IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received December 19, 2019, accepted December 29, 2019, date of publication January 3, 2020, date of current version January 17, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2963854

A Forward Collision Warning System Using Driving Intention Recognition of the Front Vehicle and V2V Communication

WEI YANG[1], BO WAN[2], AND XIAOLEI QU[3,4]
[1]School of Automobile, Chang'an University, Xi'an 710064, China
[2]Cicada Canada Inc., Toronto, ON L5V 1T7, Canada
[3]School of Instrumentation and Optoelectronic Engineering, Beihang University, Beijing 100083, China
[4]Beijing Advanced Innovation Center for Big Data-Based Precision Medicine, Beihang University, Beijing 100083, China

Corresponding author: Xiaolei Qu (quxiaolei@buaa.edu.cn)

This work was supported in part by the National Natural Science Foundation under Grant 51278062, in part by the Shaanxi Province Science Foundation for Youths under Grant 2017JQ6045, and in part by the Fundamental Research Funds for the Central Universities under Grant 300102229112.

ABSTRACT A forward collision warning (FCW) system is important for avoiding rear-end collisions. When the front vehicle slows down or the risk of rear-end collision increases, the FCW system sends a warning. However, if the warning is provided too late, the following vehicle may not have enough time to stop or slow down smoothly. Here, we propose a new FCW system that detects the driving intention of the front vehicle to provide earlier warning than previously used systems. The proposed FCW system consists of three steps. First, the driving intention of the front vehicle is determined by the driving intention recognition module. Second, the driving intention and other driving parameters of the front vehicle are transmitted to the following vehicle using vehicle-to-vehicle (V2V) communication. Finally, this information and the driving parameters of the following vehicle are used to determine the potential collision risk by the FCW module located in the second vehicle. To evaluate the proposed system, we conducted a simulation test based on PreScan (commercial software provided by TASS international) and actual road tests in various driving scenarios. The simulation test results demonstrated that the correct warning rate of the proposed system was 97.67%, which was 6.34% higher than that of the system with a fixed time-to-collision (TTC) threshold. The real vehicle test results showed that the proposed system was able to provide earlier warnings than the TTC-based system. The timely warning rate, i.e., the ratio of the number of warnings at the beginning of braking to the total number of warnings was 93.33%. The proposed system proved effective for providing early warning to the following vehicle under different driving conditions of the front vehicle.

INDEX TERMS Collision warning, driving intention, hidden Markov model, V2V communication.

I. INTRODUCTION

Road traffic accidents pose serious threats to people's lives, property safety, and road traffic efficiency. In addition, two-vehicle and multi-vehicle collisions are the most severe type of accidents [1]. Studies of road traffic accidents showed that more than 80% of these incidences resulted from the drivers' untimely responses and more than 65% resulted in rear-end collisions [2]. According to research conducted by Mercedes-Benz, most accidents can be avoided if drivers are aware of the dangers of these accidents and are able to take evasive measures within a second prior to the accident [3]. The prevention of automobile collisions and the improvement of the driving safety of vehicles are key topics in the field of automobile safety and assisted driving.

The associate editor coordinating the review of this manuscript and approving it for publication was Maurice J. Khabbaz.

To address the rear-end collision problem, forward collision warning (FCW) systems have been developed using active sensors such as vision-based [4], acoustic-based [5], radar-based [6], and laser-based [7] sensors. Some of these FCW systems were based on collision warning models with fixed parameters. Kilicarslan and Zheng [8] used the time-to-collision (TTC) model with a fixed threshold and a single camera to evaluate the potential collision danger. Nagatani [9] proposed a time-headway (THW) model, which not only considered the speed of the following vehicle, but also the distance between the two cars. Wang *et al.* [10] presented a kinematic-based model to calculate the minimum distance needed to stop safely when both vehicles were moving. Chen *et al.* [11] proposed an FCW model based on road friction. This model described the impact of vehicle deceleration on the collision warning model during braking. The minimum safe distance model proposed in Ref. [12] considered the relative motion between adjacent automobiles. These FCW models do not adapt to driver behavior under varying traffic conditions.

In order to improve the robustness of FCW systems, some studies employed adaptive models, which considered the driver's characteristics. Bella and Russo [13] proposed a new FCW algorithm based on the risk perception of the driver. The distance calculated by the proposed model was considered the collision warning threshold. Tawfeek and El-Basyouny [14] proposed an FCW model based on the analysis of the natural following behavior of the driver. The relative speed, host vehicle speed, and acceleration were used to determine the warning threshold. Brown *et al.* [15] proposed an FCW system based on a human performance model; a simple deterministic model was proposed to analyze the driver performance under various collision situations. Muehlfeld *et al.* [16] presented a statistical driver behavior model based on the analysis of the driving history. Pugeault and Bowden [17] proposed a statistical learning approach based on driver braking behavior. Wang *et al.* [18] developed an adaptive longitudinal driving assistance system that adapted to the driver's habits. Su *et al.* [19] proposed an FCW system based on a Gaussian mixture model to recognize the driver's driving behavior. Iranmanesh *et al.* [20] designed an adaptive FCW framework based on detecting driver distraction. Xiong *et al.* [21] proposed an FCW algorithm based on online risk level classification. The parameters reflecting the level of risk were identified using fuzzy logic rules. Arbabzadeh *et al.* [22] established a kinematics-based FCW system using a hybrid physical/data-driven approach, which took into account the driver's reaction time. Reinmueller and Steinhauser [23] suggested that the driver's reactions to failures and associated safety implications should be considered in adaptive FCW systems. Wu *et al.* [24] proposed a collision warning model. The authors considered the driving behavior of the front vehicle and road geometry information and used the model for predicting the vehicle position and vehicle distance. Jo *et al.* [25] presented a unified vehicle tracking and behavior algorithm, which simultaneously estimated the dynamic state of the surrounding vehicles and driver intentions. Yuan *et al.* [26] proposed a front vehicle lane-change prediction method for an adaptive cruise control system. In their method, a hidden Markov model was used to predict the lane-changing maneuver of the front vehicle. These FCW systems focused primarily on the driving behavior of the following vehicle and less on the driving behavior of the front vehicle, which may be equally important.

With the rapid development of wireless communication technology, the behavior of the driver in the front vehicle can be transmitted to the following vehicle to improve the performance of the FCW system [27]. Xiang *et al.* [28] presented a dedicated short-range communication (DSRC)-based FCW system. A neural network-based collision warning model was proposed to improve the system performance. Patra *et al.* [29] presented an FCW system for smartphones. This FCW system used license plate recognition and vehicle-to-vehicle (V2V) communication to warn the drivers of both vehicles. Lei and Wu [30] designed an FCW system based on ZigBee technology at slow speeds. They established a safe distance collision warning model to detect future collision risk of the target vehicles. Chen and Hsiung [31] proposed a visibility-based collision warning system; human factors and weather conditions were considered in this collision warning model. The aforementioned FCW systems only took into account the behavior of the driver of the front vehicle but did not consider driving intention, which can be used to predict the near-future action of vehicles and speed up the response of FCW systems.

In this article, we propose an FCW system that detects the driving intention of the front vehicle and transmits the information to the following vehicle using V2V communication techniques. The proposed driving intention recognition method results in better efficiency of the FCW system and gives the following vehicle additional time for smooth braking. The rest of the paper is organized as follows: Section 2 provides the methods. Section 3 and Section 4 provide the test results and discussion, respectively. Section 5 is the conclusion.

II. METHODS

The proposed FCW system includes two modules: the driving intention recognition module and the FCW module that uses V2V communication. First, the driving intention recognition module determines the driving intention of the front vehicle using a double-layer hidden Markov model (HMM). Second, this information and other related driving parameters of the front vehicle are transmitted to the following vehicle using V2V communication. The FCW module then determines whether an FCW should be given based on the relative distance that is detected by the system and the transmitted information from the front vehicle.

A. THE DRIVING INTENTION RECOGNITION MODULE

Driving intention refers to the driver's determination to act in a particular manner. There are four kinds of driving intentions related to FCW, including driving at a constant speed, acceleration, normal braking, and emergency braking. The driving intention can be inferred by the driver's behavior and vehicle movement. The driving behavior reflects the driver's actions; the key actions are braking and acceleration (Figure 1). Braking results in a decrease in the speed and acceleration results in an increase in speed. Both behaviors can be classified into five classes (Figure 1).

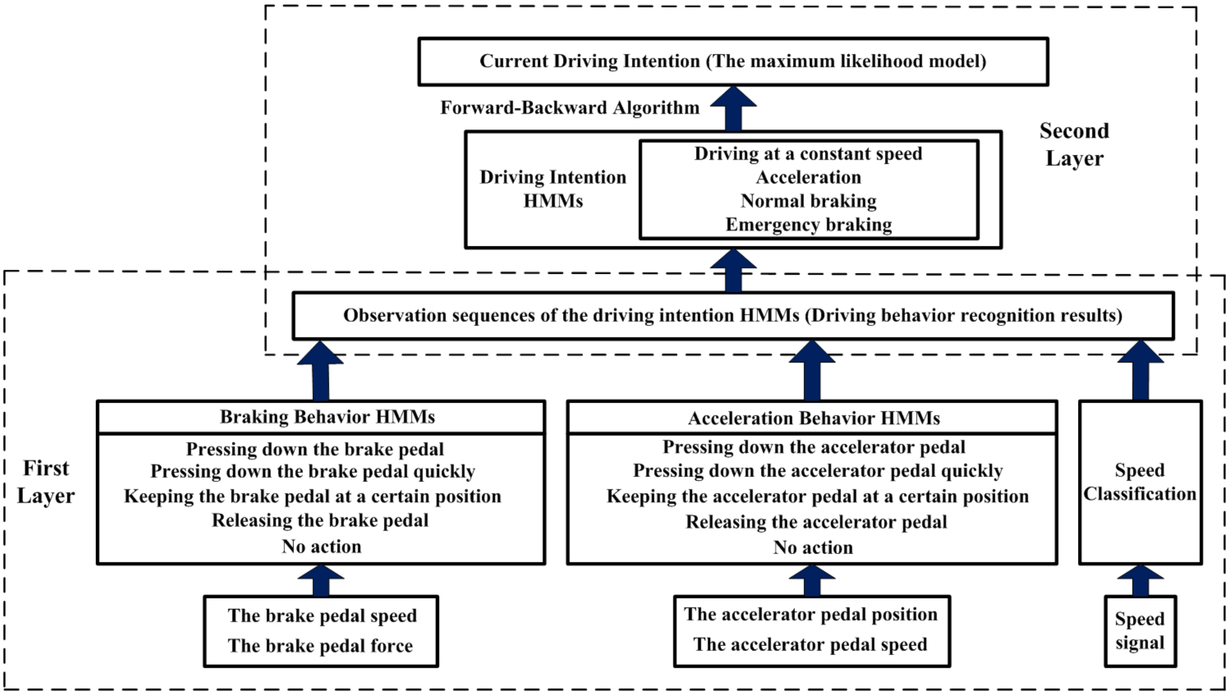


FIGURE 1. The structure of the proposed double-layer HMM.

The HMM has a double random process: a Markov chain is used to describe unobservable state transitions, and a random process is used to describe the relationship between states and observations. The driving behavior and driving intention are represented by driving operation data and driving behavior data with a strong temporal relationship, which is consistent with the HMM characteristics. Compared with other neural network methods that can process time series, such as the Long Short-Term Memory (LSTM) network, the HMM model requires fewer sample data and has higher training speed. In addition, the HMM is a Bayesian network. Compared with the Kalman filter (KF), the HMM can infer the state of the hidden layer from the observed value, whereas the state of the Kalman filter is a continuous value, whose state is unobservable due to the presence of noise.

The traditional HMM is usually a single layer and can be used to recognize driving intention. However, the single-layer HMM only uses the time relationship of the sensor data to recognize the driving intention but ignores the influence of the time relationship of the driving behavior on the driving intention. Therefore, a single-layer HMM is not ideal for driving intention recognition [32], [33]. In this article, we propose a double-layer HMM for driving intention recognition.

Figure 1 shows the proposed double-layer HMM for driving intention recognition. In the first layer, the driving behavior is detected using sensor data. In the second layer, the driving intention is determined using the driving behavior obtained from the first layer. As Figure 1 shows, the braking behavior can be classified into five classes: pressing down the brake pedal, pressing down the brake pedal quickly, keeping the brake pedal at a certain position, releasing the brake pedal, and no action. The acceleration behavior also can be classified into five classes: pressing down the accelerator pedal, pressing down the accelerator pedal quickly, keeping the accelerator pedal at a certain position, releasing the accelerator pedal, and no action. After the braking behavior and acceleration behavior are classified by the first layer of the HMM, the classification results and speed classification results are passed on to the second layer for driving intention classification.

Figure 2 shows a flowchart of the training process of the double-layer HMM for driving intention recognition. The first step consists of training the driving behavior layer and the second step is to train the driving intention layer.

1) THE TRAINING PROCESS OF THE DRIVING BEHAVIOR LAYER

In this study, we assume that the braking and acceleration behaviors are independent of each other. Therefore, we train and process them independently. In this sub-section, we will introduce these behaviors.

With regard to braking behavior recognition, we classify the data samples into the five classes and establish the five braking behavior HMMs. The observation sequence of the braking behavior HMMs is described as:

$$O_{1(t)} = \{a\,(t)\,,b(t)\} \tag{1}$$

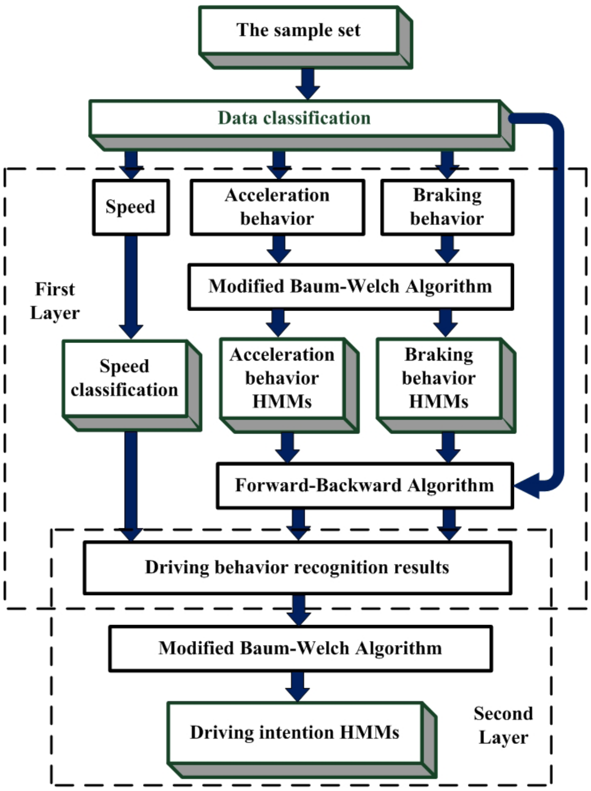


FIGURE 2. The training process of the proposed double-layer HMM.

where t indicates the time; $a(t)$ and $b(t)$ denote the brake pedal force and the brake pedal speed, respectively.

The HMM is a double random process that is expressed as the initial state probability distribution π and state transition matrix A; the general random process is described by the observed state probability matrix B. For a given observation sequence $O_{1(t)}$, the corresponding state is determined by the model $\lambda = (A,B,B,\pi)$. The braking behavior HMM is expressed as:

$$\lambda_1 = (A_1, B_1, B_2, \pi_1) \tag{2}$$

where B_1 and B_2 represent the observed values of the probability matrix of the brake pedal force and brake pedal speed, respectively.

The Baum-Welch algorithm [34] is used to train the five braking behavior HMMs. The Baum-Welch algorithm is an iterative algorithm. The four tuples of the braking behavior are initialized to obtain the model $\lambda_1^{(0)} = (A_1^{(0)}, B_1^{(0)}, B_2^{(0)}, \pi_1^{(0)})$. Then, the iterative revaluation formula is defined as follows:

$$a_{ij}^{(n+1)} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \tag{3}$$

$$b_j(k)^{(n+1)} = \frac{\sum_{t=1,O_{1(t)}=V_{(k)}}^{T} \gamma_t(j)}{\sum_{t=1}^{T-1} \gamma_t(j)} \tag{4}$$

$$\pi_i^{(n=1)} = \gamma_t(i) \tag{5}$$

The Baum-Welch variables are obtained as follows:

$$\gamma_t\,(i) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{j=1}^{N} \alpha_t(j)\beta_t(j)} \tag{6}$$

$$\xi_t\,(i,j) = \frac{\alpha_t(i)a_{ij}b_j(O_{1(t+1)})\beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t(i)a_{ij}b_j(O_{1(t+1)}\,(j))} \tag{7}$$

where $a_{ij}^{(n+1)}$, $b_j(k)^{(n+1)}$, and $\pi_i^{(n+1)}$ represent the evaluation of the state matrix, confusion matrix, and probability matrix, respectively.$V_{(k)}$ is the value of all possible observed values in the set V. $\gamma_t\,(i)$ represents the probability of the braking behavior q_i at time t, $\xi_t\,(i,j)$ represents the probability of the braking behavior q_i at time t and q_j at time $t+1$.

Since the observation sequence of the braking behavior HMMs is a two-dimensional vector, the forward and backward variables of the Baum-Welch algorithm are modified as follows:

$$\alpha_{t+1}\,(j) = [\sum_{i=1}^{N} \alpha_t(i)a_{ij}] \prod_{l=1}^{2} b_j(O_{1(t+1)}(l)) \tag{8}$$

$$\beta_t\,(i) = [\sum_{j=1}^{N} \beta_{t+1}(j)\alpha_{ij}] \prod_{l=1}^{2} b_i(O_{1(t)}(l)) \tag{9}$$

where the forward variable $\alpha_t(i)$ is the probability of the partial observation sequence $O_{1(1)}O_{1(2)}\cdots O_{1(t)}$ in the state q_i before time t and the backward variable $\beta_t(i)$ is the probability of the partial observation sequence $O_{1(t+1)}O_{1(t+2)}\cdots O_{1(T)}$ in the state q_i after time t. Here, a_{ij} is the probability of the transition from state q_i to state q_j and $b_i(O_{1(t)}(l))$ is the probability of the observation value $O_{1(t)}(l)$. The revaluation formulas of the initial probability vector and the state transition probability matrix of the Baum-Welch algorithm remain unchanged, whereas the calculation formulas of the probability matrix of the two observation values are changed to:

$$\bar{b}_j^{(l)}\,(k) = \text{count}(k^{(l)}|j)/\text{count}(j)) \tag{10}$$

where count$(k^{(1)}|j)$ is the expected value of the number of observations k occurring in the observation sequences set l in the state q_j and $l(l = 1,2)$ is the number of observation sequences.

The parameters of each braking behavior HMM under a single driving condition were optimized by the modified Baum-Welch algorithm step-by-step until the maximum probability was reached. After optimization, the forward-backward algorithm [35] was used to calculate the likelihood of the newly acquired braking behavior relative to the braking behavior HMM. Finally, the HMM with maximum likelihood was chosen as the most likely braking behavior.

With regard to acceleration behavior recognition, similar to the method for braking behavior, we also established five acceleration behavior HMMs. The process and method of acceleration behavior recognition were the same as for braking behavior recognition.

For speed classification, we simply divided the speed in the range of 0-100 km/h into 10 different classes. For example, if the speed was in the range of 60-70 km/h, the speed grade was 7.

Finally, the recognized driving behaviors such as braking, acceleration, and vehicle speed, were categorized into observation sequences. Those observation sequences were transmitted to the second layer for driving intention recognition.

2) THE TRAINING PROCESS OF THE DRIVING INTENTION LAYER

The input for the driving intention layer is the driving behavior obtained from the first layer and the output is the driving intention. First, we prepared the labeled data for driving behaviors and driving intentions. The driving behaviors included braking, acceleration, and speed, which we obtained from the first layer. The driving intentions were already known because we asked drivers to drive with a given intention in our experiment. Second, the labeled data were used to train the second HMM layer to determine the driving intention. The observation sequences of the driving intention HMMs were expressed as:

$$O_{2(t)} = \{x\,(t)\,, y\,(t)\,, z(t)\} \tag{11}$$

where $x\,(t)$, $y(t)$ and $z(t)$ represent the labeled results of the braking behavior, acceleration behavior, and speed classification, respectively. The driving intention HMMs are described as:

$$\lambda_2 = (A_2, B_1^{'}, B_2^{'}, B_3^{'}, \pi_2) \tag{12}$$

where π_2 is the initial probability vector, A_2 is the state transfer probability matrix vector. $B_1^{'}$, $B_2^{'}$, and $B_3^{'}$ represent the probability matrix of the braking observation sequence, acceleration observation sequence, and speed observation sequence, respectively. The Baum-Welch algorithm was modified using Equations (8) to (10). The parameters of the driving intention HMMs were obtained from the modified Baum-Welch algorithm.

B. THE FCW USING V2V COMMUNICATION

In this section, we introduce the proposed kinematic-based FCW model that uses the obtained driving intention and other driving parameters of the front vehicle. In the FCW model, the front vehicle was detected by a double-channel Gabor filter and an AdaBoost classifier algorithm [36]. The relative distance between the two vehicles was estimated using a monocular camera model [37]. The driving parameters of the front vehicle and the following vehicle were determined using multiple sensors.

In order to transmit the obtained driving intention from the front vehicle to the following vehicle, an appropriate communication method is required. The performance of ZigBee and WIFI are poor in vehicles moving at high speed. The communication distance of Bluetooth and near-field communication (NFC) is too small for vehicle safety applications because a minimum communication distance of 300 m is required. Long-term evolution (LTE) technology requires a base station, which also is not suitable for V2V communication [38].

In this study, DSRC was chosen as the on-board communication method for a V2V communication network. The proposed system uses the American IEEE 802.11p DSRC protocol with communication distances of up to 1 km; the method is also suitable for the high-speed mobile vehicle environment. The DSRC module uses an MK5 device produced by Cohda Wireless Comapany The SAF5100 wireless processor produced by the NXP semiconductor Comapany and the TEF5100 rf chip were used to complete the hardware design of the communication module based on the IEEE 802.11p protocol, including the main control module and the rf module, to achieve real-time data transmission.

The driving intention data and the driving state data of the front vehicle were combined into a data frame and sent to the following vehicle as a basic safety message (BSM), using the user datagram protocol (UDP) interface of the MK5 sender in the front vehicle. The MK5 receiver in the following vehicle decoded the received data to obtain the BSM packet and finally completed the data transmission through the UDP port.

Rear-end collisions are caused when the following vehicle is faster than the front vehicle. Therefore, the FCW system should consider both vehicles. We used a kinematic-based FCW model in the following vehicle that considered not only the following vehicle but also the driving intention of the front vehicle that was transmitted via V2V communication. We assumed that the front and following vehicles were in the same lane and only considered the potential collision between the two vehicles in the same lane. The proposed FCW model considered four situations: the front vehicle traveled at a constant speed, acceleration, normal deceleration, and emergency deceleration.

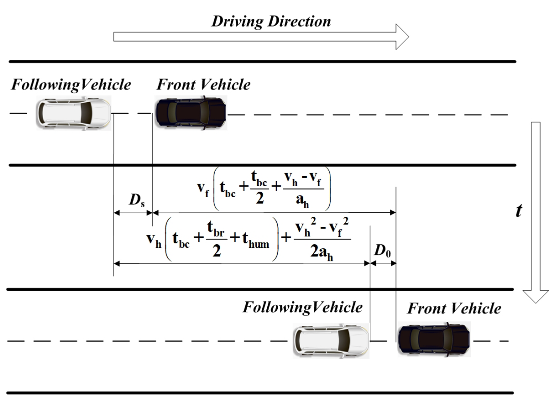


FIGURE 3. The critical distance at a constant speed or acceleration.

The front vehicle was moving at a constant speed or was accelerating. If the following vehicle was moving faster than the front vehicle, it would eventually reach a point that was called the "critical distance", as shown in Figure 3. In this situation, the most dangerous time occurs when the following vehicle slows down but still travels faster than the vehicle in front.

The critical distance was calculated as follows:

$$D_s = v_{rel}\left(t_{bc}+\frac{t_{br}}{2}+t_{hum}\right)+\frac{v_h^2-v_f^2}{2a_h}-v_f\frac{v_{rel}}{a_h}+D_0 \tag{13}$$

where v_f is the speed of the front vehicle; v_h is the speed of the following vehicle; v_{rel} is the relative speed of the two vehicles; a_h is the deceleration of the following vehicle; t_{bc} is the time between pressing the brake pedal of the following vehicle and the braking effect, which is defined as 0.15 s; t_{br} is the deceleration time of the following vehicle, which is defined as 0.45 s; t_{hum} is the driver response time of the following vehicle, which is defined as 1.2 s according to a previous study [22]; D_0 is a predetermined safe distance between the two vehicles, which is defined as 2 m.

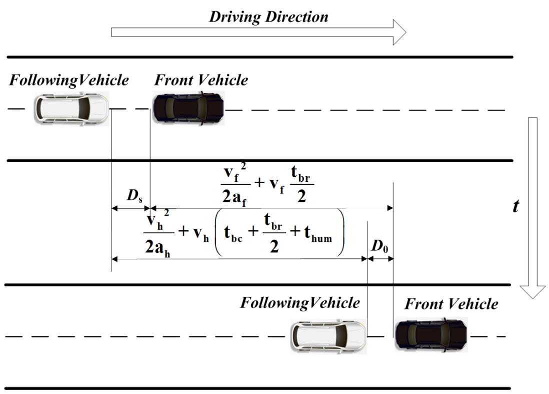


FIGURE 4. The critical distance during deceleration.

When the front vehicle slows down, the driver of the following vehicle reacts and adjusts the speed to match that of the front vehicle. The critical distance between the two vehicles for this case is shown in Figure 4. The critical distance is calculated as:

$$D_s = \frac{v_h^2}{2a_h} - \frac{v_f^2}{2a_f} + v_h\left(t_{bc} + t_{hum}\right) + v_{rel}\frac{t_{br}}{2} + D_0 \quad (14)$$

where a_f is the deceleration of the front vehicle.

If the front vehicle suddenly brakes, the critical distance is:

$$D_s = \frac{v_h^2}{2a_{hmax}} - \frac{v_f^2}{2a_{fmax}} + v_h\left(t_{bc} + t_{hum}\right) + v_{rel}\frac{t_{br}}{2} + D_0 \quad (15)$$

where a_{hmax} is the maximum deceleration of the following vehicle and a_{fmax} is the maximum deceleration of the front vehicle. According to a previous study [11], we assumed that the road friction was negligible and the parameters of a_{hmax} and a_{fmax} were defined as 6 m/s^2.

The critical distance model was established under ideal conditions. In reality, the vehicle information transmission delay t_{tran} results in differences in the distance between the front vehicle and the following vehicle. We assumed that the information transmission time between the two vehicles was very short and v_{rel} was constant during this time. Thus, the critical distance was approximately expressed as:

$$D_w = D_s + v_{rel}t_{tran} \quad (16)$$

In summary, if the actual distance was less than the distance obtained from the proposed FCW algorithm, the collision warning was triggered and sent to the driver of the following vehicle.

C. EXPERIMENTAL AND EVALUATION METHODS

In this study, a driving intention recognition test and collision warning test were conducted. The objective of the driving intention recognition test was to determine the accuracy of the proposed double-layer HMM; a simulation experiment was conducted for this purpose. The objective of the collision warning test was to evaluate the FCW system and both simulations and real vehicle experiments were performed.

FIGURE 5. The driving simulation system.

1) THE DRIVING INTENTION RECOGNITION SIMULATION

We used a driving simulation system consisting of Logitech G29 hardware and PreScan software to simulate a two-way four-lane highway scene. Figure 5 shows the driving simulation system. Ten experienced drivers were recruited as experimental subjects, including five males and five females. The test was conducted under four driving scenarios. These scenarios included the front vehicle driving at a constant speed, acceleration, normal braking, and emergency braking. Each driver used Logitech G29 to simulate driving intentions 35 times in each scenario; therefore, 1400 samples were obtained (10 (drivers) * 35 (repeat times) * 4 (scenarios)). The training set consisted of 800 samples and the remaining samples were used as the test set [39].

2) THE COLLISION WARNING SIMULATION TEST

In order to evaluate the performance of the proposed FCW system, we conducted simulations and real vehicle tests; we compared the performance of the proposed FCW system and a previously developed FCW system with a fixed TTC threshold algorithm [40].

The fixed TTC threshold algorithm has a two-level warning threshold: the dangerous warning threshold (5s) and the very dangerous warning threshold (3s). The TTC is calculated as follows:

$$TTC = \frac{D_{rel}}{V_{rel}} \quad (17)$$

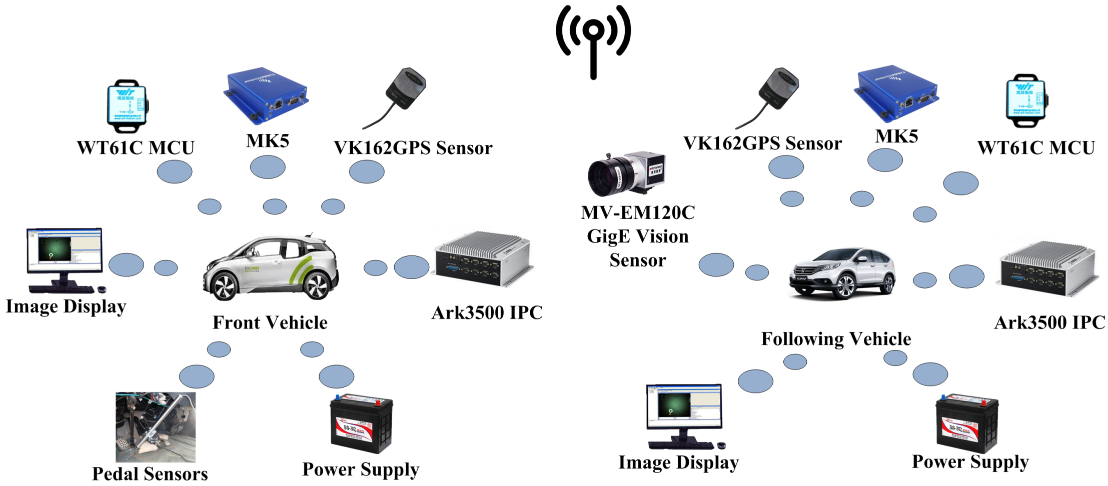


FIGURE 6. Experimental passenger vehicles and devices.

where D_{rel} represents the relative distance between the front vehicle and the following vehicle.

The simulation test was carried out using the PreScan simulation environment. The test road was a two-way two-lane road with 5 km length, each lane was 3.5 m wide, and the road surface was dry asphalt. In the simulation environment, the two-dimensional simple vehicle dynamics model was used for the front and following vehicles. The camera sensor and V2V wireless communication equipment of the PreScan software were used as simulation sensors. Five experienced drivers were recruited as experimental subjects to drive the front vehicle using the Logitech G29 hardware (Figure 5). We asked each driver to drive the vehicle based on a predetermined driving intention and the test was repeated 10 times. Therefore, we knew the driving intentions in each test.

The vehicle test was divided into six groups. The forward and the following vehicles in each group were moving at low, medium, and high speeds. The low speed of the driving vehicle was 10-30 km/h, the medium speed was 30-50 km/h, and the high speed was 50-70 km/h. Each driver repeated the experiment ten times in each speed range. Each group consisted of the front vehicle traveling at a constant speed, accelerating, normal braking, and emergency braking. We determined whether a rear-end collision occurred during the warning displays and during braking.

Two evaluation indices were developed, i.e., the correct warning rate and the false warning rate. The correct warning rate is the ratio of correct warnings to the total number of warnings in the simulation test. The correct warning rate was calculated as follows:

$$F_{\mathrm{W}} = \frac{N_{\mathrm{F}}}{N_{\mathrm{S}}} \times 100\% \tag{18}$$

where N_{F} represents the number of vehicle collisions that were prevented after the collision warning and N_{S} represents the total number of warnings. The false warning rate is the ratio of the number of false warnings to the total number of warnings. The false warning rate was calculated as follows:

$$M_{\mathrm{W}} = \frac{N_{\mathrm{M}}}{N_{\mathrm{S}}} \times 100\% \tag{19}$$

where N_{M} represents the number of vehicle collisions occurring after the collision warning.

3) THE COLLISION WARNING ROAD TEST

Figure 6 shows the experimental vehicles and devices used for the road test. Two vehicles were used in the experiment: the front vehicle and the following vehicle. The two vehicles communicated with each other via a V2V link. Each vehicle carried an Ark3500 processing terminal, a WT61C MCU unit, a VK162 GPS sensor, an MK5 V2V communication device, and a power supply system. In addition, the front vehicle system was equipped with brake and accelerator pedal sensors. The following vehicle had an MV-EM 120C GigE vision sensor and an image display unit.

The MV-EM 120C GigE vision sensor installed on the front windshield of the following vehicle was connected to the processing system. It was used for detection and estimation of the distance to the front vehicle. The speed and acceleration information of the vehicles was obtained using two VK162 GPS sensors and the WT61C MCU sensors, respectively. The brake and accelerator pedal sensors were used to collect data from the driver of the front vehicle. The MK5 V2V communication devices were used to transmit the obtained driving intention and other driving data of the front vehicle to the following vehicle.

Since we could not cause a collision, the experimental method focused on testing the performance of the collision warning model using a statistical analysis of the warning timing. We recruited five experienced drivers as experimental subjects to drive the experimental vehicles. Four drivers respectively operated the front vehicle and one driver operated the following vehicle. The test road was a suburban road with two lanes in each driving direction. The total length of

TABLE 1. Driving intention recognition results of the proposed double-layer HMM.

Actual intention	Recognized intention				Correct recognition rate/%
	Constant speed	Acceleration	Normal braking	Emergency braking	
Constant speed	146	2	2	0	97.3
Acceleration	3	147	0	0	98.0
Normal braking	1	0	144	5	96.0
Emergency braking	0	0	4	146	97.3

TABLE 2. Driving intention recognition results of the proposed double-layer HMM and the single-layer HMM.

Actual intention	Proposed double-layer HMM		Single-layer HMM	
	Correctly recognized number	Correct recognition rate (%)	Correctly recognized number	Correct recognition rate (%)
Constant speed	146	97.33	137	91.3
Acceleration	147	98.00	136	90.6
Normal braking	144	96.00	138	92.0
Emergency braking	146	97.33	140	93.3
Average	145.75	97.17	137.75	91.83

the test road was about 7.5 km and the test was conducted on a part of this road. The traffic flow on the road was low. In the experiment, we investigated six speed levels of the front and following vehicles (Table 5). The ranges of the low, medium, and high speeds were 10-30 km/s, 30-50 km/s, and 50-70 km/s, respectively. Each driver repeated two tests at each speed level. Therefore, 60 tests were conducted in this experiment.

To ensure safety, an experienced driver drove the following car and conducted braking based on his judgment. In addition, the FCW system provided warning information. When the warning was given within 1 s of the driver initiating braking, the warning was considered as occurring "during braking", which provided nearly the same results as the experienced driver. When the warning was given more than 1 s before or after the driver was braking, the warning was considered as occurring "before braking" or "after braking", respectively [41].

In order to verify the real-time performance of the proposed FCW warning model, we record the warning display times that occurred before, during, or after the time of the braking action with different warning algorithms under various moving conditions. The warning indicates whether it occurred before, during, or after the time of the braking action.

Three evaluation indices were used, namely, the premature warning rate, the timely warning rate, and the late warning rate. The premature warning rate is the ratio of the number of warnings before braking to the total number of warnings. The premature warning rate was calculated as follows:

$$R_P = \frac{N_P}{N_T} \times 100\% \tag{20}$$

where N_P represents the number of warnings before braking and N_T represents the total number of warnings.

The timely warning rate is the ratio of the number of warnings at the beginning of braking to the total number of warnings. The timely warning rate was calculated as follows:

$$R_A = \frac{N_A}{N_T} \times 100\% \tag{21}$$

where N_A represents the number of warnings at the beginning of braking.

The late warning rate is the ratio of the number of warnings after braking to the total number of warnings. The late warning rate was calculated as follows:

$$R_L = \frac{N_L}{N_T} \times 100\% \tag{22}$$

where N_L represents the number of warnings after braking.

III. RESULTS

A. RESULTS OF THE DRIVING INTENTION RECOGNITION SIMULATION

Table 1 gives the results of the driving intention recognition test using the proposed double-layer HMM. In the test, 600 samples were used to determine the recognition rate of 4 different intention conditions and 150 samples were used for each condition. As shown in Table 1, the correct recognition rates of the proposed double-layer HMM were higher than 95% for each driving condition. Table 2 compares the performance of the driving intention recognition for the proposed double-layer HMM and the single-layer HMM. The correct recognition rates of the proposed double-layer HMM are obviously higher than those of the single-layer HMM.

TABLE 3. Warning results of the proposed algorithm and TTC algorithm.

Front vehicle	Following vehicle	Proposed algorithm warning results		TTC algorithm warning results	
		No Collision	Collision	No Collision	Collision
Low speed	Low speed	50	0	50	0
Low speed	Medium speed	50	0	49	1
Low speed	High speed	49	1	47	3
Medium speed	Medium speed	49	1	46	4
Medium speed	High speed	48	2	43	7
High speed	High speed	47	3	39	11

TABLE 4. Correct warning rate of the proposed algorithm and TTC algorithm.

Algorithm	Correct warning rate (%)	False warning rate (%)
TTC fixed threshold algorithm	91.33	8.67
Proposed algorithm	97.67	3.33

TABLE 5. Warning time results of the proposed algorithm and TTC algorithm.

Front vehicle	Following vehicle	Proposed algorithm warning time results			TTC fixed threshold algorithm warning time results		
		Before braking	During braking	After braking	Before braking	During braking	After braking
Low speed	Low speed	0	10	0	3	7	0
Low speed	Medium speed	0	10	0	0	6	4
Low speed	High speed	0	9	1	0	3	7
Medium speed	Medium speed	0	10	0	0	4	6
Medium speed	High speed	0	9	1	0	1	9
High speed	High speed	0	8	2	0	0	10

B. RESULTS OF THE COLLISION WARNING SIMULATION TEST

Table 3 shows the warning results of the simulation test for the proposed methods and the TTC fixed threshold method. For each speed level, 50 collision warning simulations were conducted and a total of 600 simulation tests were conducted for each speed level. The number of collisions of the proposed FCW system (fourth column) is lower than that of the TTC system (sixth column) and the number of no collisions of the proposed system (third column) is higher than that of the TTC system (fifth column). Table 4 lists the correct and false warning rates of the proposed FCW system and the TTC system; the results demonstrate that the proposed method has a higher correct warning rate than the TTC system.

C. RESULTS OF THE COLLISION WARNING TIME IN THE ROAD TEST

Table 5 shows the collision warning time results of the road test of both systems. For each speed condition, 10 collision warning tests were conducted and a total of 120 tests were conducted for each speed condition. The proposed algorithm provided 56 collision warnings during braking, which means the collision warning time is close to the reaction time of the experienced driver, whereas the TTC with the fixed threshold algorithm had only 21 collision warnings during braking. The premature, timely, and late warning rates of the two algorithms are listed in Table 6.

IV. DISCUSSION

The results indicated (Table 1 and 2) that the proposed double-layer HMM was able to accurately recognize the driving intention. As shown in Table 2, the average recognition accuracy of the proposed double-layer HMM was 97.17%, which was 5.34% higher than that of the single-layer HMM.

As shown in Table 3, with the increase in vehicle speed, the number of rear-end collisions increased for the TTC algorithm. However, the proposed FCW system significantly reduced the number of rear-end collisions in the low to medium speed range.

The correct warning rate of the proposed algorithm was 97.67% compared to 91.33% of the TTC algorithm (Table 4); this represented an increase of 6.34%. The false warning

TABLE 6. Warning rates of the proposed algorithm and TTC algorithm.

Algorithm	Premature warning rate (%)	Timely warning rate (%)	Late warning rate (%)
TTC fixed threshold algorithm	5.00%	35.00%	60.00%
Proposed algorithm	0.00%	93.33%	6.67%

rate of the proposed algorithm was 3.33%, which was 5.34% lower than that of the TTC algorithm. The proposed algorithm provided a timely warning to the driver of the following vehicle to avoid a rear-end collision based on the driving behavior of the front vehicle.

As shown in Table 5, when the two vehicles traveled at low speed, the collision warnings of the proposed algorithm were provided nearly at the same time as when the driver was braking (during braking). When the car was moving at a high rate of speed, there were a few late warnings because the vehicle was moving too fast and the driver was acting slightly early. When both vehicles traveled at high speeds, almost all the danger warnings of the TTC fixed threshold algorithm occurred after braking. If the driver had taken measures according to this method, it would be easy to lose trust in the system.

As shown in Table 6, the premature warning rate of the TTC fixed threshold algorithm was 5%, the timely warning rate was 35%, and the late warning rate was 60%. In contrast, the timely warning rate of the proposed FCW algorithm was 93.33%. Therefore, the proposed FCW algorithm provided earlier warnings to the driver of the following vehicle at different speeds. The driver had sufficient time to react to the potential collision risk caused by the front vehicle's sudden deceleration. The effective collision warnings also increase the safety and user acceptability of the FCW system.

In our study, we only proposed an early warning strategy for the collision risk between two vehicles in the same lane. In a future study, we plan to improve the early warning strategy for collision risks and consider sudden lane changes, lateral crossing of obstacles, and other emergencies.

V. CONCLUSION

In this article, we proposed a novel FCW system, which uses V2V communication to transmit the driving intention of the front vehicle to the driver of the following vehicle. A double-layer HMM was proposed to identify the driving intention of the front vehicle. This information was then transmitted to the following vehicle to ensure rapid response of the FCW system and gain more time to brake smoothly. The results of the driving intention experiments showed that the proposed double-layer HMM exhibited high accuracy for detecting the driving intention of the front vehicle. The results of the FCW experiments demonstrated that the proposed system provided earlier warning than the FCW system with the TTC fixed threshold. This proposed system not only provided earlier warnings to prevent rear-end collisions but also contributed to more effective braking.

ACKNOWLEDGMENT

Wei Yang would like to acknowledge Prof. L. Wei at Chang'an University for providing suggestions and helpful discussions.

REFERENCES

[1] *The 2017 National Road Traffic Accident Statistical Analysis*, Ministry Public Secur., Beijing, China, 2017.

[2] K. D. Kusano and H. C. Gabler, "Safety benefits of forward collision warning, brake assist, and autonomous braking systems in rear-end collisions," *IEEE Trans. Intell. Transp.*, vol. 13, no. 4, pp. 1546–1555, Dec. 2012, doi: 10.1109/tits.2012.2191542.

[3] A. H. Jamson, F. C. Lai, and O. M. Carsten, "Potential benefits of an adaptive forward collision warning system," *Transp. Res. C, Emerg. Technol.*, vol. 16, no. 4, pp. 471–484, Aug. 2008, doi: 10.1016/j.trc.2007.09.003.

[4] Y. L. Chen, H. H. Chiang, C. Y. Chiang, C. M. Liu, S. M. Yuan, and J. H. Wang, "A vision-based driver nighttime assistance and surveillance system based on intelligent image sensing techniques and a heterogamous dual-core embedded system architecture," *Sensors*, vol. 12, no. 3, pp. 2373–2399, Feb. 2012, doi: 10.3390/s120302373.

[5] D. F. Llorca, S. Sánchez, M. Ocaña, and M. A. Sotelo, "Vision-based traffic data collection sensor for automotive applications," *Sensors*, vol. 10, no. 1, pp. 860–875, Oct. 2010, doi: 10.3390/s100100860.

[6] C. C. Wang, C. Thorpe, and A. Suppe, "Ladar-based detection and tracking of moving objects from a ground vehicle at high speeds," in *Proc. Intell. Vehicles Symp.*, Jun. 2003, pp. 416–421.

[7] P. J. Hartzell, C. L. Glennie, and D. C. Finnegan, "Empirical waveform decomposition and radiometric calibration of a terrestrial full-waveform laser scanner," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 1, pp. 162–172, May 2015, doi: 10.1109/TGRS.2014.2320134.

[8] M. Kilicarslan and J. Y. Zheng, "Predict vehicle collision by TTC from motion using a single video camera," *IEEE Trans. Intell. Transp.*, vol. 20, no. 2, pp. 522–533, May 2018, doi: 10.1109/TITS.2018.2819827.

[9] T. Nagatani, "Bunching transition in a time-headway model of a bus route," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 63, nos. 3–2, p. 036115, Apr. 2001, doi: 10.1103/PhysRevE.63.036115.

[10] X. Wang, M. Chen, M. Zhu, and P. Tremont, "Development of a kinematic–based forward collision warning algorithm using an advanced driving simulator," *IEEE Trans. Intell. Transport. Syst.*, vol. 17, no. 9, pp. 2583–2591, Sep. 2016, doi: 10.1109/tits.2016.2528508.

[11] T. Chen, K. Liu, Z. Wang, G. Deng, and B. Chen, "Vehicle forward collision warning algorithm based on road friction," *Transp. Res. D, Transp. Environ.*, vol. 66, pp. 49–57, Jan. 2019, doi: 10.1016/j.trd.2018.04.017.

[12] M. Abdel-Aty, R. J. Cunningham, V. V. Gayah, and L. Hsia, "Dynamic variable speed limit strategies for real–time crash risk reduction on freeways," *Transp. Res. Rec.*, vol. 2078, no. 1, pp. 108–116, Jan. 2008, doi: 10.3141/2078-15.

[13] F. Bella and R. Russo, "A Collision warning system for rear-end collision: A driving simulator study," *Procedia-Social Behav. Sci.*, vol. 20, pp. 676–686, 2011, doi: 10.1016/j.sbspro.2011.08.075.

[14] M. H. Tawfeek and K. El-Basyouny, "A perceptual forward collision warning model using naturalistic driving data," *Can. J. Civil Eng.*, vol. 45, no. 10, pp. 899–907, May 2018, doi: 10.1139/cjce-2017-0592.

[15] T. L. Brown, J. D. Lee, and D. V. Mcgehee, "Human performance models and rear–end collision avoidance algorithms," *Hum. Factors*, vol. 43, no. 3, pp. 462–482, Sep. 2001, doi: 10.1518/001872001775898250.

[16] F. Muehlfeld, I. Doric, R. Ertlmeier, and T. Brandmeier, "Statistical behavior modeling for driver–adaptive precrash systems," *IEEE Trans. Intell. Transport. Syst.*, vol. 14, no. 4, pp. 1764–1772, Dec. 2013, doi: 10.1109/tits.2013.2267799.

[17] N. Pugeault and R. Bowden, "How much of driving is preattentive?" *IEEE Trans. Veh. Technol.*, vol. 64, no. 12, pp. 5424–5438, Dec. 2015, doi: 10.1109/tvt.2015.2487826.

[18] J. Wang, C. Yu, S. E. Li, and L. Wang, "A forward collision warning algorithm with adaptation to driver behaviors," *IEEE Trans. Intell. Transp.*, vol. 17, no. 4, pp. 1157–1167, Apr. 2016, doi: 10.1109/TITS.2015.2499838.

[19] C. Su, W. Deng, H. Sun, J. Wu, B. Sun, and S. Yang, "Forward collision avoidance systems considering driver's driving behavior recognized by Gaussian mixture model," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 535–540.

[20] S. M. Iranmanesh, H. N. Mahjoub, H. Kazemi, and Y. P. Fallah, "An adaptive forward collision warning framework design based on driver distraction," *IEEE Trans. Intell. Transp.*, vol. 19, no. 12, pp. 3925–3934, Dec. 2018, doi: 10.1109/TITS.2018.2791437.

[21] X. Xiong, M. Wang, Y. Cai, L. Chen, H. Farah, and M. Hagenzieker, "A forward collision avoidance algorithm based on driver braking behavior," *Accident Anal. Prevention*, vol. 129, pp. 30–43, Aug. 2019, doi: 10.1016/j.aap.2019.05.004.

[22] N. Arbabzadeh, M. Jafari, M. Jalayer, S. Jiang, and M. Kharbeche, "A hybrid approach for identifying factors affecting driver reaction time using naturalistic driving data," *Transp. Res. C, Emerg. Technol.*, vol. 100, pp. 107–124, Mar. 2019, doi: 10.1016/j.trc.2019.01.016.

[23] K. Reinmueller and M. Steinhauser, "Adaptive forward collision warnings: The impact of imperfect technology on behavioral adaptation, warning effectiveness and acceptance," *Accident Anal. Prevention*, vol. 128, pp. 217–229, Jul. 2019, doi: 10.1016/j.aap.2019.04.012.

[24] C. Wu, L. Peng, Z. Huang, M. Zhong, and D. Chu, "A method of vehicle motion prediction and collision risk assessment with a simulated vehicular cyber physical system," *Transp. Res. C, Emerg. Technol.*, vol. 47, pp. 179–191, Oct. 2014, doi: 10.1016/j.trc.2014.07.002.

[25] K. Jo, M. Lee, J. Kim, and M. Sunwoo, "Tracking and behavior reasoning of moving vehicles based on roadway geometry constraints," *IEEE Trans. Intell. Transport. Syst.*, vol. 18, no. 2, pp. 460–476, Feb. 2017, doi: 10.1109/tits.2016.2605163.

[26] W. Yuan, Z. Li, and C. Wang, "Lane-change prediction method for adaptive cruise control system with hidden Markov model," *Adv. Mech. Eng.*, vol. 10, no. 9, pp. 1–9, Sep. 2018, doi: 10.1177/1687814018802932.

[27] N. Kapileswar and G. P. Hancke, "A survey on urban traffic management system using wireless sensor networks," *Sensors*, vol. 16, no. 2, p. 157, Jan. 2016, doi: 10.3390/s16020157.

[28] X. Xiang, W. Qin, and B. Xiang, "Research on a DSRC-based rear-end collision warning model," *IEEE Trans. Intell. Transp.*, vol. 15, no. 3, pp. 1054–1065, Jun. 2014, doi: 10.1109/TITS.2013.2293771.

[29] S. Patra, P. Veelaert, C. Calafate, J. C. Cano, W. Zamora, P. Manzoni, and F. González, "A forward collision warning system for smartphones using image processing and V2V communication," *Sensors*, vol. 18, no. 8, pp. 1–17, 2018, doi: 10.3390/s18082672.

[30] Y. Lei and J. Wu, "Study of applying ZigBee technology into forward collision warning system (FCWS) under low-speed circumstance," in *Proc. Adv. Wireless Opt. Commun. (WOCC)*, Nov. 2016, pp. 1–4.

[31] K. P. Chen and P. A. Hsiung, "Vehicle collision prediction under reduced visibility conditions," *Sensors*, vol. 18, no. 9, p. 3026, Sep. 2018, doi: 10.3390/s18093026.

[32] S. Al-Sultan, A. H. Al-Bayatti, and H. Zedan, "Context-aware driver behavior detection system in intelligent transportation systems," *IEEE Trans. Veh. Technol.*, vol. 62, no. 9, pp. 4264–4275, May 2013, doi: 10.1109/TVT.2013.2263400.

[33] L. He, C. Zong, and C. Wang, "Driving intention recognition and behaviour prediction based on a double-layer hidden Markov model," *J. Zhejiang Univ. Sci. C*, vol. 13, no. 3, pp. 208–217, Mar. 2012, doi: 10.1631/jzus.C11a0195.

[34] L. R. Welch, "Hidden Markov models and the Baum-Welch algorithm," *IEEE Inf. Theory Soc. Newslett.*, vol. 53, pp. 194–211, Jan. 2003.

[35] S.-Z. Yu and H. Kobayashi, "Practical implementation of an efficient forward-backward algorithm for an explicit-duration hidden Markov model," *IEEE Trans. Signal Process.*, vol. 54, no. 5, pp. 1947–1951, May 2006, doi: 10.1109/tsp.2006.872540.

[36] W. Yang, J. Q. Gong, and L. Wei, "Preceding vehicle image recognition based on multivariate feature information fusion," *J. Chang'an Univ. (Natural Sci. Edition)*, vol. 36, no. 4, pp. 79–85, Jul. 2016, doi: 10.19721/j.cnki.1671-8879.2016.04.011.

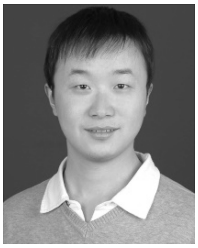
[37] J. W. Chu, L. S. Jiang, L. Guo, and R. B. Wang, "Study on method of detecting preceding vehicle based on monocular camera," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2004, pp. 750–755.

[38] R. A. Gheorghiu and V. Iordache, "Use of energy efficient sensor networks to enhance dynamic data gathering systems: A comparative study between Bluetooth and ZigBee," *Sensors*, vol. 18, no. 6, p. 1801, Jun. 2018, doi: 10.3390/s18061801.

[39] T.-H.-S. Li, M.-C. Kao, and P.-H. Kuo, "Recognition system for home-service-related sign language using entropy-based K -means algorithm and ABC-based HMM," *IEEE Trans. Syst. Man, Cybern., Syst.*, vol. 46, no. 1, pp. 150–162, Jan. 2016, doi: 10.1109/tsmc.2015.2435702.

[40] X. Yan, Q. Xue, L. Ma, and Y. Xu, "Driving-simulator-based test on the effectiveness of auditory red-light running vehicle warning system based on time-to-collision sensor," *Sensors*, vol. 14, no. 2, pp. 3631–3651, Feb. 2014, doi: 10.3390/s140203631.

[41] Q. Liu, X. Qiu, L. Xie, J. Wang, and S. Fang, "Anti-collision warning time algorithm based on driving speed of vehicle," *Trans. CSAE*, vol. 33, no. 12, pp. 99–106, Jun. 2017, doi: 10.11975/j.issn.1002-6819.2017.12.013.

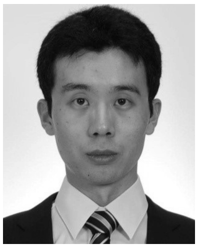


WEI YANG was born in Pucheng, Shaanxi, China, in 1985. He received the B.E., M.E., and Ph.D. degrees in vehicle engineering from Chang'an University, Xi'an, China, in 2007, 2010, and 2013, respectively.

Since 2013, he has been a Lecturer with the School of Automobile, Chang'an University. He is the author of more than 20 articles. He holds 15 patents and six software copyright. His research interests include intelligent transportation systems, machine vision, and driverless car.

BO WAN was born in Jiuquan, Gansu, China, in 1984. He received the B.E. degree in software engineering from Xi'an Jiaotong University, Xi'an, China, in 2007, and the M.S. degree in computer science from the University of Ottawa, in 2012.

From 2012 to 2013, he was a Senior IT Associate with Morgan Stanley, Montreal, Canada. From 2013 to 2015, he worked as a Senior Software Developer with Citi Group, Toronto, Canada. In 2015, he joined Merrill Lynch Canada as a Senior Technical Consultant. Since 2016, he has been a Model Developer and an AI Research with the Bank of Montreal in Toronto. He is also a Co-Founder of an AI company, Cicada Canada.



XIAOLEI QU was born in Pucheng, Shaanxi, China, in 1984. He received the B.E. degree in software engineering from Xi'an Jiaotong University, Xi'an, China, in 2007, the M.S. degree in pattern recognition from the Huazhong University of Science and Technology, Wuhan, China, in 2009, and the Ph.D. degree in bioengineering from the University of Tokyo, Japan, in 2012.

From 2012 to 2014, he was a Senior Engineer with the Techwin Research Center (Samsung Group), Fukuoka, Japan. From 2014 to 2017, he was a Project Researcher with the University of Tokyo. Since 2017, he has been an Associate Professor with the School of Instrumentation and Optoelectronic Engineering, Beihang University, Beijing, China. He is the author of more than 20 articles. He holds four patents. His research interests include medical ultrasound imaging, image processing, and recognition.