Chapter 4
Two Major Applications in Vehicular Ad Hoc Networks

Rear-End Collision Warning & Automatic Incidents Detection

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Abstract Vehicular ad hoc networks (VANETs) have emerged in the past decades as a significant type of networks, which consists of vehicles with sensors to communicate. For its ad-hoc nature, VANETs have great potential in a large number of applications, within which rear-end collision warning and traffic automatic incidents detection are two major applications. Because of the large number of injury and consequent economic loss, rear-end traffic collision has become an important issue and attracted a large number of attentions. In the past decades, there have been lots of efforts paid on this field. Existing work usually employed mathematical approaches or machine-learning approaches. In this study, we develop a collaborative rear-end collision warning algorithm (CORECWA), which is able to estimate and assess traffic risk in a collaborative and real-time way, and further notify drivers the warning message timely. Experiments results have shown that our algorithm outperforms the predominant method, HONDA algorithm. On the other hand, traffic incidents detection has been a critical problem in the past decades, due to the considerable economical cost and inestimable disgruntlement from numerous drivers. We present a support vector machines (SVM)-based approach for automatic incident detection (AID), in which the traffic data are collected by VANETs techniques. We process collected data and utilize traffic variables in the SVM model to confirm whether an incident occurs. Several experiments have been conducted to evaluate our approach's performance, and the results show that our approach could outperform the other two approaches in most cases.

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4.1 Introduction

Vehicular Ad Hoc Networks (VANETs) have emerged in the past decades as a significant type of networks, which consists of vehicles with sensors to communicate. For its ad-hoc nature, VANETs have great potential in a large number of applications, within which rear-end collision warning and traffic automatic incident detection (AID) are two major applications.

It is well-acknowledged that the increasing traffic accidents can bring growing injury and consequent economic damage. So, it has become a severe social problem worldwide. Among them, rear-end traffic collision has attracted lots of attentions, due to the high-frequent occurrence (almost 30 %) [1, 2]. Therefore, it is urgent to develop rear-end collision warning system for message transferring and notification.

In the past, lots of efforts have been paid on this field [3–21]. All computation methods would take traffic data into consideration, either traffic data from probe vehicles or experimental data. In order to cover the aforementioned drawbacks, we propose a COllaborative REar-end Collision Warning Algorithm (CORECWA), to assess traffic risk in a real-time way and notify drivers the useful information timely. Compared with HONDA algorithm, our method is able to get better performance using a publically available dataset.

Meanwhile, traffic congestion has become a huge and increasingly severe problem worldwide nowadays, due to the growing demand on transportation and constraint resources supported by existing traffic infrastructures. Traffic incidents play a crucial role in the traffic congestion problem. In this way, incidents refer to abnormal events that occur to obstruct the normal satiny traffic flows and affect the utilization of traffic infrastructures, i.e., traffic accidents, interception because of hazard weather conditions. Hence, AID has been proposed and developed in the past decades, and attracted the interest of a number of scholars. Accurate and effective incidents detection could be helpful not only to relieve congestion, improve traffic efficiency, and decrease fuel cost but also to provide reliable information to drivers to reduce their travelling time. Usually, a large amount of traffic data utilized for AID has been a sharp problem. Data collection methods using current detectors (i.e., inductive loops and video cameras) have lots of shortcoming, e.g., the limited detection range and high costs of implementation and maintenance. Hence, we employ sensors nodes, which are widely used in VANETs, to detect, transmit, and fuse traffic data.

We employ a support vector machines (SVM)-based approach to detect the VANET-based incidents. And, we extract the most critical features related to incidents occurrence, such as speed, occupancy, and volume, and then train SVM through various feature combinations. Finally, we conduct experiments to evaluate the proposed approach's performance, and results present that our approach can outperform the relevant state-of-the-art approaches in three well-acknowledged evaluation metrics.

4.2 Rear-End Collision Warning

Existing work in rear-end collision warning can be reviewed from two groups: mathematical approaches and machine-learning approaches. There have been lots of mathematical methods for rear-end collision warning problems. Minimum Safety Distance-based methods and Minimum Safety Time-based methods are two well-acknowledged methods. They mainly consider the essential distance or time between two preceding and following cars as thresholds [3–8]. Based on the two methods, there have developed some related methods, including MAZDA [9, 10] and Honda [11]. Perception reaction time has been an important factor in the methods [12, 13]. Its value varies from 0.5 to 2.5 s [13, 14]. They also consider the minimum computed predictable time as a factor in the algorithm design [15, 16]. There are also several machine learning-based studies in this field. Researchers have focused on drivers' behavior to improve traffic collision warning methods [17, 18]. Neural networks have been used to adapt to warning message for drivers by learning behavior models of drivers, using genetic algorithms to optimize related parameters [17]. Wang et al. developed a driving-assistance system, to push collision warning notices. Recursive least square methods can be used to identify and transform drivers' behavior information into the model and also adjust parameters [18]. Furthermore, lots of studies using machine learning-based methods to achieve improvement of reaction time-involved traffic collision warning issues [16, 19–21]. Chang et al. developed a fuzzy-based method for traffic pre-crash reminder using quantum-tuned BPNN-fused heterogeneous data, which are identified and transmitted through vehicle-to-vehicle (V2V) communication [16]. Wei et al. proposed a multilayer perception NN-based approach for minimum safety distance computation using the probe vehicle data [19]. There are also some studies combining Fuzzy logic and MLPNN together to this problem, providing warning notices for multidirectional collision situations [20] and automobiles in highways [21], respectively.

Before processing for different goals for these existing methods, researches need the traffic data first. Generally, they use sensors for the detection of preceding vehicles or other traffic information. The information usually need a real-time transmission to achieve the real-time traffic risk assessment, by V2V communication and vehicle-to-infrastructure (V2I) communication.

To cover these drawbacks, we have proposed an algorithm named as CORECWA that can assess traffic risk in a real-time way and notify drivers the corresponding collision warning notices timely. CORECWA is utilizing some collaboratively collected real-time traffic data, such as position and speed of preceding and following cars, etc. Traffic risk can be evaluated in a real-time way, considering space headway and current speed of the preceding and following vehicles, and also drivers' behavior characteristics, such as perception–reaction time. The results depict that CORECWA could achieve better performance comparing with *HONDA* algorithm.

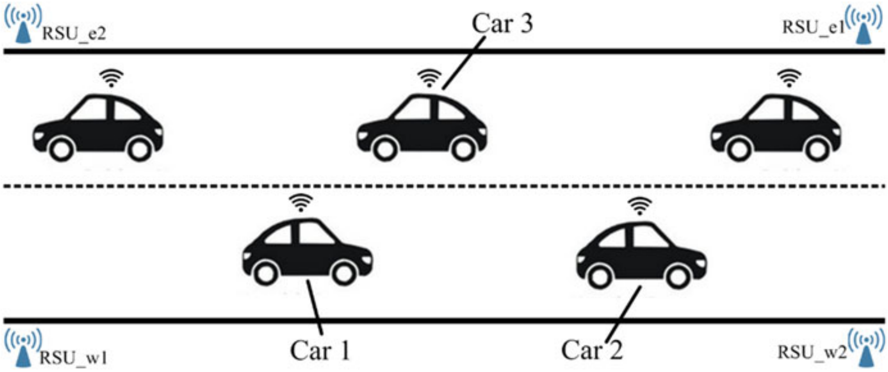

Fig. 4.1 An example of traffic scenarios

4.2.1 Problem Description

We formulate this rear-end collision warning problem as to notify drivers a warning message when in necessary situation. Therefore, these drivers are able to keep safe distance with appropriate actions.

To formulate this problem, we take an example of traffic scenarios in consideration (Fig. 4.1). From the figure, we can see that a road segment having four roadside units (RSU) has been illustrated, and all cars are able to monitor the surrounding environment and transfer information. All cars in this road segment would be detected by RSUs. For instance, when a car comes into this road from the west, this car would be monitored by RSU_w1 immediately, and then RSU_w2 can receive this information that there is a car with unique car id entering in this road segment.

Considering a rear-end collision warning problem, Car 1 is defined as a following car. We should confirm the corresponding preceding car, and then estimate current traffic risk. We define a threshold to discretize the traffic risk into three levels, under-risk, slight-danger, and emergent situation. Here, $\mathrm{TR}(V)$ is defined as traffic risk of car V. The objective is to estimate $\mathrm{TR}(V)$ and obtain a maximum threshold value $\mathrm{Thresh}(V)$ to determine in which risk case drivers must take actions to keep safe, as presented in Eq. 4.1:

$$\mathrm{Max} \quad \mathrm{Thresh}(V) \tag{4.1}$$

There are many relevant factors for the parameter. It is obvious that the distance between preceding–following cars is important. $\mathrm{Dst}(V, \mathrm{RSU}_{i1})$ and $\mathrm{Dst}(V, \mathrm{RSU}_{i2})$ are defined as distance between car V to RSU_{i1} and RSU_{i2} of the same direction and road segment, respectively, $i \in \{\mathrm{east}, \mathrm{west}\}$. $\mathrm{vlc}(V)$ is defined as V' speed, and $\mathrm{rs}(V)$ is defined as the corresponding road segment which car V belongs to.

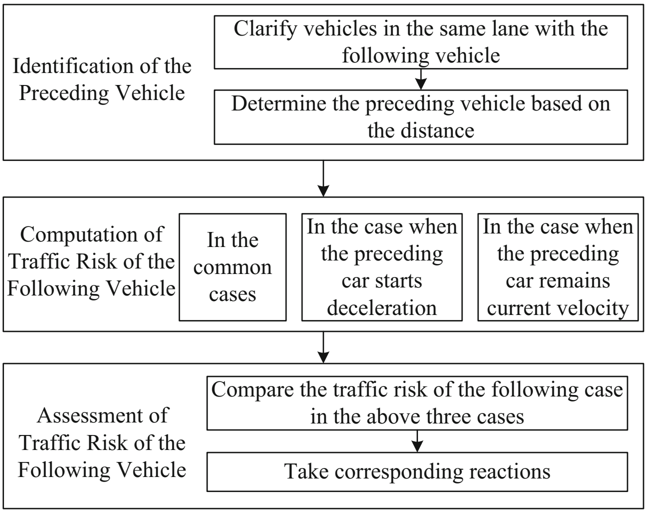

Fig. 4.2 Process of collaborative rear-end collision warning algorithm (CORECWA)

4.2.2 *Our Collaborative Real-Time Rear-End Collision Warning Algorithm*

In this section, we propose CORECWA as shown in Fig. 4.2. The algorithm contains three steps: the preceding vehicle identification, traffic risk computation of the following vehicle, and traffic risk assessment of the following vehicle. The first step is to confirm the preceding vehicle of the following vehicle. The second step is to compute traffic risk of following car, and meanwhile estimate the maximum and minimum thresholds of traffic risk. The last step is to assess traffic risk of following car.

4.2.2.1 Identification of the Preceding Vehicle

In this step, the preceding vehicle of one particular following car would be determined. As shown in Fig. 4.1, it is obvious that preceding vehicle of Car 1 is Car 2, not Car 3 which has the shortest distance to Car 1. Therefore, preceding car identification cannot adopt the nearest distance method. The whole process of preceding car identification is shown in Fig. 4.3.

At first, two cars V_P and V_F would be in the same road covered by RSUs of the same roadside. When a car V_F enters into the road from the west, it will send a message to the nearest RSU_w1. After that, RSU_w1 notifies RSU_w2 the event of a newly arriving car. And then, these two RSUs would store this vehicle's information, and broadcast message to cars in the same road to inform them the arrival of V_F. At that time, all vehicles in front of V_F would communicate with V_F and estimate distances between them. The distance computation would have some errors, because the location data would have some errors.

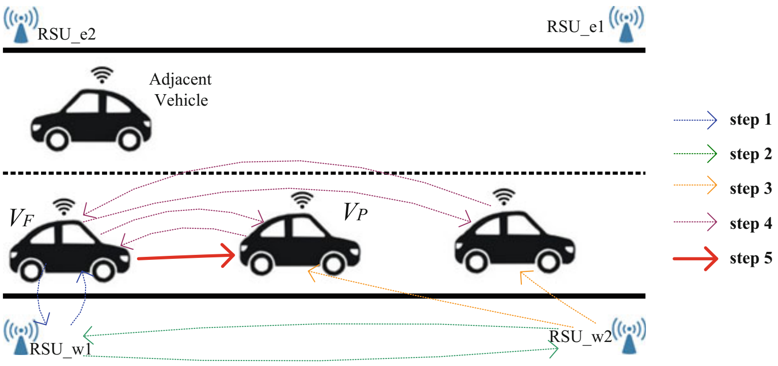

Fig. 4.3 Process of preceding car identification

At last, V_F will compare all distances between one car in front of V_F and V_F, and choose the vehicle with the shortest distance as the preceding vehicle.

4.2.2.2 Computation of Traffic Risk of the Following Vehicle

Then, traffic risk of V_F, which is defined as TR(V_F), can be estimated with the basis of the minimum safety distance. As presented in Fig. 4.4a, there have been two cars V_P and V_F in the same road with speed vlc(V_P) and vlc(V_F), respectively, and Dst(V_F,V_P) defined as the distance between two cars is what we want to know, and calculated in Eq. (4.2). After a certain time T, as shown in Fig. 4.4b, V_F catches V_P after a running distance of $s(V_F)$ and $s(V_P)$, respectively. With the consideration of perception reaction time, 1.5 s is employed in our method due to the previous work suggesting that 60 % rear-end collision can be eliminated with 0.5 s earlier warning and 90 % rear-end collision can be prevented with 1.5 s earlier warning [22]. Here, $a(V_F)$ and $a(V_P)$ are defined as the acceleration rate. sh(V_F,V_P) is defined as the space headway of V_F and V_P.

$$\begin{aligned} \mathrm{Dst}\,(V_F, V_P) \geq s\,(V_F) - s\,(V_P) &= (\mathrm{vl\,c}\,(V_F) - \mathrm{vl\,c}\,(V_P)) \times (T + 1.5) \\ &\quad + \frac{1}{2}\,(a\,(V_F) - a\,(V_P)) \times (T + 1.5)^2 \end{aligned} \tag{4.2}$$

We also consider two typical traffic scenarios. From that moment on, V_P starts to decelerate until it stops running with a distance of $s(V_P)$ after time T. Once V_P stops, V_F just catches V_P with the same velocity vlc(V_F) and a running distance of $s(V_F)$. In this scenario, Dst(V_F,V_P) would be calculated in Eq. (4.4), and we define this Dst(V_F,V_P) as Thresh_min(V_F) which refers to the minimum value of Thresh(V_F).

$$T = \frac{\mathrm{vl\,c}\,(V_P)}{a\,(V_P)} \tag{4.3}$$

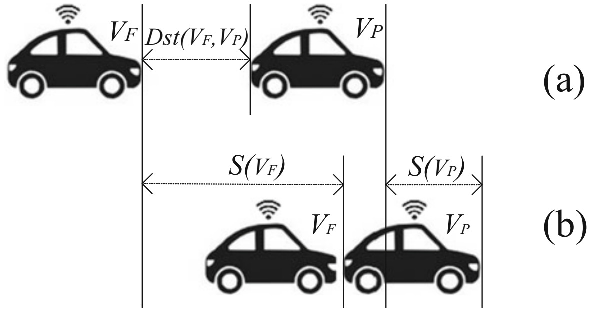

Fig. 4.4 An example scenario of traffic collision

$$\text{Thresh\_min}\,(V_\mathrm{F}) = (\mathrm{vl\,c}\,(V_\mathrm{F}) - \mathrm{vl\,c}\,(V_\mathrm{P})) \times \left(\frac{\mathrm{vl\,c}\,(V_\mathrm{P})}{a\,(V_\mathrm{P})}\right)$$
$$+1.5 + \frac{1}{2}\,(a\,(V_\mathrm{F}) - a\,(V_\mathrm{P}))\left(\frac{\mathrm{vl\,c}\,(V_\mathrm{P})}{\mathrm{a}\,(V_\mathrm{P})} + 1.5\right)^2 \quad (4.4)$$

As in another typical traffic scenario, V_P keeps running in the same velocity of vlc(V_P) with a running distance of s(V_P), and V_F just catches V_P with the same velocity vlc(V_F) and a running distance of s(V_F). Under this case, the Dst(V_F,V_P) would be calculated in Eq. (4.5), and we define this Dst(V_F,V_P) as Thresh_max(V_F) which refers to the maximum value of Thresh(V_F).

$$\text{Thresh\_max}\,(V_\mathrm{F}) = (\mathrm{vl\,c}\,(V_\mathrm{F}) - \mathrm{vl\,c}\,(V_\mathrm{P})) \times (T + 1.5) \quad (4.5)$$

4.2.2.3 Assessment of Traffic Risk of the Following Vehicle

After the computation of Dst(V_F,V_P)T, Thresh_min(V_F), and Thresh_max(V_F), we would compare their value, and take actions as show in Eq. (4.6). If Dst(V_F,V_P) is larger than Thresh_max(V_F), which means that it is a safe traffic situation and there is enough long distance between V_P and V_F, there is not any warning message or suggestion message should be sent. If Dst(V_F,V_P) is larger than Thresh_min(V_F) and smaller than Thresh_max(V_F), which means that it is in somehow a traffic risk situation with a certain safe degree although. Hence, a warning suggestion message should be put forward. If Dst(V_F,V_P) is equal to Thresh_min(V_F), that refers to an urgent situation occurs. In this circumstance, we should send a collision warning message timely. Because these three steps run cyclical, the case that Dst(V_F,V_P) greater than Thresh_min(V_F) would not occur.

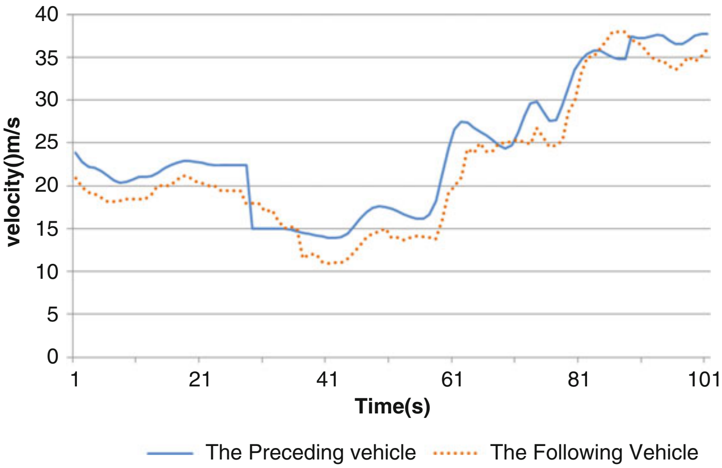

Fig. 4.5 Velocity trend of two vehicles

$$\text{Dst}\ (V_F, V_P)\begin{cases} = \text{Thresh\_min}\,(V_F), \text{put forward a warning message and take brake;} \\ \geq \text{Thresh\_min}\,(V_F)\ \text{and} < \text{Thresh\_max}\,(V_F), \text{put forward a suggestion on message;} \\ > \text{Thresh\_max}\,(V_F), \text{nothing to do;} \end{cases} \tag{4.6}$$

4.2.3 *Evaluation*

Since a number of traffic data are not easy to collect, we adopt a public trajectory dataset, known as Next Generation Simulation (NGSIM) trajectory data, for experiments evaluation. These trajectory data contain car's speed, acceleration, location information, and so forth. To evaluate our algorithm's performance, we choose a well-acknowledged and popular algorithm *HONDA*.

As shown in Fig. 4.5, we compare the speed trends of preceding and following cars on the basis of trajectory data with sampling rate of 0.1 s. We also present the development trend of acceleration of the pair cars in Fig. 4.6. As presented in these two figures, we can see that several relationships exist between the pair cars in speed and acceleration. For instance, when the preceding vehicle has a sharp deceleration, the following vehicle needs to conduct responsive actions to keep safe.

To validate our method's effectiveness, we present the performance of HONDA method in Fig. 4.7 for comparison. From this figure, we can see that HONDA method is able to estimate traffic risk accurately in several critical durations, e.g., when the acceleration value or deceleration value is larger than 5 m/s^2. However,

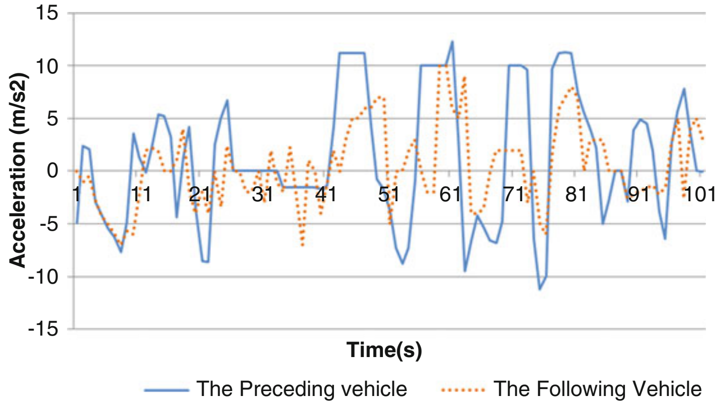

Fig. 4.6 Acceleration trend of two vehicles

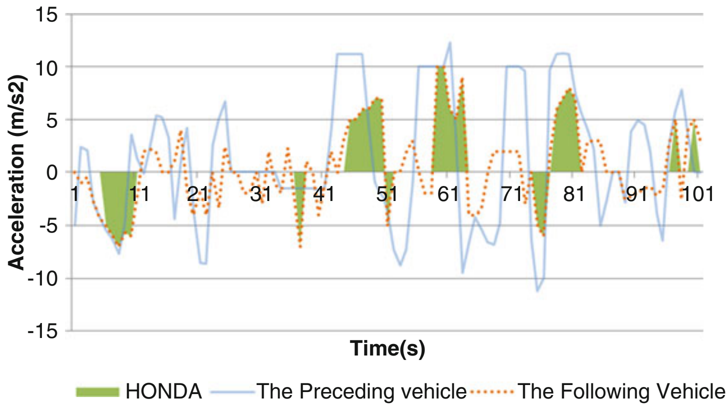

Fig. 4.7 Performance of HONDA

there also have been some moments that HONDA method cannot detect the risk situation accurately, such that it cannot notify the drivers the necessary information timely, e.g., when the acceleration value or deceleration value is not high.

Our CORECWA algorithm has been presented in Fig. 4.8. It is obvious that our method is able to monitor most of the risk traffic occasions. After that, drivers are able to receive corresponding collision warning information. For instance, when the acceleration value or deceleration value of following car grows sharply, our method can recognize and estimate traffic risk of this following car, with warning decision generation.

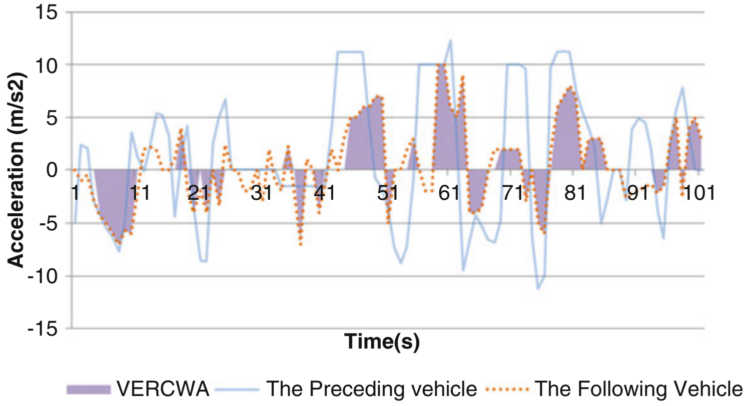

Fig. 4.8 Performance of CORECWA algorithm

4.3 Automatic Incidents Detection

There has been a large amount of studies adopting various techniques for AID in recent years [23–37]. From the perspective of application fields, previous AID approaches are mainly applied in two fields, freeways and urban roads. These two application areas have different traffic characteristics. In freeways, traffic flow would present in a smooth and satiny way with various traffic density, which result in relatively homogenous traffic patterns [19]. On the contrary, traffic flow in urban zones are guided and controlled by traffic signals and traffic police, which would lead to a remarkable difference of traffic pattern compared with in freeways.

From the perspective of detection techniques, previous research generally can be categorized into four groups, machine learning (ML)-inspired algorithms, time series analysis (TSA), other comparative approaches, and hybrid approaches. ML-based methods focus on traffic patterns and estimate the current detected traffic variables whether it is incident-free [24–30]. TSA approaches underline dynamic and abnormal changes of traffic [31–34]. There are also some comparative approaches [35, 36] and hybrid approaches [37, 38].

We choose an SVM-based approach to detect the VANET-based automatic incidents. SVM can be used for data analysis and pattern recognition through its supervised learning models companied with associated learning algorithms [39, 40]. SVM are effective tools in a broad area of classification problems and robust to irrelevant features [41]. We also extract the most critical features related to incidents occurrence, such as speed, occupancy, and volume and then train an SVM. Experiments have been conducted to evaluate the proposed approach's performance, on a publicly available dataset containing real-world traffic data in California, which is used in a wide range of relevant studies. The simulation results present that our approach can outperform the relevant state-of-the-art approaches in three well-acknowledged evaluation metrics.

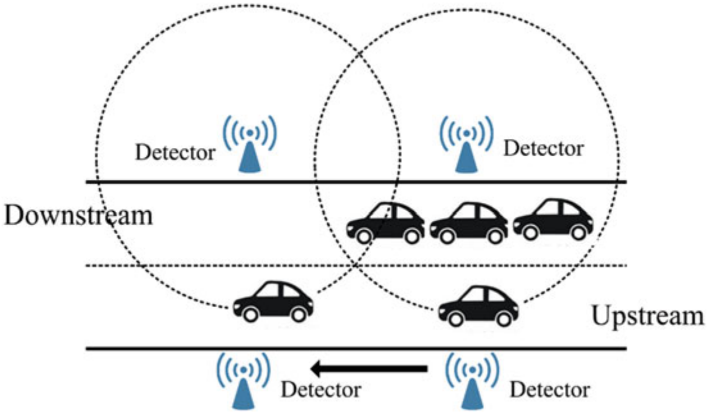

Fig. 4.9 A road scenario

4.3.1 Problem Formulation

The problem of AID is how to detect the considerable abnormal traffic situation from plentiful and dynamic changing traffic states, with only two results, incident occurred or incident-free. It is similar to the binary classification problem. Our objective is to find the red line to separate these green circles and blue triangles into different sides. In this way, when some traffic variables are detected real-timely and inducing a traffic situation deviation with regular traffic patterns, we can utilize the red line to confirm which side these traffic variables should take place in.

To model this problem, we would consider a detector-equipped freeway road scenario (see Fig. 4.9) which is divided into several segments due to detector's detection range. We assume that when each vehicle comes into a road segment, the corresponding detector can sense its existence successfully.

We represent traffic variables in different segments as vectors $x(i)$, $i = 1,2,3,\ldots,N$, defined as a road segment label. Each $x(i)$ has its own final result, defined as $y(i)$, $y(i)$ $\{-1,1\}$. Our objective is to find a function F in the following expression:

$$F : \xi \rightarrow y \tag{4.7}$$

4.3.2 Our Automatic Incidents Detection Approach

In this section, we propose our AID approach based on the above-established model. The work flow of our approach has been depicted in Fig. 4.10. There are four steps: data collection, data preprocess, data utilization in SVM model, and situation determination.

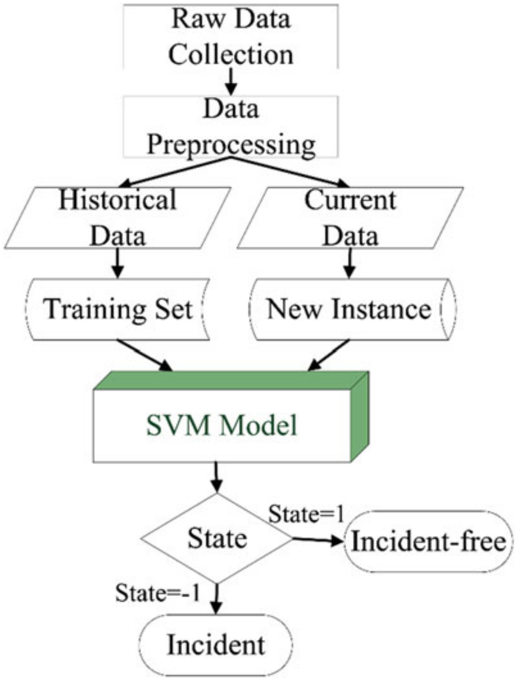

Fig. 4.10 Work flow of our support vector machines (SVM)-based automatic incident detection (AID) approach

When detecting traffic data, sensors equipped on roadside are usually the popular choices due to their convenient deployment and maintenance, such as wireless sensors. After the real-time traffic data is collected, they need to be preprocessed in order to adapt to SVM model. In this model, when an incident happens in a segment, traffic volume of this segment and following segments would grow rapidly, with tangible reduction in the segments ahead. Similar change trends would occur on segment occupancy. In terms of average traffic flow speed, the speed of this segment and following segments would decrease obviously, with distinct improvement in the segments ahead. Hence, we decide to treat both traffic volume difference and speed difference between current segment and segment ahead as input variables for the SVM model, which means that the data preprocess part should finish this job when receiving all the traffic data collected. Moreover, we treat the historical data as training data, and the real-time detected data as a new instance. The detailed mechanism of the SVM model would be presented in the following. Based on the output of the SVM model, we can confirm whether an incident happens.

Based on the analysis mentioned above, vector $x(i)$ has two elements, traffic volume difference between segment i and segment ahead $i+1$, defined as tvd(i, $i+1$), and speed difference between segment i and segment ahead $i+1$, defined as sd(i, $i+1$).

$$X(i) = (\mathrm{t\,vd}\,(i, i+1)\,, \mathrm{sd}\,(i, i+1))^T, \quad i = 1, 2, 3, \ldots, N \tag{4.8}$$

The objective is find a maximum-margin hyperplane $\omega \cdot \xi + b = 0$, which divides the variables with $y(i)$ equal to 1 from those with its value equal to -1. This problem can be transferred to its corresponding dual problem. And, its purpose is to find the optimal $\alpha^* = \left(\alpha_1^*, \alpha_2^*, \ldots \alpha_N^*\right)^T$.

$$\begin{aligned} & \min_{\alpha} \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \left\langle X_i, X_j \right\rangle - \sum_{i=1}^{N} \alpha_i \\ & \text{st.} \quad \sum_{i=1}^{N} \alpha_i y_i = 0 \\ & 0 \leq \alpha_i \leq C, i = 1, 2, 3, \ldots, N \end{aligned} \tag{4.9}$$

After optimal solution is obtained, and

$$\omega^* = \sum_{i=1}^{N} \alpha_i^* y_i \xi_l \tag{4.10}$$

$$b^* = y_i - \sum_{i=1}^{N} y_i \alpha_i^* \left\langle \xi_l, \xi_\varphi \right\rangle \tag{4.11}$$

Thus,

$$F(\xi) = \text{sign}\left(\omega^* \cdot \xi + b^*\right) \tag{4.12}$$

The well-known sequential minimal optimization (SMO) algorithm is employed for this problem with cost $O(n^{2.3})$ in training and cost $O(v)$ in testing, where n is defined as the number of data instances and v is defined as the number of support vectors [42].

4.3.3 Experiments and Analysis

4.3.3.1 Experiment Data Preparation and Evaluation Metrics

The traffic dataset used for experiments is derived from the publicly available I-880 database from the Freeway Patrol Service Project in California, USA [43, 44]. This dataset includes the traffic data we demand for, such as traffic volume and speed. And, they also include abundant incident events, almost 45 lane-blocking incidents [27].

The most common and widely acknowledged evaluation metrics for AID are detection rate (DR), false alarm rate (FAR), and mean time to detect (MTTD). DR is defined as the proportion of correctly found traffic incidents in all traffic incidents, presented in Eq. (4.13). FAR is defined as the proportion of false decisions in all incident-free cases, and presented in Eq. (4.14). MTTD is defined as the average value of each period cost from the moment a traffic incident happens to the moment the traffic incident detected, and presented in Eq. (4.15), where N is defined as the total incident number.

$$\text{DR} = \frac{\#\text{of correctly detected incidents}}{\#\text{of all incidents}} \tag{4.13}$$

$$\text{FAR} = \frac{\#\text{of false decisions}}{\#\text{of all incident-free cases}} \tag{4.14}$$

$$\text{MTTD} = \sum_{i=1}^{N} \frac{T_{\text{detection}}(i) - T_{\text{incident}}(i)}{N} \tag{4.15}$$

4.3.3.2 Experimental Design and Analysis

In automatic incident detection problems, we would prefer higher DR, lower FAR, and shorter MTTD, which leads to a multipurpose problem. The three goals are difficult to achieve optimal solution simultaneously. A higher DR may cause higher FAR and longer MTTD. Hence, we evaluate the performance separately, DR versus FAR and MTTD versus FAR, respectively. Since our approach is based on SVM and select different features in the training stage, we adopt two representative related works [4, 18] as comparative approaches.

Figure 4.11a presents the detection rate comparison between an SVM baseline approach [4], an SVM approach with speed variable [18], and our proposed approach. From the figure, we can observe that our approach can outperform the other two approaches in most cases. When the FAR is lower than 0.5 %, the SVM baseline approach presents the best performance. With the increasing incident number, all three methods have witnessed higher FAR, companied with higher DR. At that time, our approach obtains the best performance and expands the difference from the other two approaches.

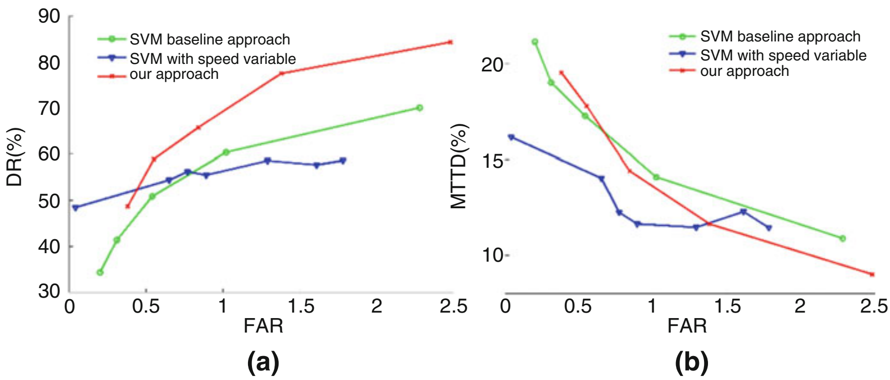

Fig. 4.11 Performance comparison. (a) DR comparison, (b) MTTD comparison

Figure 4.11b presents the mean time-to-detect comparison between the three approaches. From the figure, we can notice that the three approaches have different performances when with different FAR. When the FAR is lower than 1.4 %, the approach from [18] achieves the best performance with much lower MTTD. When the FAR is higher than 1.5 %, our approach can outperform the other two approaches.

4.4 Conclusion

VANETs have been a popular network comprised of vehicles which can communicate with each other. This kind of network can provide substantial potential for vehicles' applications, to help vehicle be more safe, smart, and flexible. Rear-end traffic collision warning and traffic incidents automatic detection are two significant applications in VANETs.

For the purpose of rear-end collision relief, we proposed a collaborative method for rear-end collision warning problem, named as CORECWA. This method is able to provide drivers the useful and timely traffic risk information, with the utilization of surrounding traffic data detected and collected in a real-time way. The traffic data used here includes location information and speed information of cars. Using these data, our method is able to recognize the preceding car of one specific following car, and then estimate current traffic risk collaboratively, taking the following factors into considerations, such as velocity of two cars and behavior data of drivers (e.g., perception–reaction time). At last, we conduct experiments with the utilization of a public traffic dataset, to verify our proposed method's effectiveness. Experiment results show that our method can have better performance compared with a well-acknowledged method HONDA.

To detect traffic incidents automatically, we have presented an AID approach based on SVM with appropriate features, with traffic data detected by VANET techniques in a real-time manner. After several experiments conducted based on a real-world dataset, we confirm that our features selected can be beneficial for incidents detection, with higher detection rate and low mean time-to-detect with a certain level FAR, compared with two representative related works. In the future, we will optimize our work to further improve the detection rate, and we would pay efforts to optimize current approach in order to apply into urban areas.

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