the computation complexity of the fuzzy system is O(mn) where m=5 and n=5.

In the light of Schemes 1–4, the experimental result is all averaged after 200 simulations, which is expressed in the above Section 6.1. And the theoretical time-consuming comparison can be expressed that Scheme 3 > Scheme 2 > Scheme 1, while Scheme 4 is similar to Scheme 3. However, it is worth mentioning that the proposed scheme is more time-consuming than the existing ones, but the time-consuming level of these schemes is constant.

6.4. Accumulation Error. As it is well-known, accumulation error is an important index to measure the localization performance of the positioning methods. From Tables 3 and 4, comparing to the three location schemes, the proposed scheme improves the location precision by combining with GPS, WiFi, and CN methods. It is clearly that the proposed scheme keeps the minimal accumulation error in different cases, which means the proposed scheme has a better performance than other schemes, which can be seen at the last row of Table 4. Moreover, the accumulation error of the proposed scheme reaches 48.21-50.37 under the different case; that is, there has no significant difference in these values, and thus it means that the proposed scheme is robust, though there is one positioning method extremely unreliable.

6.5. Cumulative Distribution Function. The CDF is defined as describing the probability that a random variable X with a given probability distribution will be found at a value less than or equal to x. We adopt the CDF to analyze the error distance of each positioning method. From Figure 5, it is easy found that, when the error distance is within 3 m, the CDF values of GPS, WiFi, and CN are less than 20%, and the CDF values of Scheme 1, Scheme 2, Scheme 3, and the proposed scheme reach 32%, 49%, 97%, and 99%, respectively, which means that the location error of the proposed scheme can be controlled within 3 m, even though

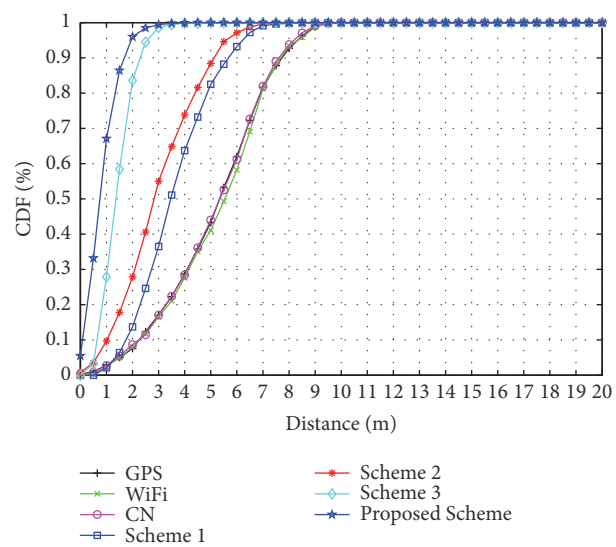

Figure 5: The CDF of each positioning method in Case 1.

the location error of GPS, WiFi, and CN methods are 10 m (Case 1). Moreover, it is worth mentioning that the proposed scheme has more than half of the probability (66%) to meet the localization requirement for critical safety applications in VANETs; that is, the positioning need of CDF less than 1 m is shown at about 0.66 in Figure 5. In Cases 2–4, from Figures 6–8, the location error of the proposed scheme also can be controlled within 4 m. Based on the above analysis, it is easy seeing that the proposed scheme has a high positioning precision, while it shows also that Scheme 4 is the better choice to utilize the proposed approach when enhancing GPS+Wifi+CN positioning precision.

7. Conclusion

This paper has investigated a hybrid urban vehicle location problem in VANETs. Since GPS is the most common locating

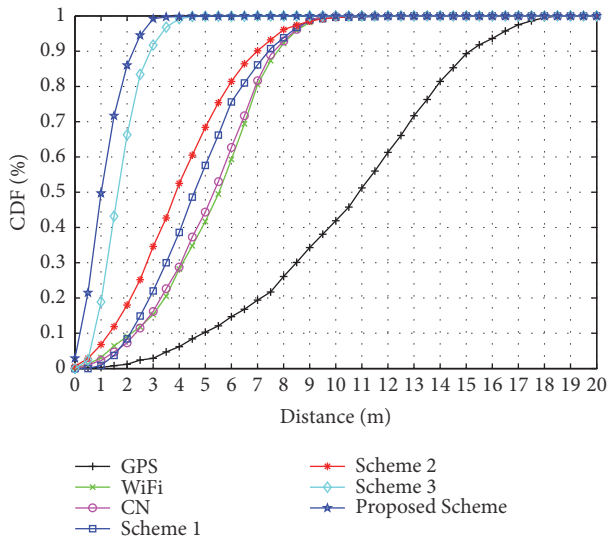

Figure 6: The CDF of each positioning method in Case 2.

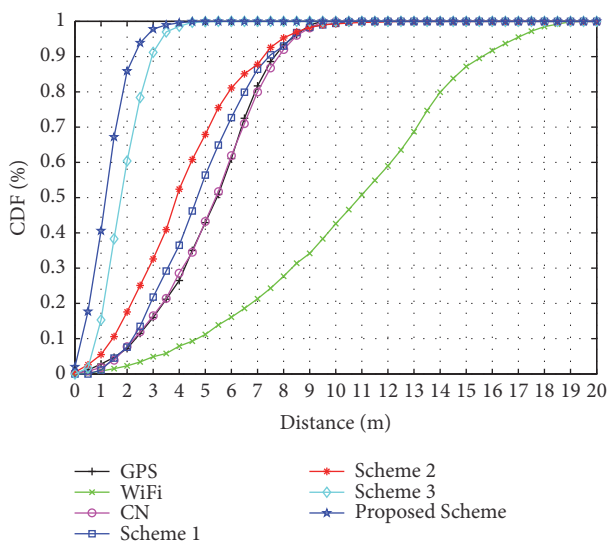

Figure 7: The CDF of each positioning method in Case 3.

method for vehicle position and the network-based positioning technology (WiFi and CN) should be supplement to GPS, a fuzzy-based hybrid vehicle locating scheme is developed by combining with GPS, WiFi, and CN positioning method, by distributing rationally the weights according to the creditability of each technology. Furthermore, the present approach can obtain the better accuracy by adjusting dynamically the measurement noise covariance via a novel FKF approach. At last, the experiment results show that the proposed approach yields the merit over the existing ones.

Data Availability

No data were used to support this study.

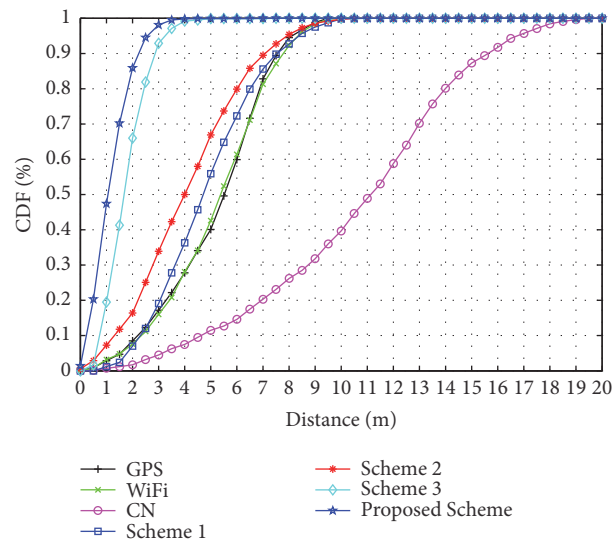

Figure 8: The CDF of each positioning method in Case 4.

Conflicts of Interest

The authors declare that there are no conflicts of interest of any kind regarding the publication of this paper.

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