Driver's Intention Identification With the Involvement of Emotional Factors in Two-Lane Roads

Xiaoyuan Wang, Yongqing Guo, Chenglin Bai, *Member, IEEE*, Quan Yuan, Shanliang Liu, and Junyan Han

***Abstract*— Driver's emotion is a psychological reaction to environmental stimulus. Driver intention is an internal state of mind, which directs the actions in the next moment during driving. Emotions usually have a strong influence on behavioral intentions. Therefore, emotion is an important factor that should be considered, to accurately identify driver's intention. This study used the support vector machine (SVM) theory to develop a driver intention recognition model, with the involvement of driver's emotions. Various materials including visual materials, auditory materials, and olfactory materials, were used to induce driver's emotions. Real driving, virtual driving and computer simulation experiments were conducted to collect human-vehicle-environment dynamic data in two-lane roads. The results present that the proposed model can achieve high accuracy and reliability in recognizing driver's intentions. Our findings of this study can be used to develop the personalized driving warning system and intelligent human-machine interaction in vehicles. This study would be of great theoretical significance for improving road traffic safety.**

***Index Terms*— Driver's emotion, driver's intention, intention recognition model, support vector machine.**

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I. Introduction

CURRENT driver-assistance systems evaluate safety situations and potential hazards, mainly relying on traffic information inputs from Lidar or visual sensors. Among, the effects of driver's emotions during driving on road safety are generally not considered [1]. However, emotion is regarded as a major driver-related factor that affects the safety of driving. Without considering the impacts on driving behavior, driver-assistance systems may provide false or unnecessary alerts [2]. This issue raises driver's annoyance and reduces trust, as a result, increasing the chance of traffic accident.

Transportation scholars have explored driver's intention recognition using various methods and models. Berndt *et al.* [3] used the Hidden Markov Model (HMM) to identify driver's intentions of turning and going-straight, based on driving data such as acceleration, pedal position, brake pressure, and steering wheel angle. Bocklisch *et al.* [4] proposed an online identification model of driver's lane-changing intention according to the fuzzy logic, using the time spending on looking up into the rearview mirrors. Ürün *et al.* [5] used the artificial neural network model and support vector machine to predict driver's behavior, based on different combinations of driving and road data including road curvature, lane position, steering wheel angle, lateral acceleration, and collision time. Peng *et al.* [6] developed a model for predicting lane-changing behavior based on the back-propagation neural network algorithm, and constructed a prediction index system for lane changes using drivers' visual search behaviors, vehicle operation behaviors, vehicle motion states, and driving conditions. Ohashi *et al.* [7] used the fuzzy set theory to identify driver's intentions of turning and going straight, using the detected data of driver's motions, speed of the target vehicle, and the distance between the vehicle and the intersection. Mccall *et al.* [8] applied the sparse Bayesian learning to recognize driver's turning intention based on the data of lane positional information, vehicle parameters and driver head motion. Auzoult *et al.* [9] found that road safety interventions have a significant impact on drivers' cognition and intention, and drivers' cognitive effects on road safety depend on their self-awareness. Wang *et al.* [10] analyzed driver's characteristics of parking, deceleration, keeping speed, acceleration, and rapid acceleration in different road environments, and used the fuzzy control theory to develop an identification model of lane-changing intention. Melnicuk *et al.* [11] adopted repeated measure design and

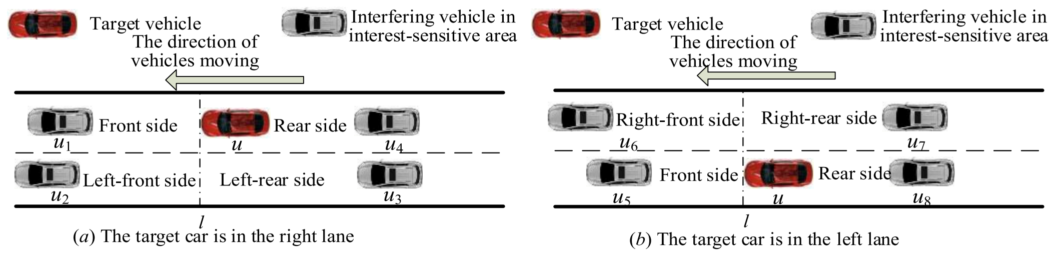


Fig. 1. Vehicle groups in two-lane environment.

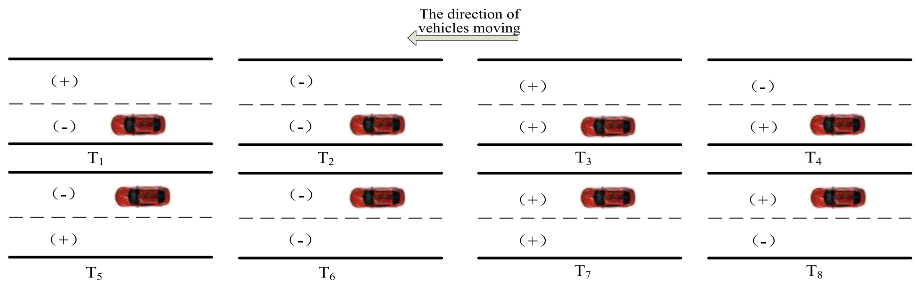


Fig. 2. Vehicle group relationship when the target vehicle locates in the left and right lanes.

multiple physiological measures to estimate driving state and intention across common driving activities.

In addition, research [12], [13] suggests that emotion has a strong influence on intention, and emotion identification would be helpful in recognizing behavioral intention. Support vector machine, as a pattern classification technique, has been widely used for emotion classification and recognition in many fields. Domínguez-Jiménez *et al.* [14] used SVM to classify amusement, sadness, and neutral emotions, based on galvanic skin response features. Bhavan *et al.* [15] proposed an algorithm combining a bagged SVM with a Gaussian kernel, to recognize emotions from speech. Ninaus *et al.* [16] applied SVMs to detect facial positive and negative emotions during game-based learning.

In conclusion, research on drivers' intention recognition has focused on developing intention recognition models based on vehicle operating parameters (such as accelerator pedal position, brake pedal opening, and driving speed), environmental parameters (such as road curvature and lane line position), the driver's visual behavior parameters (such as face orientation and sight characteristic). There is limited research related to driver's intention recognition have been conducted, considering the effects of driver's emotions. This study will use the support vector machine theory to construct a driver intention identification model concerning the involvement of driver's emotions. The real and virtual driving experiments will be carried out to collect multi-source dynamic data of human-vehicle-environment in different emotions.

II. Research Method

A. Analysis of Vehicle Groups

A vehicle group is composed of dynamic traffic entities, which has an important influence on driver's decision [17]. To analyze the impacts of driver's emotion states on driving intention, various scenarios of vehicle group situations were defined first, which are shown in Figure 1. When the target

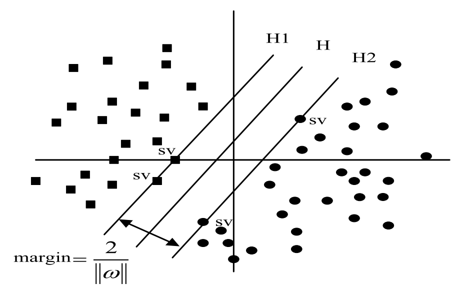


Fig. 3. Optimal classification plane of support vector machine.

vehicle (refers to the vehicle driven by subject) run in the right lane, the interest-sensitive area (refers to the area with the greatest impact on vehicle safety and driver's attention) was divided into front, left-front, left-rear and rear according to the horizontal line l of the target vehicle's front bumper and the line separating the two lanes in the same direction (the front and rear were divided by l, and the left and right were divided by the lane line.) [17]. When the target vehicle run in the left lane, the interest-sensitive area was divided into front, right-front, right -rear and rear sides.

The physical concept of "Force" was borrowed to describe the effects of the surrounding vehicles on the target vehicle in vehicle group [18]. Six factors were used in the interest-sensitive area, including gender, propensity, willpower, driving experience, and relative distances and relative speeds between target vehicle and surrounding vehicles [18]–[21]. Then, the fuzzy logic method was used to get the "force" on vehicles in the sub-regions, and the collection of these "forces" were applied to abstractly represent the vehicle group relationship. If a vehicle compelled the target vehicle to choose the same lane, it could be considered that the vehicle exerted an "attraction force" on the target vehicle. The opposite situation was considered as a "repulsive force". According to the target vehicle's locations in the left and right lanes, eight

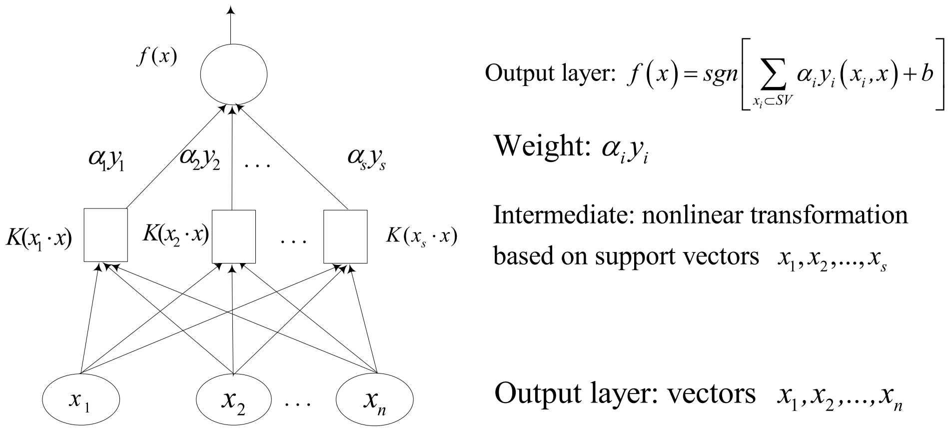


Fig. 4. Structure of support vector machine.

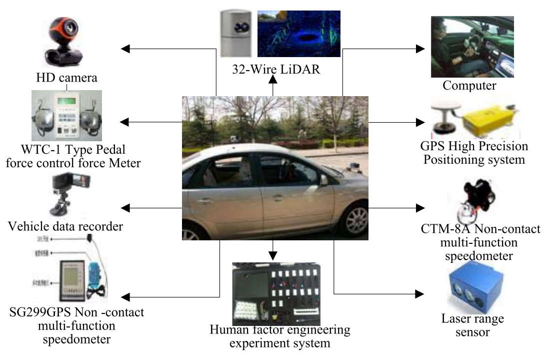


Fig. 5. Real driving experiment.

Fig. 6. Virtual driving experiment.

Fig. 7. Real driving experiment route.

Fig. 8. Parts of emotion visual stimulus materials.

vehicle group situations were obtained, shown in Figure 2. The eight vehicle group situations were represented by T_1, T_2 … T_8 respectively, and attraction and repulsion forces were denoted by "+" and "−", respectively. Thus, it could be said that vehicle group considers the effects of the vehicle (e.g. relative distances between target vehicle and surrounding vehicles) and driver-based factors (e.g. propensity), to build a specific traffic environment for driving experiments.

B. Support Vector Machine Model

Support Vector Machines are supervised learning models used for classification, regression and outlier detection. Besides performing linear classification, SVMs can also perform a non-linear classification by transforming the inputs into high-dimensional feature spaces. In a classification problem, the optimal hyperplane is the one that separates all the data while being farthest away from the data points [22], [23].

1) Linear Optimal Hyperplane: A training sample is given, of points with the form $(x_1, y_1), (x_2, y_2), \ldots, (x_l, y_l)$ [22]. Where x_i is an n-dimensional vector, $x_i \in R^n$; y_i is a sample label, $y_i \in \{-1, 1\}$. If x_i belongs to the first group, then $y_i = 1$; otherwise $y_i = -1$. As shown in Figure 3, the circular and square points represent two classes of data. H is the optimal hyperplane, H1 and H2 are the two hyperplanes parallel to H. The data points on H1 and H2 are defined as support vectors.

The optimal hyperplane can be expressed as:

$$\omega \cdot x + b = 0 \tag{1}$$

The two classes of data can be described by the equations:

$$\begin{cases} \omega \cdot x_i + b \geq 1, & y_i = 1 \\ \omega \cdot x_i + b \leq -1, & y_i = -1 \end{cases} \tag{2}$$

TABLE I
EXPERIMENTAL DESIGN

<table>
<tr><th>Items</th><th>Real driving experiment</th><th>Virtual driving experiment</th></tr>
<tr><td>Experimental materials</td><td colspan="2">Psychometric questionnaire of driver's propensity, Psychometric questionnaire of willpower, International Affective Picture System(IAPS), Chinese Affective Picture System(CAPS）</td></tr>
<tr><td>Experimental equipments</td><td>Human factor engineering experiment system, GPS high precision positioning system, 32-Wire LiDAR, SG299GPS Non-contact multi-function speedometer, and Video-capturing system, etc (shown in Figure 5).</td><td>Interactive parallel driving virtual experiment platform, Human factor engineering experiment system, Video-capturing system, etc (shown in Figure 6).</td></tr>
<tr><td>Experiment condition</td><td>Off-peak hours of good weather and road conditions</td><td>Virtual driving Laboratory</td></tr>
<tr><td>Route</td><td>Zhangzhou road between Jiangmeng road and Shanshen line in Zhangdian District of Zibo city, Shandong province (shown in Figure7). This is a three-lane road in both directions. The real driving experiments were conducted in dry weather and road conditions in the normal working day during peak hours.</td><td>Road scene created by Interactive parallel driving virtual experiment platform according to the real driving experiment route.</td></tr>
<tr><td>Subjects</td><td colspan="2">Fifty-four drivers, including 27 males and 27 females, were selected to take part in the experiments. Their ages ranged between 18 and 70 years old. The average age was 33.5 years old. The average driving mileage was12000 kilometers.</td></tr>
<tr><td rowspan="2">Emotion induction</td><td colspan="2">Driver's emotions were stimulated by picture, video, audio and other materials in IAPS and CAPS (Some emotional materials are shown in Figure 8).</td></tr>
<tr><td>In addition, angry emotion was stimulated by abusive and offensive words. Surprise emotion was stimulated by telling the world Trolltech event. Fear emotion was stimulated by telling horror stories or watching videos of terrorist traffic accident. Anxiety, helplessness, contempt emotions were stimulated by speech induction, and psychological hint, etc. Relief emotion was stimulated by sharing happy experience. Pleasure emotion was stimulated by talking, giving some gifts, smiling, singing, or reading beautiful poems.</td><td>Fear, anxiety and anger were stimulated with traffic scenes, such as setting traffic accident, waiting for a long time in intersections, or crowded vehicle road, in interactive parallel driving virtual experiment platform. Surprise emotion was stimulated through changing the weather and environment in the virtual scenes. Relief and pleasure emotions were stimulated through setting a comfortable traffic environment (such as Green Wave). Contempt emotion was stimulated using driving race scenes.</td></tr>
<tr><td>Keeping and increasing emotional level</td><td colspan="2">Driver's emotional level were kept and increased through multiple ways of listening to the music, communicating, memory, etc., during driving.</td></tr>
<tr><td>Assessing the level of the induced emotions</td><td colspan="2">Before and after the driving experiment, each driver was asked to evaluate his/her own emotional levels. Driver's physiological signals of electrocardiography (ECG), electrodermal activity (EDA), and skin temperature (SKT) were collected using PsyLAB during driving. The physiological signals were used as auxiliary to assess emotional levels, through the method developed by Haag [25]. [e.g. for ECG signals, several key indicators were extracted to analyze the emotional levels, including the average heart rate, the inter beat interval, and the amplitude and duration of QRS complex (Q wave, R wave, and S wave on a typical electrocardiogram)]</td></tr>
</table>

Eq. (2) is normalized so that the linearly separable sample $(x_i, y_i), i = 1, 2, \ldots n$, satisfies:

$$y_i[(\omega \cdot x_i) + b] \geq 1, \quad i = 1, 2, \ldots n \tag{3}$$

According to the definition of the optimal separating hyperplane, the margin can be expressed as:

$$\begin{aligned}\rho &= \min_{\{x_i, y_i = 1\}} \frac{|\omega \cdot x_i + b|}{\|\omega\|} + \min_{\{x_j, y_j = -1\}} \frac{\left|\omega \cdot x_j + b\right|}{\|\omega\|} \\ &= \frac{2}{\|\omega\|} \quad i = 1, 2, \ldots n\end{aligned} \tag{4}$$

We can maximize the optimal $\frac{2}{\|\omega\|}$, by minimizing $\frac{1}{2}\|\omega\|$ or $\frac{1}{2}\|\omega\|^2$. This becomes a convex quadratic programming problem:

$$\begin{cases} \min \dfrac{1}{2}\|\omega\|^2 & i = 1, 2, \ldots n \\ \text{Constraint conditions}: y_i[(\omega \cdot x_i) + b] \geq 1 \end{cases} \tag{5}$$

The optimal solution can be obtained by the Lagrange function:

$$L(\omega, b, \alpha) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{n} \alpha_i [y_i(\omega \cdot x_i + b) - 1] \quad i = 1, 2, \ldots n \tag{6}$$

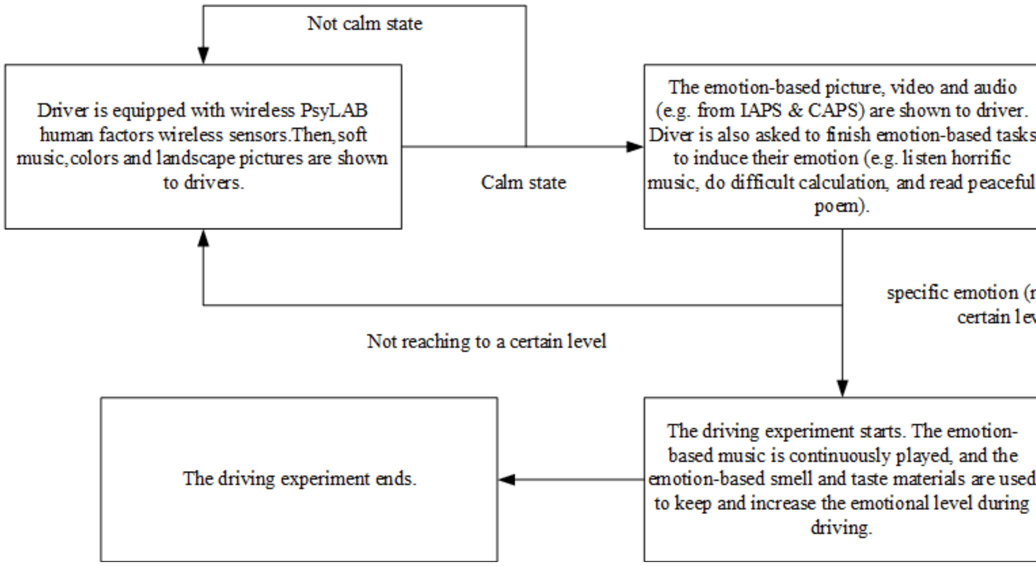


Fig. 9. The process of driving experiment.

where $\alpha_i \geq 0 (i = 1, 2, \ldots n)$ is a Lagrange multiplier. The optimal classification function can be obtained:

$$f(x) = \operatorname{sgn}(\omega \cdot x + b) = \operatorname{sgn}[\sum_{x_i \subset SV} \alpha_i y_i (x_i \cdot x) + b] \quad (7)$$

2) Generalized Optimal Hyperplane: The optimal classification hyperplane is for linearly separable patterns. However, for non-linearly separable dataset, a relaxation factor $\xi_i \geq 0$ is added to satisfy the constraints [17].

$$y_i[(\omega \cdot x) + b] \geq 1 - \xi_i \quad (8)$$

The goal is to find the minimum value of $\frac{1}{2}\|\omega\| + c\sum_{i=1}^{n} \xi_i$. Where c is the penalty parameter, and larger value of c corresponds more penalty for misclassification.

For a nonlinear problem, nonlinear mapping is performed, $Q(x) : R^n \rightarrow Z$. z is a high dimensional inner product space called feature space, and $Q(x)$ is called feature mapping. The generalized optimal hyperplane is constructed in z [22]. When constructing a generalized optimal hyperplane, a key step is to compute the inner product in high-dimensional space. A kernel function $K(x_i, y_i)$ is given, which satisfies Mercer condition. It corresponds to the inner product of a transformation space [22].

Thus, the nonlinear decision function in the input space can be constructed:

$$y(x) = \operatorname{sgn}(\omega \cdot Q(x) + b) = \operatorname{sgn}[\alpha_i y_i K(x_i, x_j) + b] \quad (9)$$

where $K(x_i, x_j)$ is kernel function. The kernel functions mainly include linear kernel function, polynomial kernel function, gauss radial basis kernel function, and neural network kernel function [22]. And, $0 \leq \alpha_i \leq c$ is a Lagrange multiplier.

The structure of the support vector machine is shown in Figure 4.

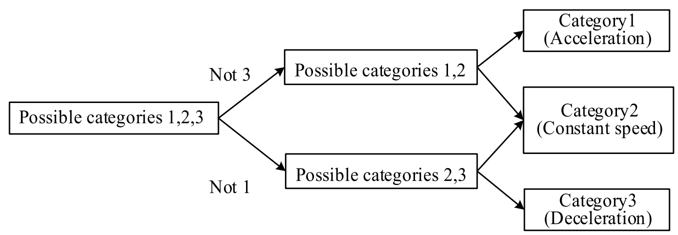


Fig. 10. Speed intention recognition based on 1-v-1 scheme.

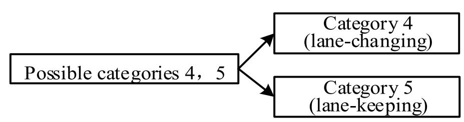
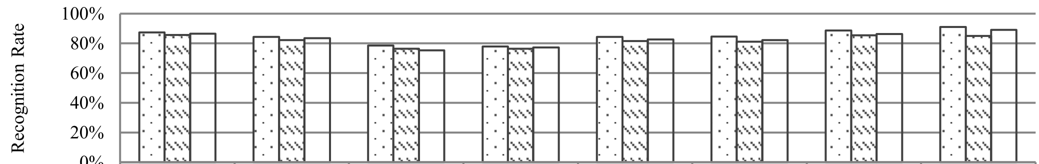


Fig. 11. Lane-changing intention recognition based on 1-v-1 scheme.

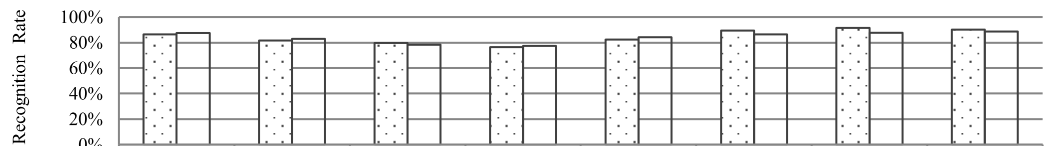
C. Experimental Design

Real driving and virtual driving experiments were designed and conducted in this study. The real driving experiment is closer to reality than the virtual one, thus more reliable data on driver's behavior and emotion can be obtained by this method. However, using real driving experiments to collect data is time-consuming, expensive, less safe and difficult to organize. It is difficult to get a large amount of real driving experimental data. Driving simulation can be used as an alternative to real vehicle experiment, because it is safety, low-cost, reproductive and easy to control. In this study, the high-fidelity simulator provided by Japanese company FORUM 8, allows users to construct 3D traffic environment and engage interactive experience. Eight kinds of common emotions, fear, helplessness, relief, pleasure, surprise, anxiety, contempt, anger, were chosen for analysis in this study, based on the emotion classification proposed by Johnston [24] and the questionnaire results for driving emotions. Details of the experimental design including experimental equipment, driving routes and emotion induction, are shown in Table I.



	fear	helplessness	relief	pleasure	surprise	anxiety	contempt	anger
accelerated speed	87.29%	84.32%	78.59%	77.95%	84.43%	84.59%	88.67%	91.01%
constant speed	85.64%	82.26%	76.37%	76.32%	81.59%	81.24%	85.49%	85.12%
reduced speed	86.58%	83.59%	75.26%	77.23%	82.65%	82.19%	86.32%	89.13%

Fig. 12. Accuracy of identifying driving speed intention (based on real driving data).



	fear	helplessness	relief	pleasure	surprise	anxiety	contempt	anger
change lane	86.32%	81.59%	79.56%	76.25%	82.32%	89.58%	91.52%	90.23%
keep lane	87.56%	82.96%	78.26%	77.28%	84.29%	86.45%	87.69%	88.74%

Fig. 13. Accuracy of identifying lane-changing intention (based on real driving data).

Before the experiment, certain personal and driving-related information of each subject was collected, including gender, age, driver's propensity, vehicle mileage traveled, and driving style. Subjects were given a detailed introduction of the experimental procedure, and were asked to learn how to manipulate the experimental vehicle. The International Affective Picture System (IAPS) and the Chinese Affective Picture System (CAPS) were used as emotional induction materials. The experiment started only when participant's emotion was induced to a certain level of arousal. During driving, driver's facial expression and action, road conditions, driving speed and pedal strength were recorded in real time with the video monitoring system, speedometer and pedal dynamics instrument. While, various methods including material incentives and spiritual motivation were used to remain and increase driver's emotional level (shown in Table I and Figure 9). After the driving experiment, drivers were asked to watch the recorded video immediately, and describe their emotional changes in the driving experiments.

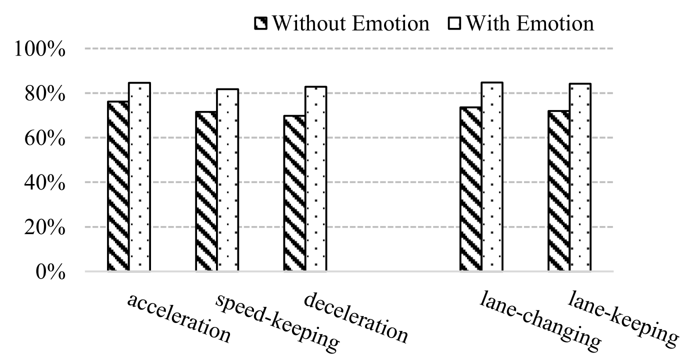
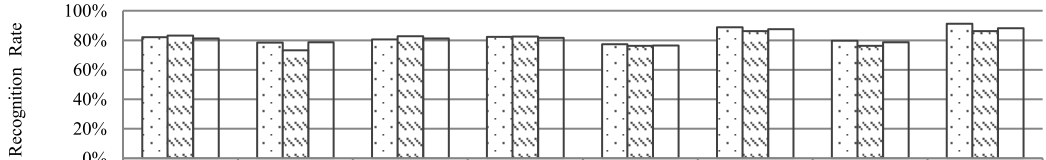


Fig. 14. Average accuracy of identifying driver's behavioral intention with and without the involvement of emotion (real driving).

III. Results

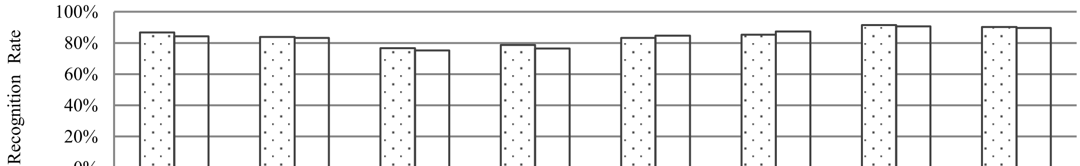
This study used the directed acyclic graph (DAG) algorithm proposed by Platt *et al.* [26] to build an identification model of driver's intentions. The algorithm was developed based on 1-v-1 (one versus one) classification. For a k-class problem, there are $k(k-1)/2$ nodes, each of which is a 1-v-1 classifier. For driving speed identification with $K = 3$ classifiers, the 1-v-1 class binarization is illustrated in Figure10. For vehicle lane-changing recognition with $K = 2$ classifiers, the 1-v-1 class binarization is illustrated in Figure11.

Feature vector $Data(t)$ and Label vector $Label(t)$ are constructed as the training parameters and the characteristic parameters of SVM model, respectively. $Data(t) = \{x_1(t), x_2(t), \ldots, x_i(t), \ldots, x_n(t)\}$. n is the number of training samples, $x_i(t)$ is the corresponding characteristic variable in t time period. The characteristic variables selected in this paper are driver's emotion and vehicle group. According to the PAD emotional models proposed by Chinese Academy of Sciences, driving emotion is expressed in 3 dimensions: pleasure (P), arousal (A) and dominance (D) [27]. The vehicle group is described by the forces on the target vehicle that vehicles in the same lane and the adjacent lane exert [18]. $Label(t) = \{y(t)\}$, where $y(t)$ represents the classification label of support vector machines at each node, $y(t) \in \{-1, 1\}$. For example, in the lane-change intention recognition model, lane-changing is denoted as 1, and lane-keeping is denoted as -1. The gauss radial basis function [19] is selected to train the model under the Matlab Lib-svm environment. The Gaussian radial basis function kernel was selected, because compared to other common kernels like polynomial kernels, the number of the kernel parameter is smaller. A total of 1609 experimental datasets were obtained, including 674 datasets for SVM training and 935 datasets for SVM testing. The training time is 0.4792s and the number of iteration is 38 times.



	fear	helplessness	relief	pleasure	surprise	anxiety	contempt	anger
□accelerated speed	82.16%	78.29%	80.52%	82.23%	77.29%	88.74%	79.65%	91.25%
□constant speed	83.25%	73.28%	82.63%	82.49%	76.25%	86.23%	76.32%	86.23%
□reduced speed	81.24%	78.64%	81.29%	81.62%	76.48%	87.59%	78.56%	88.24%

Fig. 15. Accuracy of identifying driving speed intention (based on virtual driving data).



	fear	helplessness	relief	pleasure	surprise	anxiety	contempt	anger
□change lane	86.62%	83.74%	76.59%	78.65%	83.24%	85.26%	91.35%	90.26%
□keep lane	84.32%	83.25%	75.26%	76.38%	84.68%	87.26%	90.51%	89.53%

Fig. 16. Accuracy of identifying lane-changing intention (based on virtual driving data).

IV. Discussion

A. Model Verification Based on Real Driving Experimental Data

To verify driver's intention identification model, the real driving experimental data was split into two parts. One part was used for the model training, and another one was used for the model testing. The accuracies of model identification regarding speed and lane-changing intentions are shown in Figures 12 and 13, respectively.

As shown in Figure12, the accuracies of identifying driving speed intention are above 85% under the emotional states of fear, contempt and anger. In the states of helplessness, surprise and anxiety, the accuracies of speed intention identification are more than 80%. Regarding lane-changing intention recognition shown in Figure13, the model can achieve an accuracy of above 85% for the states of fear, anxiety, contempt and anger, over 80% for the states of helplessness and surprise, as well as 75% or higher for the states of relief and pleasure.

With the involvement of driver emotion, the model is able to improve the accuracies for recognizing the three intentions of acceleration, speed-keeping and deceleration, from 76.24%, 71.58% and 69.76%, to 84.61%, 81.75% and 82.87%, respectively (see Figure 14). The model can improve the accuracies for recognizing the intentions of lane changing and lane keeping, from 73.59% and 71.96%, to 84.67% and 84.17%, respectively (see Figure 14).

Moreover, it was found that the proposed model is able to recognize driving intention provoked by negative emotions (e.g. anger and contempt) at a higher level of precision than by positive emotions (e.g. relief and pleasure).

The results indicate that the proposed identification model can obtain high accuracy in recognizing intentions of driving speed and lane change.

B. Model Verification Based on Virtual Driving Experimental Data

To verify driver's intention identification model, the virtual driving experimental data was also split into two parts. One part was used for the model training, and another one was used for the model testing. The accuracies of model identification regarding speed and lane-changing intentions are shown in Figures 13 and 14, respectively.

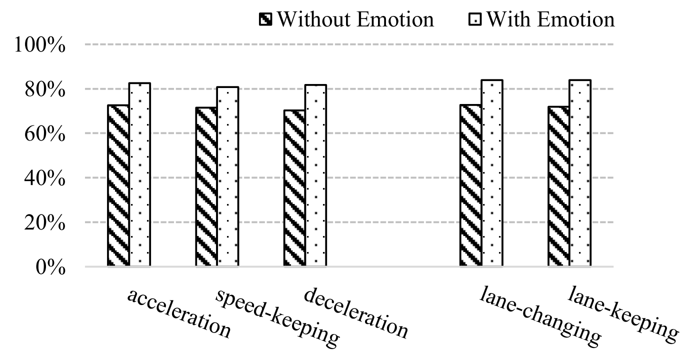


Fig. 17. Average accuracy of identifying driver's behavioral intention with and without the involvement of emotion (virtual driving).

For speed intention recognition shown in Figure 15, the model achieves an accuracy of above 85% for the states of anxiety and anger, over 80% for the states of fear, relief and pleasure, as well as 75% or higher for the states of helplessness, surprise and contempt. Regarding the lane-changing intention recognition shown in Figure 16, the model can achieve an accuracy of above 85% for the states of anxiety, contempt and anger, over 80% for the states of fear, helplessness and surprise, and 75% or higher for the states of relief and pleasure. The results indicate that the proposed identification model can get high accuracy in recognizing intentions of driving speed and lane change.

Without considering driver's emotion, the identification model only achieves the accuracies of 72.55%, 71.47% and 70.29% for recognizing the intentions of acceleration, constant speed and deceleration, respectively, as well as 72.68% and 71.92% for recognizing the intentions of lane change and lane keep, respectively. After adding the factor of driver emotion into the model, the identification accuracies are increased

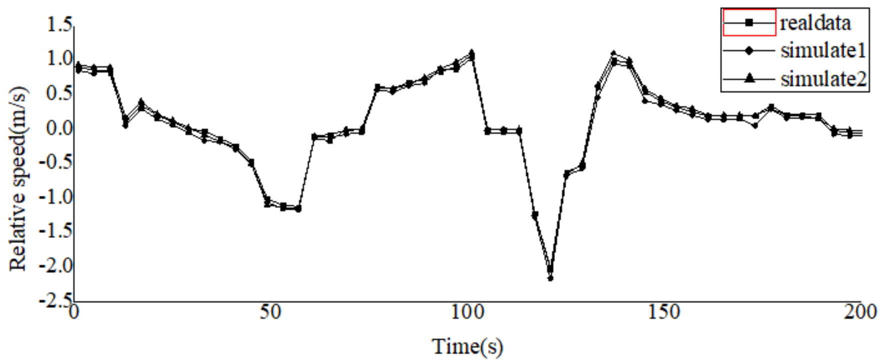


Fig. 18. The relative speed between the target vehicle and the vehicle in front.

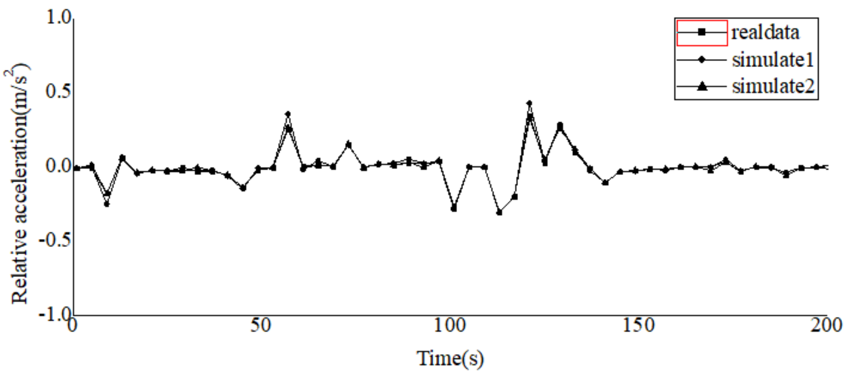


Fig. 19. The relative acceleration between the target vehicle and the vehicle in front.

to 82.52%, 80.84% and 81.71% for recognizing the intentions of acceleration, speed-keeping and deceleration, respectively, as well as 83.96% and 83.90% for recognizing the intentions of lane change and lane keep, respectively (see Figure 17). The results further confirm that the proposed identification model is reasonable and effective in recognizing intentions of driving speed and lane change.

C. Model Verification Based on Computer Simulation Data

The computer simulation was conducted to compare driver behavior characteristics with and without considering driver's emotional factors. The simulation results present the relative speed and relative acceleration between the target vehicle and the vehicle in front, shown in Figures 18 $\sim$ 19. Among them, driver's emotions are taken into account in simulation 2, and not in simulation 1. It was observed that in Figure 18, simulation 2 with emotion involvement is more consistent with the actual data than simulation 1. Especially when the target vehicle is running fast and follows the front one closely (positive relative speed, e.g. 150s $\sim$ 180s in Figure 18), speed can be predicted more accurately with the involvement of emotion. In Figure 19, when the running status of vehicles appear to abruptly change (accelerate or decelerate dramatically, e.g. 10s and 56s.), simulation 2 performs better in simulating relative acceleration than simulation 1. Overall, the results indicate that the model can more accurately predict driving behavioral intentions with the involvement of emotion, especially for the risk scenarios and abrupt changes. These results further prove the accuracy and reliability of the identification model.

V. Conclusion

This study used the support vector machine theory to develop a driver intention recognition model, considering driver's emotional factors. Real driving, virtual driving and computer simulation experiments were conducted to collect human-vehicle-environment dynamic data in two-lane roads, in order to verify the recognition model. The results present that the developed model can achieve high accuracy and reliability in identifying driver's intentions.

Our findings of this study suggest that the prediction accuracy of driver's intention can be increased with the involvement of driver emotion. It can be used to develop the personalized driving warning system and intelligent human-machine interaction in vehicles. This study would be of great theoretical significance for improving road traffic safety. Further studies are required to improve the effectiveness of the proposed model by considering more factors, such as road capacity, level of service, weather condition, driver's occupation and personality type. Moreover, further studies are also needed to recognize driver's intentions in more complex traffic environments.

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