Hindawi
Journal of Advanced Transportation
Volume 2020, Article ID 9139074, 14 pages
https://doi.org/10.1155/2020/9139074

Research Article

An Improved Automatic Traffic Incident Detection Technique Using a Vehicle to Infrastructure Communication

Muhammad Sameer Sheikh [1,2] Jun Liang [2] and Wensong Wang [3]

[1] *School of Automotive and Traffic Engineering, Jiangsu University, Zhenjiang 212013, China*
[2] *Department of Automotive and Transportation Engineering, Automotive Engineering Research Institute, Jiangsu University, Zhenjiang 212013, China*
[3] *School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798, Singapore*

Correspondence should be addressed to Muhammad Sameer Sheikh; sameer@ujs.edu.cn and Jun Liang; liangjun@ujs.edu.cn

Received 12 June 2019; Accepted 9 October 2019; Published 13 January 2020

Guest Editor: Kandaraj Piamrat

Traffic incident detection is one of the major research areas of intelligent transportation systems (ITSs). In recent years, many megacities suffer from heavy traffic flow and congestion. Therefore, monitoring traffic scenarios is a challenging issue due to the nature and the characteristics of a traffic incident. Reliable detection of traffic incidents and congestions provide useful information for enhancing traffic safety and indicate the characteristics of traffic incidents, traffic violation, driving pattern, etc. This paper investigates the estimation of traffic incident from a hybrid observer (HO) method, and detects a traffic incident by using an improved automatic incident detection (AID) technique based on the lane-changing speed mechanism in the highway traffic environment. First, we developed the connection between vehicles and roadside units (RSUs) by using a beacon mechanism. Then, they will exchange information once the vehicles get access to a wireless medium. Second, we utilized the probabilistic approach to collect the traffic information data, by using a vehicle to infrastructure (V2I) communication. Third, we estimated the traffic incident by using an HO method which can provide an accurate estimation of an event occurring. Finally, in order to detect traffic incident accurately, we applied the probabilistic data collected through V2I communication based on lane-changing speed mechanism. The experimental results and analysis obtained from simulations show that the proposed method outperforms other methods in terms of obtaining a better estimation of traffic incident which agrees well with the theoretical incident, around 30% faster detection of traffic incidents and 25% faster dissipation of traffic congestion. With regard to duration of an incident, the proposed system obtained a better Kaplan–Meier (KM) curve, influenced by the shortest duration of time to clear the traffic incident, in comparison with the other methods.

1. Introduction

In recent years, intelligent transportation systems (ITSs) draw a great deal of attention for the researcher of wireless and communication technology background. This raises concern to the transportation authorities because of the large number of vehicles on the road causing traffic incidents, congestions, road bottlenecks, etc. ITS integrates wireless communication technology with the transport networks in order to provide traffic safety, reduce traffic congestion, and improve traffic management [1, 2]. In addition to the traffic safety, ITS also provides entertainment services on vehicles such as climate information, internet access, etc. In many global cities, people are using private cars, taxi and bus to commute to their destination. Because traffic conditions on the road can rapidly become severe, it can affect the transport operations. Specifically, many metropolitan cities are suffering from severe traffic congestions in the urban and highway traffic environments, which are caused by the traffic incident [3]. As a consequence, the loss and disturbance caused by the traffic incident, is directly associated with the duration of the traffic incident which, may further deteriorate the traffic flow. In this context, early detection of incidents is necessary to investigate and to implement the traffic strategy for an ITS. These early incident detections can alleviate traffic congestion and hence improve the traffic flow for real-time traffic monitoring system in ITS [4].

The traffic incident is referred to as an abrupt change in traffic flow, which reduces the road capacity and increases traffic congestion. In the past, a traffic accident was very difficult to analyze due to the nature of an incident which is always changing and this makes the detection more complex for transportation authorities. Such complexity can cause the failure of the transportation management system. Therefore, there is a great need of designing a sophisticated algorithm, which is able to estimate and detect traffic incident. The challenging issue in ITS is to estimate and detect an incident from traffic congestion scenarios [5]. Generally speaking, an incident is referred to as an occurrence of an event that creates disturbance to the normal traffic flow [6]. Surveillance cameras are placed on the road to detect the traffic incident. An incident detection and the classification are a very important aspect in traffic management system. The traffic management system has the ability to conduct automatic incident classification (AIC) to evaluate different types of incidents [7].

As mentioned, in the past, many methods have been proposed which are used to collect data from the detectors such as loop detector, radar detector, video detector, etc. In this context, V2I communication system is used to collect data from vehicles to detect traffic incidents. V2I communication is a robust system, which is considered as a highly contributive in ITS [8, 9]. The collected data are processed by AID algorithms, which can generate incident alerts in case of any traffic incident and violations. Traffic incidents can be detected by using global positioning system (GPS) detector. Asakura et al. [10] presented the properties of traffic flow dynamics under incident by using floating data gathered from GPS. In this scheme, a proposed method is able to predict the time and location of traffic congestion influenced by a traffic incident. Surveillance cameras are placed on the road to detect the traffic incident. Incident detection and classification are a very important aspect of the traffic management system. The traffic management system has the ability to conduct automatic incident classification (AIC) to evaluate different types of incidents [7]. Ren et al. [11] presented a video-based technique to monitor and detect the traffic incident by evaluating the distribution characteristics of the traffic states on the road section. An incident detection system (IDS) play an important role in ITS which gains a lot of attention from the research community in recent years. The IDSs are designed to detect incident or unpleasant situation such as traffic incident, traffic violation and traffic congestion by using communication technology [5, 6]. The main challenging issue for an ITS is to obtain an early and accurate detection of traffic incident [12].

In past decades, machine learning techniques have been widely utilized to detect traffic incident. Many artificial neural network (ANN) were discussed [7]. Ritchie and Cheu [13] introduced an ANN technique which is able to detect the traffic incident with a better performance. However, the collection of ANN parameters is very complex and difficult to obtain. A hybrid approach is introduced by combing time series analysis and machine learning schemes to detect incidents [14]. This approach may detect traffic incidents accurately. Jin et al. [15] introduced the constructive probabilistic neural network (CPNN) in a highway traffic environment. This model is tested on I-880 and evaluated by considering online and offline traffic situations. However, this approach is able to detect only small traffic incidents.

To enhance the performance of AID, support vector machine (SVM) was introduced to detect traffic incident [4, 16, 17]. In [4], two SVMs were trained and simulated on the traffic incident data. This method did not produce a robust result because the selection criteria of SVM parameters and kernels are always very complex during the training process in order to construct a sample. Xiao [18] introduced SVM and k-Nearest Neighbor (KNN) ensemble learning method to detect traffic incident. This model trains SVM and KNN learning, and combine them to obtain better results. Wang et al. [7] introduced an incident classification of traffic data by using SVM method. However, this method cannot support small traffic data and require a much longer time to process the traffic data due to the characteristics of the ST signals. In social media such as Twitter, it has become the most famous tool used to gather information and have a large user's account database, which can share a portion of data to the public using APIs [19]. In recent years, many works have been proposed to detect the traffic incident by analyzing the location and time of an incident from tweets. In Ref. [19], Gu et al. introduced a real-time traffic detection from Twitter using the REST API. The proposed method utilizes Semi-Naive Bayes (SNB) method to detect five different incidents and obtain better performance. However, the processing of tweets from different incident situations often required large computational time. Schulz et al. [20] introduced a method to detect small incident by analyzing microblog. This method obtains a better detection of an incident, but only applicable for the low-level applications.

Dabiri and Heaslip [21] proposed a framework which is able to monitor and detect traffic incidents based on Tweeter, by using deep learning method. The proposed method utilized the numerous amount of Tweets to evaluate the traffic event condition and required a large computational time to process these tweets. Zhang et al. [22] introduced a new method to detect traffic incidents from Tweets using a deep learning method. The proposed method utilized millions of Tweets and was applied in two megacities. It also achieved better traffic incident detection, while consuming a large amount of time to process millions of Tweets. Paule et al. [23] proposed a method for geo-localization tweet, by utilizing a weight-voting algorithm where the weight of tweets votes depend on the user's reliability. The proposed method obtains a better detection of real-time traffic incident. However, due to an increase in the voting users, the proposed method is limited to the lower coverage and also limited users.

AID algorithm is used to calculate new parameters values from collected data and then compare these values to the threshold values to identify the incident detection. Several famous methods falls in this category such as McMaster Algorithm [24] and California Algorithm [25]. Recently, many approaches have been used to enhance the performance of existing AID schemes, such as integration of V2I communications with Bayesian-based scheme [26], which is focused on less traffic flow to detect an incident. He et al. [27] proposed a hybrid tree-based quantile regression method to predict and evaluate the incident duration. The presented method produced better results as compared to other predictive models. Peeta et al. [28] also proposed a variable message sign (VMS) scheme that only focused on the prediction of incident clearance time because of the delay caused by an accident.

Lu et al. [29] proposed a method to detect traffic incident based on nFoil. This method was implemented on the real traffic data and simulated traffic data generated from Singapore highway. The proposed method produced a better detection of a traffic incident. However, it required a longer time to process traffic data. Wang et al. [30] introduced an efficient multiple model particle filter (EMMPF) to estimate and detect traffic incident. The main idea is to implement an EMMPF to reduce the large computational time, which occurred in traditional AID techniques during the training of datasets. The proposed system is able to reduce the large computational time and the proposed method is only limited to the hybrid system which contains a large model. Based on GPS analysis, D'Andrea and Marcelloni [5] proposed a method to detect traffic incident and congestions to obtain a better incident detection rate. However, the proposed system was unable to differentiate between the traffic incident and congestion event due to the correlation of GPS data gathered from the moving or slow vehicles. Fogu et al. [31] introduced e-Notify system, which is able to detect traffic accident rapidly and also reduce the incident duration time, by implementing efficient communication through the combination of V2I and V2V, respectively. In the past, improved nonparametric regression based model was proposed to detect traffic incidents [32]. Popescu et al. [33] introduced an AID scheme, in which the lane changing distance and lane changing speed mechanisms were utilized to detect the traffic incident based on the collection of traffic-information data by using V2I communication. However, this method required a longer time to process the traffic data in terms of vehicle lane changing distance and also this scheme cannot distinguish the road bottleneck caused by a traffic incident.

The estimation and detection of traffic incident are one of the main challenging issues in the ITS. In the past, previous studies revealed that AID is a well-known and robust technique to detect traffic incident. Also, an AID technique can overcome the traffic congestion at the location where the occurrence of an incident caused the traffic difficulties such as road bottleneck, accident, and disabled vehicles, electronics equipment malfunctioning and other issues which can disrupt the traffic flow. Significant monitoring, estimation, and detection of traffic incident provide relevant traffic-related information to enhance the traffic safety and driving experiences, by providing a driver with real-time traffic information to assist decision. In particular, traffic monitoring, traffic incident management and traffic safety management are the main pillar for enhancing the ITS. This inspired us to further investigate the estimation and detection of the traffic incident. Specifically, the estimation of traffic incident and detection is somehow related to the pattern recognition problem, in which the incident and nonincident must be evaluated and classified. A sophisticated learning method can be applied to AID after training the data. So far, the support vector machine, neural network and deep learning techniques have been utilized to deal with this issue. These techniques depend on the propositional learning systems, which indicates that the data learned from these systems are propositional and not reliable. Also, a few AID algorithms such a McMaster algorithm [24] and California algorithm [25] are used to calculate the new parameter values from the collected data and compare these values to the threshold values to identify the incident detection. The estimation of traffic incident may not be accurate because of the hybrid modeling, in which the traffic incident can occur at any location with different traffic conditions. Estimation of traffic incident with HO method and incident detection with an improved AID technique are not covered well in the above studies. Also, the traffic data were not utilized to analyze the incident conditions.

In this paper, we presented an efficient ITS system, which is able to estimate and detect the traffic incident from the hybrid observer and an improved AID technique, respectively. The proposed system significantly utilized the PWSL observation to estimate the traffic incident and probabilistic collection of traffic data to detect the traffic incident. First, we developed the connection between vehicles and RSUs by using beacon mechanism. Once the connection is developed, they will exchange traffic-related information. Second, we employ the HO method to estimate the traffic incident, these estimations can provide an accurate estimation of an event occurring. Third, in order to detect traffic incident accurately, the proposed method exploits the probabilistic approach to collect the traffic information data by using V2I communication based on the lane changing speed mechanism.

The rest of this paper is structured as follows. Section 2 presents the system modeling in which vehicle signing and beacon signal mechanism have been discussed. Section 3 presents the probabilistic approach to obtain the traffic information data. Section 4 presents the proposed estimation of traffic incident and detection method. Section 5 discussed the comparison of the proposed model with different competent methods. Simulation results are presented in Section 6. Finally, Section 7 concludes this paper.

2. System Model

In this work, we assumed that the vehicles are equipped with a wireless module, which is used to communicate with the RSUs that are placed on the road to exchange traffic-related information with any passing vehicles. In addition, vehicles are also assumed equipped with the event data recorder (EDR) [34], which is used to monitor fast acceleration, speed, and lane information of the vehicles.

Figure 1 shows the system model of highway traffic flow on the road with the movement of vehicles in the forward direction. The RSUs are placed on the road apart from each other with a distance of nearly 1.5 km. These RSUs are able to provide equal coverage in its vicinity. Also, the RSUs situated in the adjacent and on the opposite side of the road, are used to construct infrastructure. Each RSU contains a GPS device to obtain the exact location of vehicles, a radio transceiver for developing a connection between passing vehicles and a computing device that processed traffic information data gathered from vehicles, such as lane changing speed and distance.

As shown in Figure 2, Figure 2(a) illustrates the vehicles are moving in the forward direction with the constant speed,

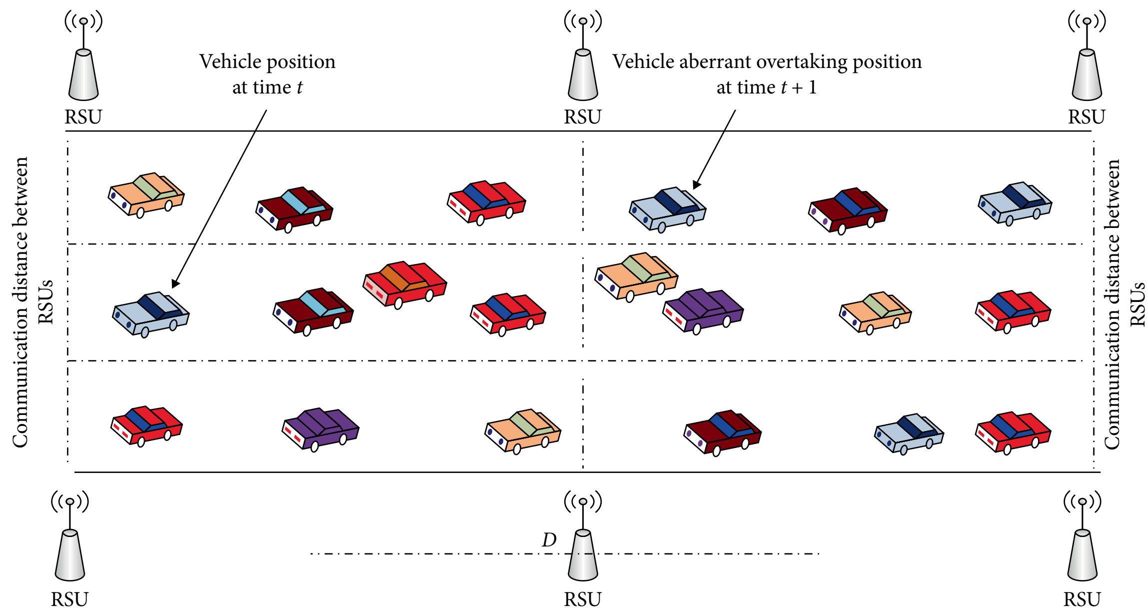

Figure 1: Traffic incident influenced by the vehicle aberrant overtaking.

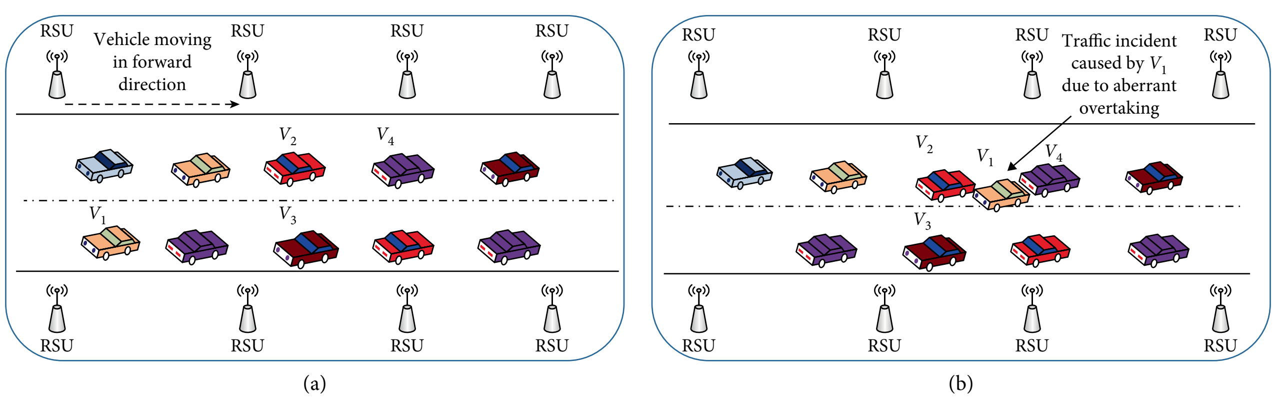

Figure 2: Traffic incident scenario. (a) Movement of vehicle in the forward direction, and (b) movement of vehicle with aberrant overtaking.

and Figure 2(b) illustrates an aberrant change in the speed of a vehicle V_1 during lane changing caused the traffic incident.

2.1. Vehicle Signing. In the proposed method each vehicle needs to sign up and register their details with the transport authority (TA). TA is responsible for managing database of the vehicles such as, vehicle ID, personal information of the drivers, and also providing certificates to the vehicles. It is important that all the vehicles must be connected with the TA.

A time-dependent secret $S_{v_{ri}}(t)$ act on behalf of the TA for verifying the identity of the vehicle v_{ri} and when it issued a message last time. The secret can be computed and encrypted as below.

Lets assume the vehicle v_{ri} sent a request for sign-up, to the TA at time t. First, TA will check the identity, *id* of v_{ri}, and then generate a reply which contains three parameters $(K_{v_{ri}}, e_{v_{ri}}, f_{v_{ri}})$, where $K_{v_{ri}}$ is a symmetric key, $e_{v_{ri}}$ and $f_{v_{ri}}$ are two integer values.

$$S_{v_{ri}}(t) = E_{kv_{ri}}\left\{e_{v_{ri}} + nf_{v_{ri}}\right\}. \tag{1}$$

Both the vehicle and TA must initialize the counter to the value of $e_{v_{ri}}$ and increment it by $f_{v_{ri}}$ at every message received by the vehicle v_{ri}.

2.2. Beacon Signal Mechanism. In this section, we discuss the beaconing signal process. After sign-in, each vehicle sends a beacon signal, periodic message, at every time τ_m second to share the detail information such as recent location, pseudo-identity and type of vehicle to the RSU.

Lets assume a vehicle v_{ri} establishs a beacon and transmits, the established beacon is expressed as below.

$$B_{v_{ri}} = \left[\mathrm{PID}_{v_{ri}}, t_i, \mu, S_{v_{ri}}(t), E_{kv_{ri}}[l(t)]\right], \tag{2}$$

where $\mathrm{PID}_{v_{ri}}$ is the pseudo-identity of the vehicle v_{ri}, t_i is used to protect from replay attack, $S_{v_{ri}}(t)$ is the sign-in process of the vehicle. $E_{kv_{ri}}[l(t)]$ is encrypted location and μ is the beacon signal using hash function $H()$ [35].

$$\mu = H\left(\mathrm{PID}_{v_{ri}}, t_i, S_{v_{ri}}(t), E_{kv_{ri}}[l(t)]\right). \tag{3}$$

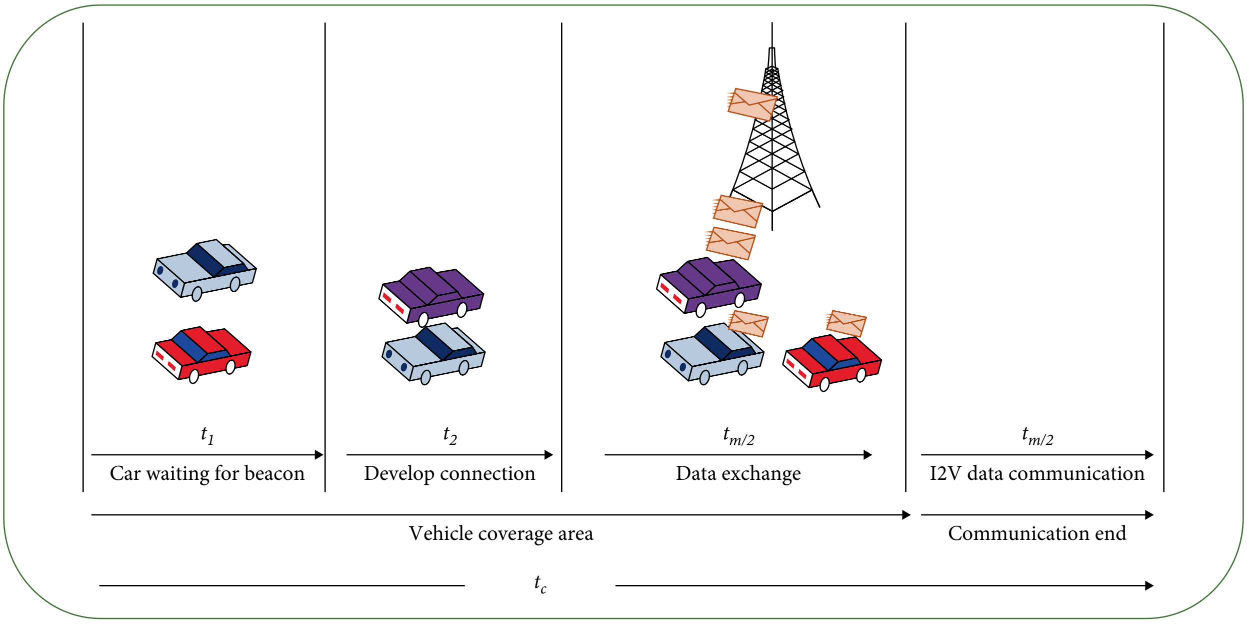

Figure 3: Developing communication between RSU and passing by vehicle.

Equation (3) is used to calculate the beacon signal, lets assume when a witness vehicle v_w received a message, it immediately checks the time-stamp t_i function of the received beacon, and then verify the beacon signal μ. If both values match, then the beacon content is correct. Therefeore, the beacon is considered valid within the vicinity of the incident vehicle.

As shown in Figure 3, the total time required to exchange the traffic information between vehicle and RSU is t_c, t_1 is the time when the vehicle are waiting to receive beacon, and at the time t_2 vehicle and RSU start to develop connection. Once the vehicle gets access to the wireless medium, it will exchange information such as ID, speed, acceleration, with RSU at time $t_{m/2}$, and exchange the information from RSU to vehicle at time $t_{m/2}$, respectively.

3. Collection of Traffic Information Data

Due to an enormous amount of traffic flow in the urban traffic environment, data from externalities on the road are often interlinked with other vehicles. Consequently, it is very difficult to collect and manage data from each vehicle passing through RSU. In order to obtain the accurate detection of traffic incident. Firstly, we applied the probabilistic approach to collect the data from the passing vehicles [36].

We assumed that the RSUs are active and able to collect the traffic-related information from the vehicles passing through the RSU with the probability of p_i. In particular, the vehicles are capable of maintaining a database of reliable traffic information to identify the traffic conditions that shows the sign of traffic incidents. The data collected from k number of vehicles with the probability of $1-\beta^n$ can lead to provide optimum aggregation. For some application β ranges from $0<\beta<1$ [36].

Lets assume A_n is an event caused by incident vehicle, i.e. vehicle A (see Figure 4), n number of vehicles passing the road for successful aggregation. Let B be the random variable which traces the number of vehicles that provided traffic data information among the n passing vehicles. So that the equation can be written as follows.

$$\begin{aligned} P_a[A_n] &= \sum_{k=0}^{n} P_a[A_n \mid B=k] P_a[B=k] \\ &= \sum_{k=0}^{n} \left(1-\beta^k\right)\binom{n}{k} p_i^k (1-p_i)^{n-k} \\ &= \sum_{k=0}^{n} \binom{n}{k} p_i^k (1-p_i)^{n-k} - \sum_{k=0}^{n} \binom{n}{k} (p_i\beta)^k (1-p_i)^{n-k}. \end{aligned} \tag{4}$$

Equation (4) observed as a binomial function,
where

$$\sum_{k=0}^{n} \binom{n}{k} p_i^k (1-p_i)^{n-k} = 1, \tag{5}$$

$$\sum_{k=0}^{n} \binom{n}{k} (p_i\beta)^k (1-p_i)^{n-k} = \left[1-p_i(1-\beta)\right]^n. \tag{6}$$

Equation (4) can be expressed as below.

$$\mathrm{P}_a[A_n] = 1-\left[1-p_i(1-\beta)\right]^n. \tag{7}$$

Lets assume Φ is the incident target caused by A_n. In order to detect the event which must satisfy the below condition.

$$\Phi \le 1-\left[1-p_i(1-\beta)\right]^n. \tag{8}$$

The transpositions can be yields as below.

$$1-\left[1-p_i(1-\beta)\right]^n \le 1-\Phi. \tag{9}$$

After applying natural logarithm to the Equation (9) and then divide by $\ln[1-p_i(1-\beta)]$, so the final equation can be expressed as below.

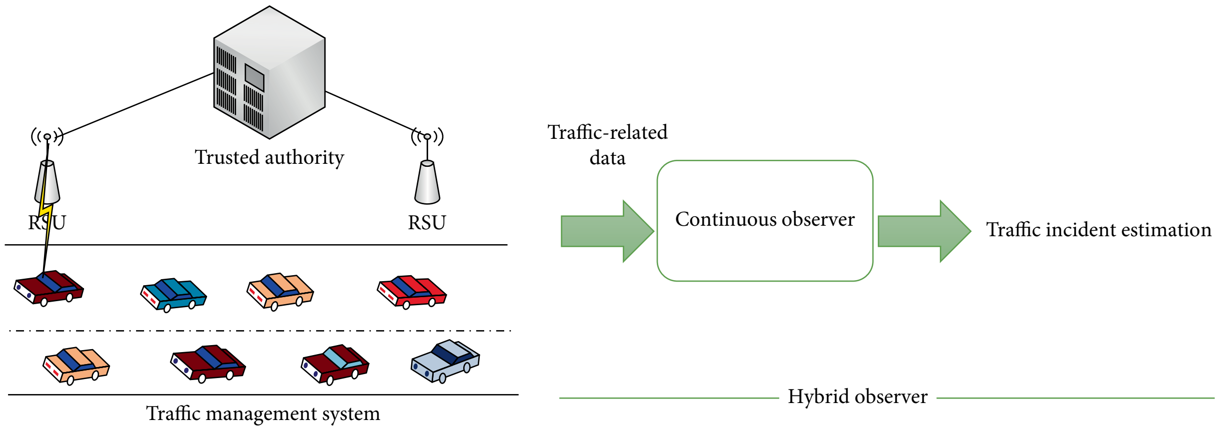

FIGURE 4: Estimation of traffic incident.

$$n = \left\lceil \frac{\ln(1-\Phi)}{\ln[1-p_i(1-\beta)]} \right\rceil. \quad (10)$$

Equation (10) is used to determine the number of vehicles which is necessary for meaningful aggregation at the event A_n caused by the incident vehicle in the highway traffic environment.

4. Proposed Traffic Incident Estimation and Detection

4.1. Designing of PWSL Hybrid Observer. A designing observer is used to estimate and reconstruct the traffic states of the dedicated system by using measurable variables. As the nature and characteristics of traffic systems are complex, a hybrid observer is able to estimate the possibility of occurring an event that detects the traffic incident. In order to obtain the accurate estimation of traffic incident, a PWSL model and hybrid observer are combined together to produce a better estimation [37].

To estimate the traffic incident, we have developed the structure of the hybrid observer with PWSL, which is written as.

$$\grave{t}(k+1) = M_s\grave{t}(k) + N_s v(k) + D_s + G_s(q_i(k) - \grave{q}_i(k)), \quad (11)$$

where G_s is the observer gain with traffic incident mode $\grave{t}$. G_s is linked with the PWSL to ensure the accurate estimation of traffic incident $\grave{t}(k)$ with the theoretical incident $t(k)$ under any traffic condition. Therefore, the observed gains ensure the convergence of estimated error and stablize the matrices $(M_s - G_s c)$.

Estimated traffic incident $\grave{t}(k)$ of the continuous state converge with the theoretical incident $t(k)$ using the continuous traffic flow $v(k)$, and the continuous output $\grave{q}_i(k)$ can be expressed as below.

$$\grave{q}_i(k) = c\grave{t}(k), \quad (12)$$

where c is the matrix with structures that depends on traffic conditions or state.

The estimation of traffic incident depends on several factors such as traffic scenarios, road conditions, traffic flow, etc. Figure 4 illustrates the estimation of the traffic incident, which rely on the traffic-related data and continuous observer. By using the continuous observer mechanism, we can obtain the accurate estimation of traffic incidents.

4.2. Traffic State Estimation. In most of the estimation approaches, the utilization of Lyapunov function ensures the asymptotic convergence of the estimated error [38]. A multiple Lyapunov function introduced a piecewise Lyapunov function due to the nature of the piecewise hybrid system to ensure the guarantee of error reduction [39].

To solve the HO problem which relies on determining the observer gain G_s, the estimated traffic incident $\grave{t}(k)$ could converge with the theoretical incident $t(k)$. Therefore, the difference of possible error between theoretical and estimated incident can be expressed as below.

$$e_i(k) = t(k) - \grave{t}(k), \quad (13)$$

$$e_i(k+1) = [M_s - G_s c]e_i(k). \quad (14)$$

The convergence of the traffic incident estimation error is required to obtain the gain G_s of the hybrid observer of (11), which ensure that $[M_s - G_s c]$ is a Hurwitz matrix.

4.3. Detection of Traffic Incident. To detect traffic incident based on lane changing speed, RSUs first collect the traffic information related to speed changing between the vehicles and then analyze and evaluate the vehicle speed in the incident and nonincident conditions. In other words, at the nonincident conditions, the average change in speed in shorter average time during changing lane as compared with the incident conditions. In this method, we used the collected traffic information from the RSU related to vehicle speed changing, to evaluate whether or not the incident has occurred when the vehicle changing lane speed falls in the critical region of the defined threshold values.

Figure 5 shows the vehicle lane-changing process which identified that the three vehicles A, B, and C vehicles are travelling along the road. Vehicle A is switching from lane 2 at "point a" to lane 1 at "point b" to pass and cross the vehicle B. The aberrant change in speed from "a" to "b" caused by the driver behavior which creates disturbance to

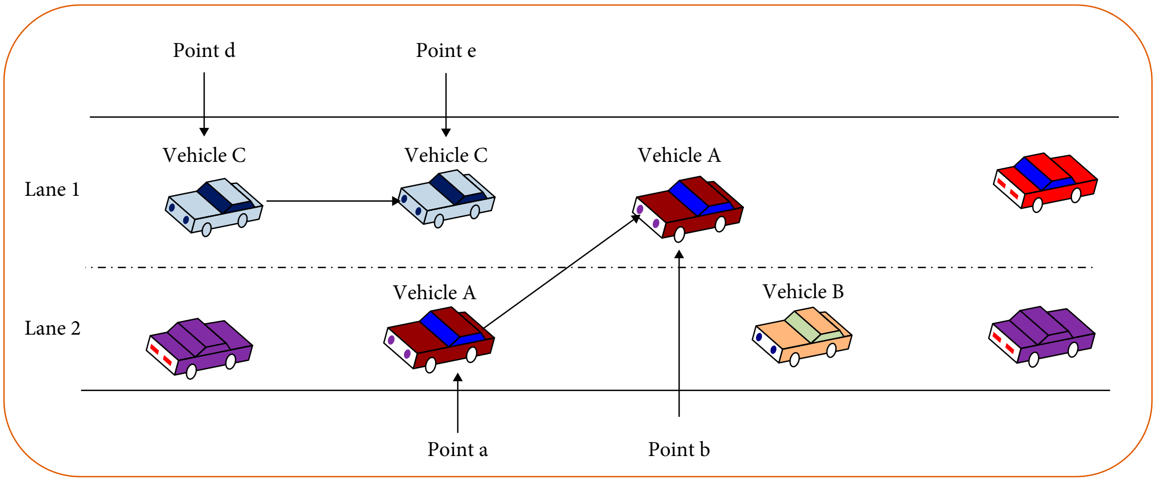

FIGURE 5: Traffic incident detection based on lane changing speed.

the other vehicles on the road, which may subsequently cause traffic incident. We assumed that the aberrant change in speed while changing lane by the vehicle A also causes variation and disturbance of the vehicle C speed. The RSU calculates the average speed variation γ_{va} which occurred during the lane-changing and the associated average time γ_{ta}. Based on these parameters, we have defined the threshold level, if the speed variation falls under the incident threshold region, then it clearly indicates that an incident has occurred, which is caused by the aberrant overspeeding during lane change.

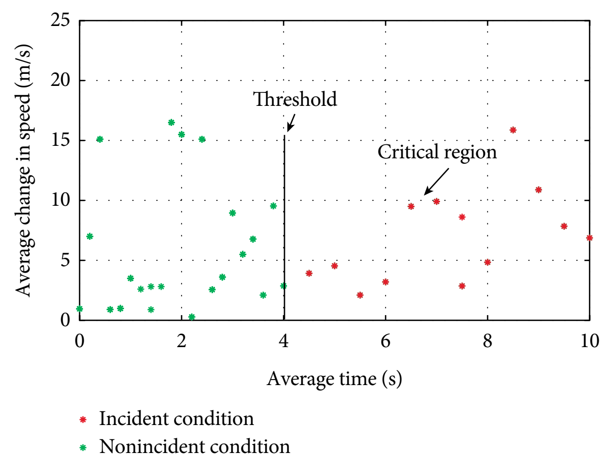

FIGURE 6: Incident detection threshold region for changing lane speed.

5. Model Comparison

In ITS, model validation is considered as an important parameter because it is able to evaluate the effectiveness of the presented method. Though, the study and empirical investigation revealed that the detection of traffic incidents is more complicated and challenging than the other traditional incidents due to the nature and characteristics of the traffic incident. These characteristics depend on the traffic structure, pattern, and collection of traffic information data from infrastructure. In the past, many traditional AID techniques have been proposed which investigates the traffic incidents in different traffic scenarios [24, 25]. In order to evaluate the performance of the proposed method, we have compared the results with traditional AID techniques. Also, the presented method is further validated by KM estimate [40], which is used to evaluate the duration and clearance of traffic incidents with other competent methods.

5.1. Incident Threshold Region. Figure 6 illustrates the average change in speed with the average time for lane changing mechanism in incident detection threshold region, i.e., incident and nonincident scenarios. It can be seen that, when a lane is congested due to road bottleneck, the average vehicle speed changes in much shorter average time under nonincident conditions as compared with the incident conditions. In this method, the proposed method uses the collected traffic-related data from the RSU related to vehicle speed changing to evaluate whether or not the incident has occurred when the changing lane speed falls in the critical region of the defined threshold values.

5.2. Estimation of Traffic Incident. Figure 7 shows the comparison of the theoretical incident with the estimated incident. In the simulation, we have considered three cases such as low, moderate and high traffic densities. Figure 7(a) illustrate the comparison of the theoretical and estimated traffic incident with low traffic density. From Figure 7(a), it can be seen that the detection of traffic incident takes a longer time to detect and clear an incident. However, the estimation of traffic incident is close to the theoretical incident, which indicated that the proposed method is able to estimate the traffic incidents in case of low traffic density.

When the traffic density is moderate, the performance of the proposed method in terms of estimation of traffic incidents shown in Figure 7(b). Clearly improved estimation of traffic incident has been obtained. Also, it has the fastest clearance

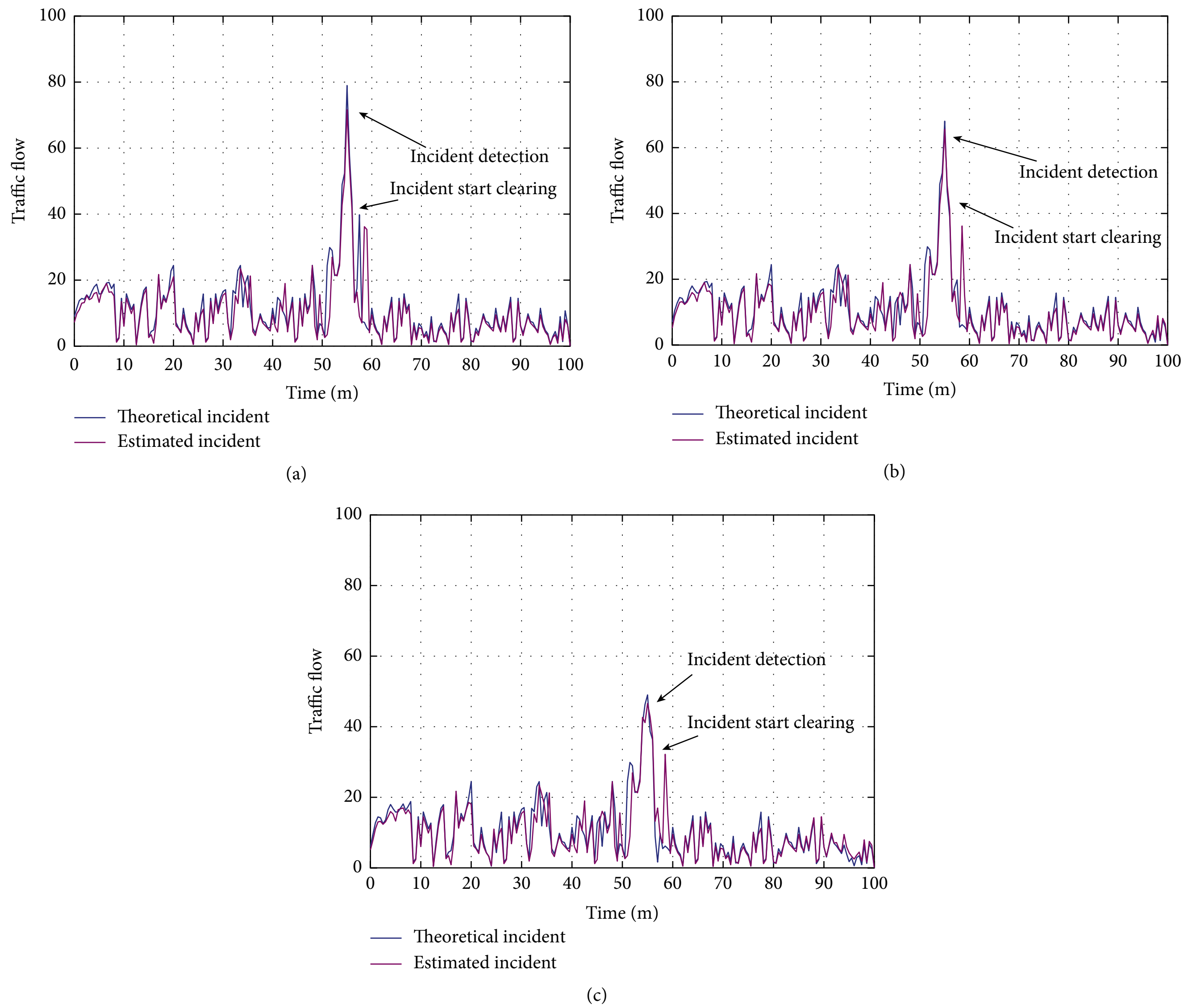

FIGURE 7: Comparison of the theoretical incident and estimated incident with three different cases. (a) Low traffic flow, (b) moderate traffic flow, and (c) heavy traffic flow.

of incident detection. More specifically, the proposed method obtained a better estimation of traffic incident than the low traffic density, and the estimation of traffic incident has somehow agreed with the theoretical traffic incident.

Figure 7(c) illustrates the comparison of the theoretical incident with the estimated incident when the traffic density is very high. The proposed method obtained the most robust estimation of the traffic incident in comparison with the low traffic and moderated traffic densities. And, the estimated traffic incident is also very close to the theoretical incident. This indicates that the proposed method agrees well with the theoretical incident.

5.3. Traffic Incident Detection. Figure 8 shows the comparison of the proposed method with other methods. In our simulation, we assumed that when the incident occurred, it introduces traffic congestion. The simulation results demonstrated in Figure 8 shows that the traffic congestion is influenced by the traffic incident. More specifically, the traffic congestion depends on the number of vehicles which take alternative routes when the incident has occurred. From Figure 8, it can be observed that the proposed system achieved the fastest detection of the traffic incident. Also, when the incident is cleared by the police, the proposed method obtains the fastest dissipation of traffic congestion.

Figure 8(a) shows the comparison of the proposed method with the heavy traffic congestion of 25% of traffic diverts. It can be seen that the improved AID technique is able to detect the fastest traffic incident as compared with the other methods. Figure 8(b) shows the comparison of the proposed method with 35% of traffic diverts. At the time, when the incident has occurred, 35% of the vehicles take other routes. By means of simulation, it can be observed that the proposed method obtains better incident detection and the fastest dissipation of traffic congestion. Figure 8(c) shows the comparison of the proposed method with 45% of traffic diverts. The proposed

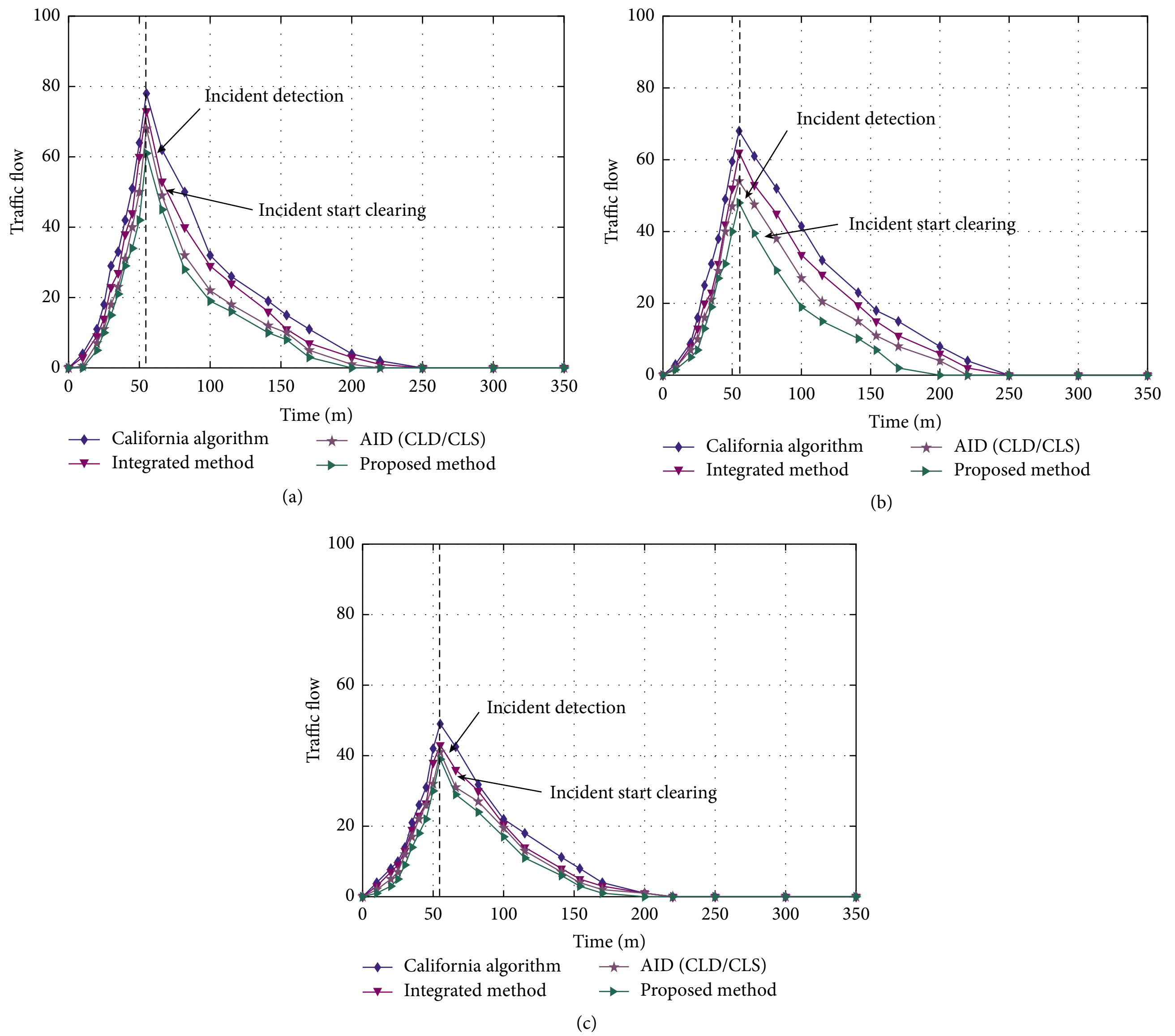

Figure 8: Shows the comparison of the proposed method with California algorithm, integrated algorithm, and AID (CLD/CLS) method with three different cases. (a) Heavy traffic congestion, (b) moderate traffic congestion, and (c) less traffic congestion.

improved AID technique is able to give the fastest incident detection and obtains the fastest dissipation of traffic congestion.

From Figure 9, we can evaluate the performance of the KM curves between the proposed method and other AID techniques. It can be seen that the duration of the incident of California algorithm and integrated method are similar to each other. The characteristics of these algorithms required a longer time to notify the police for the incident situation and also need more time to tow and clear an incident. The KM curve for the incident duration with the AID (CLD/CLS) technique obtained better performance than the Integrated and California methods. After receiving complaint, the police arrived at the incident location in the shortest time to towing the incident vehicles and subsequently clear the incident. By using the proposed method, the police were able to clear the incident in the shortest time by towing away the incident vehicles. The validation results reveal that the proposed method has the capability to estimate and detect the traffic incident with the fastest detection rate. With regard to duration of an incident, it can be seen from Figure 9 that the proposed model obtained a better KM curve by achieving the shortest duration of time to clear an incident among all other schemes.

6. Simulation Results

6.1. Exchange Communication between Vehicle and RSU. In our simulations, we assumed that the average speed of the vehicles passing from the RSU was varying from 20 mph to 80 mph in the highway traffic environment. The probability of exchange traffic information between vehicle and RSU was determined using the low data rates such as 512 kbps and

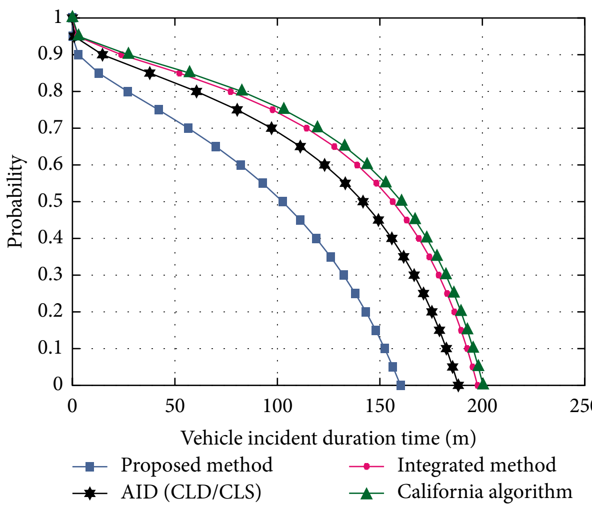

FIGURE 9: Show the comparisons of the KM curves of the proposed method with other AID techniques.

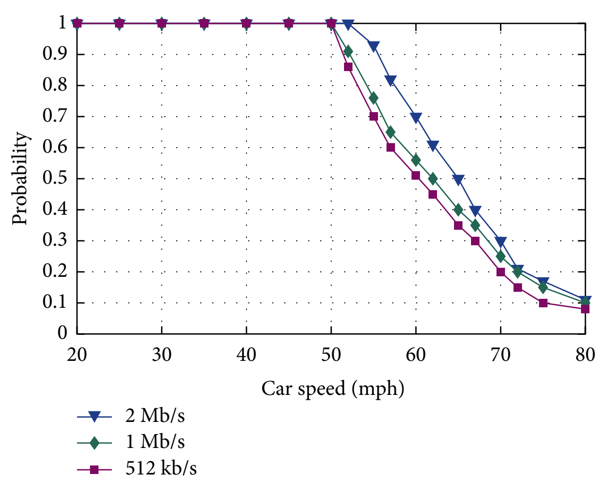

FIGURE 10: Probability of successful exchange traffic information with different data rates.

1 Mbps, and the high data rates such as 2 Mbps. As shown in Figure 10, the results obtained from the simulation revealed that the probability of exchange traffic information decreases with the increase of the average speed of the vehicles passing by the RSU. As the vehicle travels at low speed 50 mph and below, it will remain in the coverage area of the RSU for a longer time and be able to exchange the accurate traffic information at lower data rates such as 512 kbps. When the average vehicle speed exceeds 55 mph, the probability of successful exchange traffic information takes place between the passing vehicles and RSU at higher data rate such as 2 Mbps, which lead to provide the higher probability of exchange traffic information.

6.2. Vehicle Communication with Each RSU Location. The simulation test is carried out to examine the influence of vehicles traveling to each RSU on the probability of successful exchange information as illustrated in Figure 11. We have placed four RSUs with a distance of 1.5 km apart from each other that is

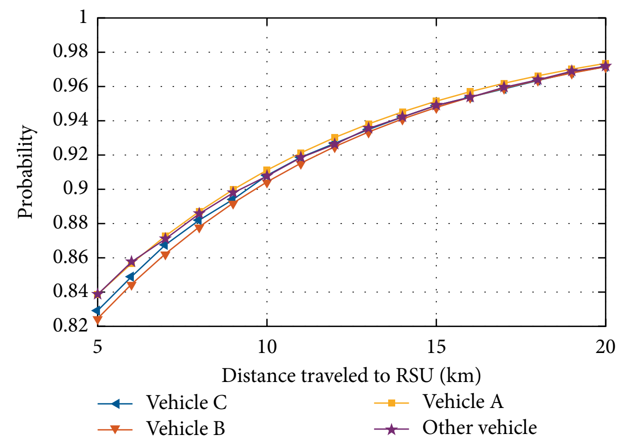

FIGURE 11: Communication between vehicle to each RSU location.

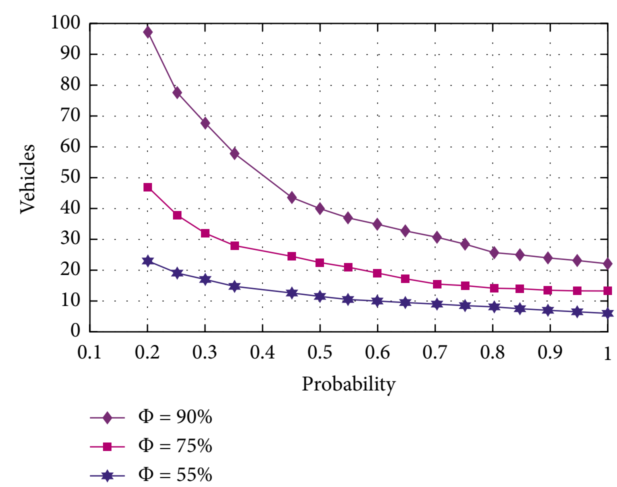

FIGURE 12: Influence of number of vehicles on the probability of traffic information data.

able to detect the change in vehicle speed which is influenced by the aberrant overtaking and may lead to causes of the traffic incident. These RSUs are able to obtain the traffic information and violence of each vehicle within their range. Four types of vehicles such as vehicle A, vehicle B, vehicle C, and other vehicles are used in a one-way three-lane traffic scenario. It can be observed that the vehicle A overtaking the other vehicle while changing lane at the distance of RSU location about 5 km–10 km. From Figure 11, it can be seen that the probability of traffic information increases as the vehicles are heading towards the next RSU location. Therefore, the strong connection between the vehicle and RSU is developed, which successfully lead to exchange of the traffic information between the passing vehicles and each RSU locations.

6.3. Probabilistic Comparison of Traffic Information Data. Figure 12 shows the effects of the number of vehicles on the probability of data collection. In order to accurately detect traffic incidents, we have assumed several parameters, the incident target $\Phi = 0.9$, application parameter which is able to detect an incident accurately $\beta = 0.90$, and the probability of

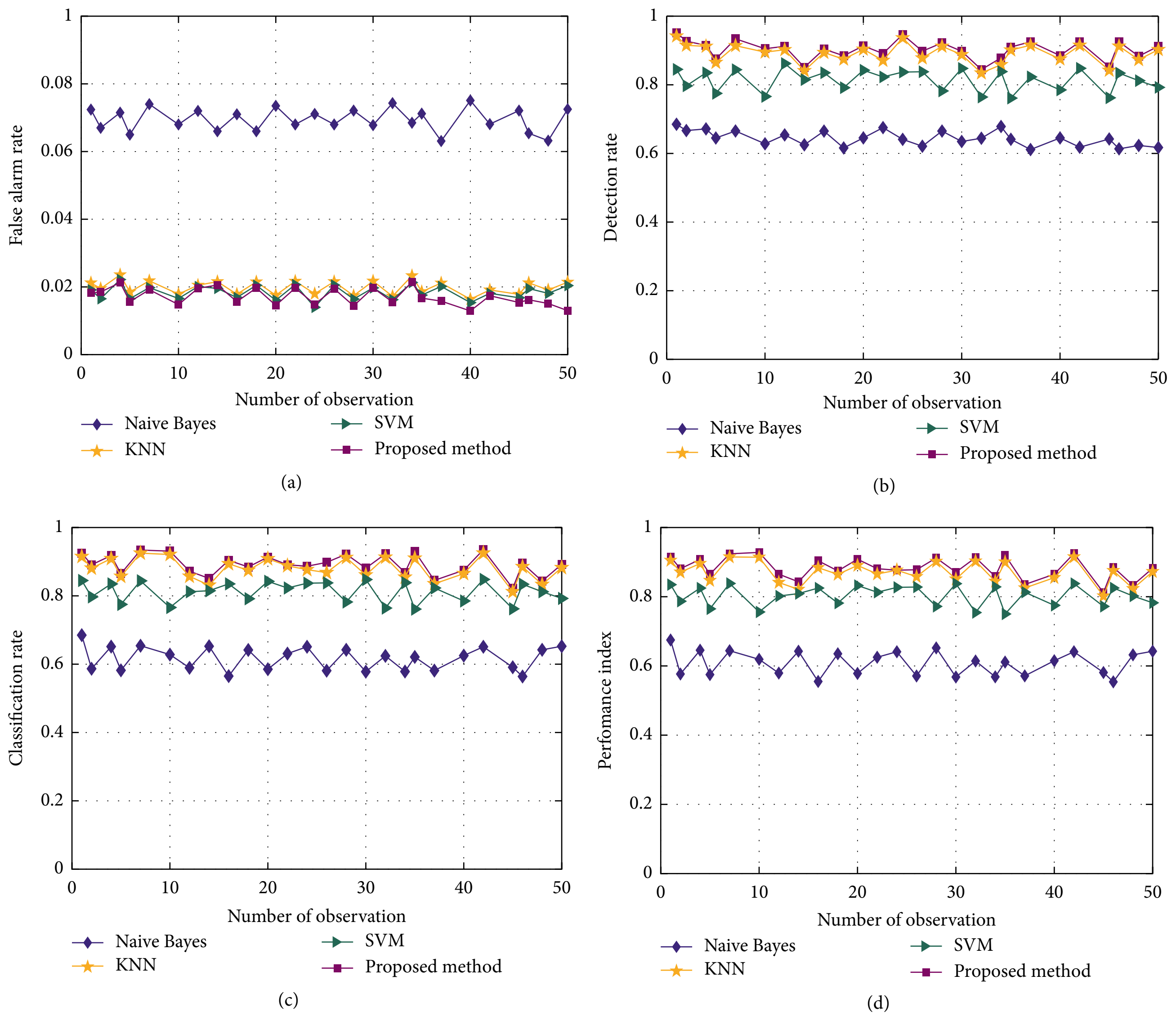

FIGURE 13: Comparisons of proposed method with other competent methods (a) FAR, (b) DR, (c) CR, and (d) PI.

a vehicle to communicate with the RSU is $p_i = 0.7$. Substitute all these values in equation (10), after solving we obtained that 32 vehicles can communicate with RSU, with the probability of 90%. Therefore, it indicates that RSU is able to acquire the traffic information data of 32 vehicles including incident vehicle, and it is also used to detect the traffic incidents caused by vehicle A with the higher accuracy of $\beta = 0.90$.

6.4. Performance Test Criteria. In this section, we evaluate the performance of the proposed method with other well-known techniques such as Naive Bayes, SVM, and KNN using three criteria i.e. false alarm rate (FAR), detection rate (DR) and classification rate (CR) [41].

$$\mathrm{FAR} = \frac{F_n}{I_{ni}} \times 100\%, \tag{15}$$

where FAR is the false alarm rate, F_n is the number of false alarm cases, and I_{ni} is the total number of nonincident cases.

$$\mathrm{DR} = \frac{I_d}{A_i} \times 100\%, \tag{16}$$

where DR is the incident detection rate, I_d is the number of incident cases detected and A_i is the total number of incident cases reported.

$$\mathrm{CR} = \frac{T_i}{C_i} \times 100\%, \tag{17}$$

where CR is the classification rate, which is used to determine the incident detection, T_i is the number of events correctly classified and C_i is the total number of events.

We further evaluate the performance of the proposed method by using performance index (PI), which can be written as below.

$$\mathrm{PI} = w_d \mathrm{DR} + w_f (1 - \mathrm{FAR}) + w_c \mathrm{CR}, \tag{18}$$

where w_d, w_f, and w_c are the weight of the DR, FAR, and CR, respectively. We assumed that the values of the weight of DR,

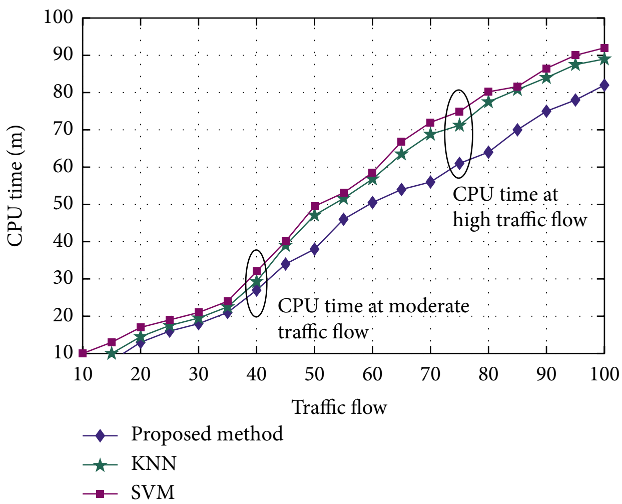

Figure 14: CPU comparison of the proposed method with other methods.

FAR, and CR are all 1/2. The larger value of PI indicates that the proposed method has obtained a better detection of traffic incidents. More specifically, the smaller the FAR values, the higher the possibility of detecting traffic incident accurately. The performance of DR indicates that, when the DR values approaching 100%. It clearly indicates that the algorithm is able to detect the traffic incident well. However, the higher DR values may generate some false alarm.

To evaluate the effectiveness of the proposed method, we further demonstrate the performance of the proposed method on I-880 datasets for evaluating FAR, DR, CR, and PI values, and compare these values with the other methods. Figure 13 shows the comparison of the proposed method with other competent methods in terms of FAR, DR, CR, and PI values. From Figure 13(a) it can be observed that the proposed method has obtained less FAR values as compared with the SVM method. Also, we can observe that the Naive Bayes and KNN methods produce worst FAR values as compared with the SVM method.

As shown in Figure 13(b), the proposed method has obtained the highest DR values which indicate that the accurate detection of traffic incident. Also, it can be seen that the KNN method has obtained better DR values to accurately detect the traffic incident as compared with the Naives Bayes and SVM methods. Due to the nature and characteristics of incident, the Naive Bayes and SVM methods are unable to detect traffic incident.

It can be noted from Figure 13(b) and Figure 13(c), the results of KNN method in DR and CR is very close to the proposed method. Also, from Figure 13(a) the FAR values of SVM are very close to the proposed method. Also from Figure 13(d), it can be observed that the proposed method has obtained better PI values as compared with other competent methods. Therefore, it clearly demonstrates that the improved values of FAR, DR, CR, and PI enhanced the performance of the proposed method, thus, the proposed method has an ability to detect traffic incident on I-880 datasets.

More specifically, from Figure 13, the observation values minimized FAR values when DR value was greater than 0.90. From the observation value, the proposed method obtained the FAR, DR, CR, and PI values of 0.018, 0.952, 0.925, and 0.915, respectively as compared with the KNN 0.1912, 0.937, 0.909, and 0.905, respectively. Clearly, the improved values indicate that the proposed method has obtained the better FAR, DR, CR, and PI values as compared with the other well-known techniques such as Naive Bayes, KNN, and SVM methods.

6.5. CPU Timing. Figure 14 shows the CPU comparison of the proposed method with KNN and SVM methods. When the traffic flow is 10, the CPU time of the proposed method and other methods were very low. As the traffic flow increases, the CPU required a longer time to process input dataset. From Figure 14, it can be observed that the KNN and SVM methods required a longer CPU time due to exploiting more input data, which subsequently required a longer time to process dataset. The proposed method obtains the less CPU time to process input dataset as compared with other competent methods.

7. Conclusion

The incident estimation and detection are the important parameters in the ITS for reducing the traffic congestion, improving traffic and road safety. However, the traffic incident may cause road bottlenecks, traffic congestion and disrupt the normal traffic flow. In this paper, we proposed an ITS model which is able to estimate the traffic incident from HO method, and then detect the traffic incident from an improved AID technique in the highway traffic environment. First, we present a hybrid observer method to estimate the traffic incident based on the combination of the PWSL model and a model estimation technique. Second, we designed a probabilistic approach to collect traffic information data by using a V2I communication based on lane-changing speed mechanism capable of detecting traffic incident accurately. The analysis shows that the proposed method can estimate the traffic incident more precisely and has the potential to estimate the traffic incident with three different traffic densities. By mean of the simulation, the proposed method has obtained a better estimation of the traffic incident, which agrees well with the theoretical incident. Furthermore, by comparing the effectiveness of the proposed method for detecting traffic incident, the proposed method outperforms other methods by obtaining the fastest incident detection rate, and the fastest dissipation of traffic congestion. The comparison with the other methods in terms of duration of an incident, the proposed method obtains the shortest duration of time to clear an incident. Moreover, we have further evaluated the performance of the proposed method with well-known techniques such as Naive Bayes, KNN, and SVM using I-880 traffic data. Experimental results show that the proposed method obtained a better performance compared with other methods.

In the future, we will enhance the proposed model by using joint learning and support vector machine (SVM) techniques which can produce the robust detection of traffic incidents. Also, we will utilize the 5G wireless network to obtain the robust accuracy of traffic information data which will be successfully applied to estimate the traffic incident.

Data Availability

The performance test data used to support the finding of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgments

This work was supported in part by National key research and development program under Grant 2018YFB1600503, in part by the Natural Science Foundation of China under Grants U1564201, 1664258, and 61773184.

References

[1] G. Anastasi, M. Antonelli, A. Bechini et al., "Urban and social sensing for sustainable mobility in smart cities," in *2013 Sustainable Internet and ICT for Sustainability (SustainIT)*, pp. 1–4, IEEE, Palermo, Italy, 2013.

[2] M. N. Mejri, J. Ben-othman, and M. Hamdi, "Survey on VANET security challenges and possible cryptographic solutions," *Vehicular Communications*, vol. 1, no. 2, pp. 53–66, 2014.

[3] J. Luk, C. Han, and D. A. Chin, "Freeway incident detection: technologies and techniques," 2010.

[4] F. Yuan and R. L. Cheu, "Incident detection using support vector machines," *Transportation Research Part C: Emerging Technologies*, vol. 11, no. 3-4, pp. 309–328, 2003.

[5] E. D'Andrea and F. Marcelloni, "Detection of traffic congestion and incidents from GPS trace analysis," *Expert Systems with Applications*, vol. 73, pp. 43–56, 2017.

[6] S. Kamran and O. Haas, "A multilevel traffic incidents detection approach: identifying traffic patterns and vehicle behaviours using real-time GPS data," in *2007 IEEE Intelligent Vehicles Symposium*, pp. 912–917, IEEE, Istanbul, Turkey, 2007.

[7] L. L. Wang, H. Y. T. Ngan, and N. H. C. Yung, "Automatic incident classification for large-scale traffic data by adaptive boosting SVM," *Information Sciences*, vol. 467, pp. 59–73, 2018.

[8] V. Milanes, J. Villagra, J. Godoy, J. Simo, J. Perez, and E. Onieva, "An intelligent V2I-based traffic management system," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 1, pp. 49–58, 2012.

[9] J.-M. Chung, M. Kim, Y.-S. Park, M. Choi, S. Lee, and H. S. Oh, "Time coordinated V2I communications and handover for WAVE networks," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 3, pp. 545–558, 2011.

[10] Y. Asakura, T. Kusakabe, L. X. Nguyen, and T. Ushiki, "Incident detection methods using probe vehicles with on-board GPS equipment," *Transportation Research Part C: Emerging Technologies*, vol. 81, pp. 330–341, 2017.

[11] J. Ren, Y. Chen, L. Xin, J. Shi, B. Li, and Y. Liu, "Detecting and positioning of traffic incidents via video-based analysis of traffic states in a road segment," *IET Intelligent Transport Systems*, vol. 10, no. 6, pp. 428–437, 2016.

[12] D. Srinivasan, X. Jin, and R. L. Cheu, "Evaluation of adaptive neural network models for freeway incident detection," *IEEE Transactions on Intelligent Transportation Systems*, vol. 5, no. 1, pp. 1–11, 2004.

[13] S. G. Ritchie and R. L. Cheu, "Simulation of freeway incident detection using artificial neural networks," *Transportation Research Part C: Emerging Technologies*, vol. 1, no. 3, pp. 203–217, 1993.

[14] J. Wang, X. Li, S. S. Liao, and Z. Hua, "A hybrid approach for automatic incident detection," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 3, pp. 1176–1185, 2013.

[15] X. Jin, R. L. Cheu, and D. Srinivasan, "Development and adaptation of constructive probabilistic neural network in freeway incident detection," *Transportation Research Part C: Emerging Technologies*, vol. 10, no. 2, pp. 121–147, 2002.

[16] Z. Zhou and L. Zhou, "An automatic incident of freeway detection algorithm based on support vector machine," in *2010 International Symposium on Intelligence Information Processing and Trusted Computing*, pp. 543–546, IEEE, Huanggang, China, 2010.

[17] R. L. Cheu, D. Srinivasan, and E. T. Teh, "Support vector machine models for freeway incident detection," in *Proceedings of the 2003 IEEE International Conference on Intelligent Transportation Systems*, pp. 238–243, IEEE, Shanghai, China, 2003.

[18] J. Xiao, "SVM and KNN ensemble learning for traffic incident detection," *Physica A: Statistical Mechanics and its Applications*, vol. 517, pp. 29–35, 2019.

[19] Y. Gu, Z. Qian, and F. Chen, "From Twitter to detector: Real-time traffic incident detection using social media data," *Transportation Research Part C: Emerging Technologies*, vol. 67, pp. 321–342, 2016.

[20] A. Schulz, P. Ristoski, and H. Paulheim, "I see a car crash: real-time detection of small scale incidents in microblogs," *The Semantic Web: ESWC 2013 Satellite Events*, pp. 22–33, Springer, 2013.

[21] S. Dabiri and K. Heaslip, "Developing a Twitter-based traffic event detection model using deep learning architectures," *Expert Systems with Applications*, vol. 118, pp. 425–439, 2019.

[22] Z. Zhang, Q. He, J. Gao, and M. Ni, "A deep learning approach for detecting traffic accidents from social media data," *Transportation Research Part C: Emerging Technologies*, vol. 86, pp. 580–596, 2018.

[23] J. D. G. Paule, Y. Sun, and Y. Moshfeghi, "On fine-grained geolocalisation of tweets and real-time traffic incident detection," *Information Processing & Management*, vol. 56, no. 3, pp. 1119–1132, 2019.

[24] C. K. Lin and G. L. Chang, "Development of a fuzzy-expert system for incident detection and classification," *Mathematical and Computer Modelling*, vol. 27, no. 9–11, pp. 9–25, 1998.

[25] R. Weil, J. Wootton, and A. Garcia-Ortiz, "Traffic incident detection: sensors and algorithms," *Mathematical and Computer Modelling*, vol. 27, no. 9–11, pp. 257–291, 1998.

[26] M. Abuelela, S. Olariu, M. Cetin, and D. Rawat, "Enhancing automatic incident detection using vehicular communications," in *2009 IEEE 70th Vehicular Technology Conference Fall*, pp. 1–5, IEEE, Anchorage, AK, USA, 2009.

[27] Q. He, Y. Kamarianakis, K. Jintanakul, and L. Wynter, "Incident duration prediction with hybrid tree-based quantile regression," *IBM Research*, 2011.

[28] S. Peeta, J. L. Ramos, and S. Gedela, "Providing real-time traffic advisory and route guidance to manage Borman incidents on-line using the Hoosier helper program," Joint Transportation Research Program, Indiana Department of Transportation and Purdue University, West Lafayette, Indiana, 2000.

[29] J. Lu, S. Chen, W. Wang, and B. Ran, "Automatic traffic incident detection based on nFOIL," *Expert Systems with Applications*, vol. 39, no. 7, pp. 6547–6556, 2012.

[30] R. Wang, S. Fan, and D. B. Work, "Efficient multiple model particle filtering for joint traffic state estimation and incident detection," *Transportation Research Part C: Emerging Technologies*, vol. 71, pp. 521–537, 2016.

[31] M. Fogu, P. Garrido, F. J. Martinez, J. C. Cano, C. T. Calafate, and P. Manzoni, "Automatic accident detection: assistance through communication technologies and vehicles," *IEEE Vehicular Technology Magazine*, vol. 7, no. 3, pp. 90–100, 2012.

[32] S. Tang and H. Gao, "Traffic-incident detection-algorithm based on nonparametric regression," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 1, pp. 38–42, 2005.

[33] O. Popescu, S. Sha-Mohammad, H. Abdel-Wahab, D. C. Popescu, and S. El-Tawab, "Automatic incident detection in intelligent transportation systems using aggregation of traffic parameters collected through V2I communications," *IEEE Intelligent Transportation Systems Magazine*, vol. 9, no. 2, pp. 64–75, 2017.

[34] D. Sapper, H. Cusack, and L. Staes, "Evaluation of electronic data recorders for incident investigation, driver performance, and vehicle maintenance," National Center for Transit Research (NCTR) Center for Urban Transportation Research, University of South Florida, 2009.

[35] M. Özkul and I. Çapuni, "Police-less multi-party traffic violation detection and reporting system with privacy preservation," *IET Intelligent Transport Systems*, vol. 12, no. 5, pp. 351–358, 2018.

[36] S. El-Tawab, A. Alhafdhi, D. Treeumnuk, D. C. Popescu, and S. Olariu, "Physical layer aspects of information exchange in the NOTICE architecture," *IEEE Intelligent Transportation Systems Magazine*, vol. 7, no. 1, pp. 8–18, 2015.

[37] A. Zeroual, F. Harrou, and Y. Sun, "Road traffic density estimation and congestion detection with a hybrid observer-based strategy," *Sustainable Cities and Society*, vol. 46, p. 101411, 2019.

[38] W. Heemels and S. Weiland, "Observer design for a class of piecewise linear systems," *International Journal of Robust and Nonlinear Control*, vol. 17, no. 15, pp. 1387–1404, 2007.

[39] H. Lin and P. J. Antsaklis, "Stability and stabilizability of switched linear systems: a survey of recent results," *IEEE Transactions on Automatic Control*, vol. 54, no. 2, pp. 308–322, 2009.

[40] E. L. Kaplan and P. Meier, "Nonparametric estimation from incomplete observations," *Journal of the American Statistical Association*, vol. 53, no. 282, pp. 457–481, 1958.

[41] J. Xiao and Y. Liu, "Traffic incident detection using multiple-kernel support vector machine," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2324, no. 1, pp. 44–52, 2012.


Journal of Engineering
The Scientific World Journal
International Journal of Rotating Machinery
Journal of Sensors
Advances in Multimedia
Advances in Civil Engineering
Hindawi
Submit your manuscripts at
www.hindawi.com
Journal of Control Science and Engineering
Journal of Robotics
Journal of Electrical and Computer Engineering
Advances in OptoElectronics
VLSI Design
International Journal of Navigation and Observation
Modelling & Simulation in Engineering
International Journal of Aerospace Engineering
International Journal of Chemical Engineering
International Journal of Antennas and Propagation
Active and Passive Electronic Components
Shock and Vibration
Advances in Acoustics and Vibration