Transition characteristics of driver's intentions triggered by emotional evolution in two-lane urban roads

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Abstract: Driver's intention is a self-internal state that represents a commitment to carrying out driving action at the next moment, which could be affected by driver's emotion. Therefore, understanding driver's emotion is an important basis for developing driver intention recognition models. This study aims to gain a better insight of the characteristics of driver intention transition triggered by driver's emotion. The Hidden Markov model was used to develop a driver intention recognition model with the involvement of driver's emotions. Assorted materials including visual, auditory and olfactory stimuli were used to evoke driver's emotions before the driving experiments, as well as keep and increase the emotional level during driving. Real and virtual driving experiments were conducted to collect human-vehicle-environment dynamic data in two-lane roads. The results show that the proposed model can achieve high accuracy and reliability in estimating driver's intention transition with the evolution of driver emotion. 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.

1 Introduction

With the rapid development of road transportation systems, the growing number of vehicles causes more severe human-vehicle-environment conflicts, and further raises the risk of road crashes [1]. To improve road traffic safety, a set of advanced driver assistance systems (ADAS) have been developed and applied in practice, including Adaptive Cruise Control (ACC), Lane Departure Warning System (LDWS), and Lane Change Assistance (LCA) [2]. Accurately identifying driver's intentions is an important foundation for developing these safety systems [3-5]. Therefore, many studies have been conducted on driver intention recognition to provide theoretical support for establishing the safety systems.

Kinnear et al. [6] analyzed the relationship between driver's overtaking intention and the dynamic variables including queue length, the proportion of freight vehicles, the urgency level of driving task, driving speed, and congestion duration. The results indicated that driver's overtaking intention is closely related to queue length and driving speed. Zoellck et al. [7] analyzed the relationship between behavioural intentions and emotions towards automated vehicles using realistic traffic settings and in-vivo experience with the emerging technology. The results suggested that the positive emotion amusement positively and the negative emotion fear negatively correlates with the behavioural intentions. Sani et al. [8] determined the link between risky driving behaviour and emotion regulation, and found that emotional self-regulation is related significantly to driving violations. Welch et al. [9] provided a review of using sensor technologies to understand how emotions affect dangerous driving habits. Wang et al. [10] identified driver's intentions and human-vehicle interaction by recognizing driver's emotions dynamically.

Some previous studies have been proposed to recognize driver's behaviour intention using various methods and models. Dogan et al. [11] used the artificial neural network model and support vector machine to predict driver's behavior, based on different combinations of road and driving data including road curvature, lane position, steering wheel angle, lateral acceleration, and collision time. Bocklisch et al. [12] proposed an online identification model of driver's lane-changing intention according to the fuzzy logic in pattern recognition, and the time spending on looking up into the rearview mirrors. Berndt et al. [13] used the Hidden Markov model (HMM) to identify driver's intentions of turning and going-straight, based on driving data such as acceleration, accelerator pedal position, brake pressure, and steering wheel angle. Aoude et al. [14] combined the Support Vector Machine and Bayesian filtering to determine driver's intention of a suspicious vehicle at an intersection, using the driving data including the steering wheel angle of target vehicle and the speeds of the surrounding vehicles. Li et al. [15] proposed a BP neural network model based on the Extended Kalman Filter learning to recognize driver's lane-change intention, according to the driving data such as time headway, steering wheel angle and driver's head position.

In conclusion, there has been much research about driver intention identification, primarily based on vehicle operating parameters (such as acceleration pedal opening, brake pedal opening, and driving speed), environmental parameters (such as road curvature and lane line position), and driver's visual behavior parameters (such as face orientation and sight characteristics). But little research has been conducted to develop driver intention recognition model considering the impacts of driving emotion on intention. This study aims to gain a better understanding of the characteristics of driver intention transition triggered by driver's emotions. We will use the Hidden Markov model to build a driver intention identification model with 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.
2 Driving intention transition model

Seven kinds of driver's intentions were considered for analysis in this study, which are going straight at a constant speed (11), going straight with acceleration (12), going straight with deceleration (13), lane-changing at a constant speed (14), lane-changing with acceleration (15), lane-changing with deceleration (16), and stopping (17). Eight types of common emotions were included in this study, which are anger (Em1), surprise (Em2), fear (Em3), anxiety (Em4), helplessness (Em5), contempt (Em6), relief (Em7), and pleasure (Em8). It should be noted that driver's intentions were selected by analyzing the vehicle driving status in two-lane environment. Driver's emotions were selected based on the emotion classification developed by Johnston [16], and the results of the survey questionnaire for driving emotions.

2.0.1 Hidden markov model of driver emotion transition

The Hidden Markov model [17] is developed based on enhancing the Markov chain. HMM is used to describe the statistical properties of stochastic process. It represents a double stochastic process, including the Markov chain and general stochastic process [18]. HMM, as a tool for modelling time series data, has been widely used for emotion classification and recognition in many fields [19, 20]. The Markov chain is used to describe the transition of driver's emotional states, with an assumption of that the probability of an emotional state depends only on the previous state. General stochastic process is used to describe the output observation of driver's intention, with another assumption of that the probability of an emotional state transfers from state to state only upon the emotional state at the same moment.

HMM can be represented by a combination of five parameters, and the \( \lambda = (\text{Em, I, } \pi, A, B) \) parameters are specified as follows:

(i) \( \text{Em} \) is a set of emotional states, \( \text{Em} = \{ \text{Em}_1, \text{Em}_2, \ldots, \text{Em}_8 \} \), and the state of the Markov chain at moment \( t \) is \( x_t \).

(ii) \( I \) is a set of observations of driver's intentions, \( I = \{ I_1, I_2, \ldots, I_8 \} \), and the state of driver's intention at moment \( t \) is \( y_t \).

(iii) \( \pi \) is the probability matrix of the initial state of emotion, \( \pi = [\pi_{ij}], \pi_{ij} = P(x_1 = \text{Em}_j | \text{Em}_i), i, j = 1, 2, \ldots, 8 \). It represents the probability when the driver is in state \( \text{Em}_i \) at the time \( t = 1 \).

(iv) \( A \) is a probability matrix of emotional state transition. \( A = (a_{ij})_{8 \times 8}, a_{ij} = P(x_{i+1} = \text{Em}_j | x_i = \text{Em}_i), i, j = 1, 2, \ldots, 8 \). \( a_{ij} \) denotes the probability that driver's emotional state transfers from \( x_i \) to \( x_j \) at time \( t \).

(v) \( B \) is a probability matrix of driver's intention in an emotional state sequence. \( B = (b_{ij}(u_k))_{8 \times 7}, b_{ij}(u_k) = P(y_{i+1} = u_k | x_i = \text{Em}_j), j = 1, 2, \ldots, 8, k = 1, 2, \ldots, 7 \). \( b_{ij}(u_k) \) denotes the probability of driver's intention \( y_{i+1} = u_k \) when the driver is in the emotional state \( x_i = \text{Em}_j \) at time \( t \). \( u_k \) represents an element in \( I = \{ I_1, I_2, \ldots, I_8 \} \).

The emotional state transition follows from the assumption that driver's intention state is only affected by the emotion at the same time. The relationship between driver's emotion and intention is shown in Fig. 1.

In the model, the emotional state sequence \( X(t) = x_1, x_2, \ldots, x_t \) and the driver's intention state sequence \( Y(t) = y_1, y_2, \ldots, y_t \) are selected. Because the selected sequence data is finite, the final values of \( x_t \) and \( y_t \) cannot be determined if the values of \( x_{t-1} \) and \( y_{t-1} \) are not considered. Therefore, the sequence capacity can be regarded as \( t = 1 \) when the probability of a state occurrence is calculated in the following.

It is assumed that in the sequence of emotional state \( x_t, x_{t+1}, \ldots, x_{t+n-1} \), if there is \( N_i \) number of data for the state \( \text{Em}_i \), the probability of state \( \text{Em}_i \) is calculated as follow:

\[
\alpha_i = \frac{N_i}{t-1} \quad i = 1, 2, \ldots, 8
\]  

(1) If there are \( N_{ij} \) emotional states transferring to state \( \text{Em}_j \) at next time period, the transition probability from state \( \text{Em}_i \) to state \( \text{Em}_j \) is:

\[
b_{ij} = \frac{N_{ij}}{N_i} \quad i, j = 1, 2, \ldots, 8
\]  

(2) For driver's intention state sequence \( y_t, y_{t+1}, \ldots, y_{t+n-1} \), when the emotion transfers from state \( \text{Em}_m \) to state \( \text{Em}_n \), the probability of driver's intention state \( I_m \) is \( b_{jmn} \).

\[
b_{jmn} = \frac{M_{jmn}}{M_{jm}} \quad m, n = 1, 2, \ldots, 7
\]  

(3) When the emotion is transferred from state \( \text{Em}_m \) to state \( \text{Em}_n \), \( M_{jmn} \) represents the number of driver's intention to maintain state \( I_m \), \( N_{ij} \) represents the number of emotions transferred from state \( \text{Em}_m \) to state \( \text{Em}_j \).

If there are \( M_{jmn}(\text{of } M_{jm}) \) number of driver's intention transferred to state \( I_n \) at next time period, and driver's emotion transfers from state \( \text{Em}_m \) to state \( \text{Em}_j \), the transition probability of driver's intention from \( I_m \) to \( I_n \) is \( b_{jmn} \).

\[
b_{jmn} = \frac{M_{jmn}}{M_{jm}} \quad m, n = 1, 2, \ldots, 7
\]  

(4) Where \( M_{jmn} \) denotes the number of driver's intention transferred to \( I_n \) next time period, when driver's emotion is transferred from \( \text{Em}_m \) to \( \text{Em}_j \).

2.0.2 Training hidden markov model

For training hidden Markov transition model \( \lambda = (\text{Em, I, } \pi, A, B) \), the Baum-Welch estimation algorithm is used for parameter selection and optimization in this study. The forward variable \( \alpha_l(i) \) and the backward variable \( \beta_l(i) \) are defined in (5) and (6).

\[
\alpha_l(i) = P(u_i, u_{i+1}, \ldots, u_t; x_i = \text{Em}_j) \quad 1 \leq i \leq 8
\]  

(5) The forward variable \( \alpha_l(i) \) indicates the probability that driver's intention \( y_i = u_i \) (one of the values in \( l \) at moment \( k \)) at moment \( k \) \((k = 1, 2, \ldots, t)\) when the emotion is in state \( \text{Em}_j \) at moment \( t \). \( \alpha_l(i) = \pi_i b_i(u_k) \) represents the probability that the emotion is in state \( \text{Em}_j \) and driver's intention sequence is \( y_i = u_i \) at initialization \( t = 1 \).
\[ \beta_t(i) = P(u_{i+1}, u_{i+2}, \ldots, u_{t}; x_t = Em_t) \quad 1 \leq i \leq 8 \quad 1 \leq t \leq L - 1 \]  \quad (6) \]

The backward variable \( \beta_t(i) \) indicates the probability that driver's intention \( y_t = u_t \) (one of the values in \( L \) at moment \( k = t + 1, t + 2, \ldots, L \)) when the emotion is in state \( Em_t \) at time \( t \). The initial value \( \beta_1(i) = 1 \) means the probability of the end state of driver's intention \( y_L = u_t \) at time \( t = L \), when the emotional state is \( Em_L \).

Recursion formulas \( \alpha_t(i) \) and \( \beta_t(i) \) are obtained according to the influences of driver's emotion on intention at different times.

(see (7))
(see (8))

The two variables can be combined. Specifically, for an observation sequence \( u_1, u_2, \ldots, u_8 \), the probability of recurrence is derived by \( \alpha_t(i) \) using one part of the sequence \( u_1, u_2, \ldots, u_8 \), and by \( \beta_t(i) \) using another part of the sequence \( u_1, u_2, \ldots, u_8 \). Then, the probability \( P(u_1, u_2, \ldots, u_8) \) of the entire state sequence \( u_1, u_2, \ldots, u_8 \) can be obtained with \( \alpha_t(i) \) and \( \beta_t(i) \):

(see (9))

In addition, the probability of the state sequence \( P(u_1, u_2, \ldots, u_8) \) can also be derived in another way, as follows:

(see (10))

\( \alpha_t(i) \) and \( \beta_t(i) \) can be used for parameter adjustment and model optimization. The variables \( \epsilon_t(i, j) \) and \( \gamma_t(i) \) are defined as follows:

(see (11))

Where \( \epsilon_t(i, j) \) represents the probability of a given driver's intention sequence \( u_1, u_2, \ldots, u_8 \) when the emotional state is \( Em_t \) at moment \( t \) and \( Em_j \) at moment \( t + 1 \).

(see (12))

\[ a_{t+1}(j) = P(u_1, u_2, \ldots, u_{t+1}; x_{t+1} = Em_{t+1}) \]
\[ = P(u_1, u_2, \ldots, u_t; x_t = Em_t)P(u_{t+1}; x_{t+1} = Em_{t+1}) \]
\[ = P(u_1, u_2, \ldots, u_t; x_t = Em_t) \sum_{i=1}^{8} P(u_{i+1}; x_{i+1} = Em_{i+1})P(x_{i+1}; x_t = Em_t) \]
\[ = P(u_1, u_2, \ldots, u_t; x_t = Em_t) \sum_{i=1}^{8} a_t(i)a_t(j) \]
\[ = \left[ \sum_{i=1}^{8} a_t(i)a_t(j) \right] b_t(u_{t+1}) \]

\[ b_t(i) = P(u_{i+1}, u_{i+2}, \ldots, u_{t}; x_t = Em_t) = \sum_{j=1}^{8} P(u_{i+1}, u_{i+2}, \ldots, u_t; x_t = Em_t) b_t(u_{t+1}) \]
\[ = \sum_{j=1}^{8} P(x_{i+1} = Em_t) = Em_t)P(u_{i+1}, u_{i+2}, \ldots, u_{t}; x_t = Em_t) \]
\[ = \sum_{j=1}^{8} P(x_{i+1} = Em_t) = Em_t)P(u_{i+1}, u_{i+2}, \ldots, u_{t}; x_t = Em_t) \sum_{i=1}^{8} a_t(i)P(u_{i+1}; x_{i+1} = Em_{i+1}) \]
\[ = \sum_{j=1}^{8} a_t(i)P(u_{i+1}; x_{i+1} = Em_{i+1}) \]
\[ = \sum_{j=1}^{8} a_t(i)P(u_{i+1}; x_{i+1} = Em_{i+1}) \]
\[ = \sum_{j=1}^{8} a_t(i)P(u_{i+1}; x_{i+1} = Em_{i+1}) \]
\[ = \sum_{j=1}^{8} a_t(i)P(u_{i+1}; x_{i+1} = Em_{i+1}) \]

\[ L - 1 \]

\[ P(u_1, u_2, \ldots, u_8) = \sum_{j=1}^{8} P(u_1, u_2, \ldots, u_8; x_t = Em) \]
\[ = \sum_{j=1}^{8} P(u_1, u_2, \ldots, u_8; x_t = Em)P(u_{i+1}, u_{i+2}, \ldots, u_t; x_t = Em) \]
\[ = \sum_{j=1}^{8} a_t(i)P(u_{i+1}) \]

(9)
Where \( \gamma(i) \) represents the probability of a given driver's intention sequence \( u_i, u_{i+1}, \ldots, u_{i+L} \), when the emotional state at moment \( t \) is \( E_{m_i} \). Variables \( e(i, j) \) and \( \gamma(i) \) are combined as follows:

\[
y(i) = \sum_{j=1}^{L} e(i, j)
\]

(13)

According to (9)–(12), the optimized formula of emotion transformation probability is obtained by:

\[
a_j = \frac{\sum_{i=1}^{L} p(x_i = E_{m_i}, x_{i+1} = E_{m_{i+1}})}{\sum_{i=1}^{L} p(x_i = E_{m_i}, \ldots, x_L)}
\]

\[
= \frac{\sum_{i=1}^{L} e(i, j)}{\sum_{i=1}^{L} \gamma(i)} = \frac{\sum_{i=1}^{L} \gamma(i)}{\sum_{i=1}^{L} \alpha(i) \beta(i)}
\]

(14)

The algorithm for optimizing the probability distribution of driver's intention is given by:

\[
b(j) = \frac{\sum_{i=1}^{L} p(x_i = E_{m_i}, \ldots, x_j = E_{m_j})}{\sum_{i=1}^{L} p(x_i = E_{m_i}, \ldots, x_L)}
\]

(15)

The algorithm for optimizing the probability distribution \( \pi \) of the initial emotional state is given by:

\[
\pi = \gamma(i) = \frac{\sum_{i=1}^{L} \alpha(i) \beta(j)}{\sum_{i=1}^{L} \alpha(i) \beta(i)}
\]

(16)

\[
P(u_1, \ldots, u_L)
\]

\[
= \sum_{i=1}^{L} \sum_{i=1}^{L} \sum_{j=1}^{L} p(u_i, u_{i+1}, \ldots, u_{i+L}, x_{i+1} = E_{m_{i+1}})
\]

\[
= \sum_{i=1}^{L} \sum_{i=1}^{L} \sum_{j=1}^{L} p(u_i, u_{i+1}, \ldots, u_{i+L}, x_{i+1} = E_{m_{i+1}}) p(u_{i+1}, u_{i+2}, \ldots, u_{i+L}, x_{i} = E_{m_i})
\]

\[
= \sum_{i=1}^{L} \sum_{i=1}^{L} \sum_{j=1}^{L} \alpha(i) \alpha(j) \beta(j) \beta(j)
\]

(11)

\[
e(i, j) = p(x_i = E_{m_i}, x_{i+1} = E_{m_{i+1}}, \ldots, u_{i+L} = E_{m_{i+1}})
\]

\[
= \frac{p(x_i = E_{m_i}, x_{i+1} = E_{m_{i+1}})}{p(u_1, u_2, \ldots, u_L)}
\]

\[
= \frac{p(x_i = E_{m_i}, u_1, u_2, \ldots, u_{i+L}) p(u_{i+1}, u_{i+2}, \ldots, u_L, x_{i+1} = E_{m_{i+1}})}{p(u_1, u_2, \ldots, u_L)}
\]

\[
= \frac{\alpha(i) \alpha(j) \beta(j) \beta(j)}{\sum_{i=1}^{L} \sum_{j=1}^{L} \alpha(i) \alpha(j) \beta(j) \beta(j)}
\]

\[
\gamma(i) = p(x_i = E_{m_i}, \ldots, x_L = E_{m_L}) = \frac{p(x_i = E_{m_i}, u_1, \ldots, u_L)}{p(u_1, \ldots, u_L)}
\]

\[
= \frac{p(x_i = E_{m_i}, u_1, \ldots, u_{i+L}) p(u_{i+1}, \ldots, u_L | x_{i+1} = E_{m_{i+1}})}{p(u_1, \ldots, u_L)}
\]

(12)

\[
= \frac{\alpha(i) \beta(j)}{\sum_{i=1}^{L} \alpha(i) \beta(i)}
\]

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and surrounding vehicles) and driver-based factors (e.g. respectively. Thus, it could be said that vehicle group considers the attraction and repulsion forces were denoted by ‘+’ and ‘−’, to analyze the impacts of driver’s emotion states on driving intention, left lane, the interest-sensitive area was divided into front, right-rear and rear sides. When the target vehicle run in the right lane, the interest-sensitive area (refers to the 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 line lane.) [21]. 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. Six factors were used in the interest-sensitive area, including gender, propensity, determination, driving experience, and relative distances and relative speeds between target vehicle and surrounding vehicles [21–26]. Then, the fuzzy logic method was used to get the ‘force’ on vehicles in the sub-regions, and the collection of these ‘forces’ was 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 location in the left and right lanes, eight vehicle group situations were obtained, shown in Fig. 3. The eight vehicle group situations were represented by T1, T2... T8 respectively, and the 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.

3 Materials and methods

3.1 Analysis of vehicle group relationship

The vehicle group situation is composed of dynamic traffic entities, which has an important influence on driver’s decision [21]. To analyze the impacts of driver’s emotion states on driving intention, various scenarios of vehicle group situations were defined, shown in Fig. 2.

When the target vehicle (refers to the vehicle driven by subject) running 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 line lane.) [21]. 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. Six factors were used in the interest-sensitive area, including gender, propensity, determination, driving experience, and relative distances and relative speeds between target vehicle and surrounding vehicles [21–26]. Then, the fuzzy logic method was used to get the ‘force’ on vehicles in the sub-regions, and the collection of these ‘forces’ was 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 location in the left and right lanes, eight vehicle group situations were obtained, shown in Fig. 3. The eight vehicle group situations were represented by T1, T2... T8 respectively, and the 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.

3.2 Experimental design

Real and virtual driving experiments were 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 obtain 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. Moreover, the high-fidelity driving simulator used in this study offers the potential of recreating a real traffic environment.

3.2.1 Experimental materials and equipment: The experimental materials mainly include the psychological survey questionnaire of driver’s propensity [10], the survey questionnaire of determination [10], the International Affective Picture System (IAPS) and the Chinese Affective Picture System (CAPS). Parts of the emotion induction materials are shown in Figs. 4 and 5. The experimental equipment primarily includes PSYLAB human factor system, GPS high-precision positioning system, SG299GPS Non-contact multi-function speedometer, 32-Wire LiDAR, and Video-capturing system. Parts of the experimental equipment are shown in Fig. 6.

3.2.2 Experimental routes and subjects: A total of 27 males and 27 females were selected as participants in this study. Age of the subjects ranged from 18 to 60 year, and the average age was 33.5 year. Each subject was involved in both real and virtual driving experiments, with different kinds of emotional experiences. The selected route was a part of Zhangzhou road between Jiangmeng road and Shanshen line, in Zibo city, Shandong province (shown in Fig. 6, the total length of 4.7 km). The real-driving experiments were conducted in dry weather during off-peak hours.

In the virtual driving experiments, the high-fidelity simulator allows users to construct 3D traffic environment and engage interactive experience. The simulation-based experimental platforms of the human-vehicle-environment comprehensive road system was constructed for the virtual driving experiments, based on road attributes, traffic volume, and other parameters of the field driving experiments. The virtual driving experimental equipments are shown in Fig. 7.

3.2.3 Driving experiment:
Emotion Induction. The International Affective Picture System (IAPS) and the Chinese Affective Picture System (CAPS) were used as emotion induction materials. Firstly, the drivers were showed the IAPS and CAPS pictures with strong emotional content, and were also told the stories about pictures, in order to make emotional association memory. Next, the CAPS videos were presented to further increase the level of driver's emotion. The driving experiment started when driver's emotion was induced successfully to a certain level of arousal. During driving, the same types of music were continuously played, as well as spiritual.

Fig. 4 Parts of visual stimulus materials

Fig. 5 Parts of emotional face pictures

Fig. 6 Real driving experimental equipment and route

Fig. 7 Virtual driving experimental equipment and route
incentives and material reward were provided, to maintain or increase driver's emotional level. For example, loud music, subdued light and irritating odors were provided in order to increase drivers' anxiety level. Meanwhile, drivers were also asked to finish some difficult tasks in a limited time such as mathematical calculation or overtaking during driving. Anger emotion was stimulated with traffic scenes, such as setting traffic accident, waiting for a long time in intersections, or crowded vehicle road, in the interactive driving virtual experiment platform. Relief emotion was stimulated by sharing happy experience. PsyLAB system was used to collect drivers' physiological characteristics, including electrocardiography (ECG), electrodermal activity (EDA), skin temperature (SKT), and respiration (RESP). These physiological characteristics, combining with the descriptions of drivers' own emotions, were applied to identify their emotion types and emotion levels. The process of emotion induction and enhance is shown in Fig. 8.

(ii) Experimental Process. Before an experiment, certain personal information and driving-related information of each subject was collected, such as gender, age, driver's propensity, vehicle mileage travelled, and driving style. And, subjects were given a detailed introduction of the experimental procedures, and were asked to learn how to manipulate the experimental vehicle. 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. After the driving experiment, drivers were asked to watch the recorded video immediately, and describe their emotional changes in the driving experiments. At the end, the emotion data and the corresponding intention data were arranged in a timeline, to obtain a complete chain of emotion-intention double-state transition, for each vehicle group.

Experimental variables and symbols are shown in Table 1. An example of experimental data set is shown in Table 2. Before processing the data, the data sets with missing values were removed. Meanwhile, the data sets were also removed, in which drivers' emotional levels were low or ambiguous.

4 Results

Based on a large amount of experimental data, the transition probability matrix was obtained for driver's intention of each emotional state in different vehicle groups, shown as follows:

\[
P_{IJ} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{18} \\ p_{21} & p_{22} & \cdots & p_{28} \\ \vdots & \vdots & \ddots & \vdots \\ p_{81} & p_{82} & \cdots & p_{88} \end{bmatrix}
\]

where, \(P_{IJ}\) represents the transition probability matrix of driver's intention under emotional state in different vehicle groups. \(P_{1jmn}\) represents the probability matrix that driver's emotional state is transferred from \(Em_i\) to \(Em_j\), and driver's intention is transferred from \(I_m\) to \(I_n\) in vehicle group \(T_i\).

There are a total of eight vehicle groups that were analyzed in this study. The transition probability matrixes of the driver's intention in vehicle group \(T_i\) are presented below, as an example.

\[
P_{12} = \begin{bmatrix} 0.310 & 0.030 & 0.029 & 0.020 & 0.090 \\ 0.227 & 0.012 & 0.011 & 0.012 & 0.382 \\ 0.245 & 0.034 & 0.022 & 0.038 & 0.081 \\ 0.203 & 0.011 & 0.029 & 0.052 & 0.094 \\ 0.030 & 0.032 & 0.037 & 0.027 & 0.483 \\ 0.004 & 0.013 & 0.036 & 0.016 & 0.187 \\ 0.010 & 0.038 & 0.000 & 0.016 & 0.090 \\ 0.091 & 0.031 & 0.015 & 0.008 & 0.200 \end{bmatrix}
\]
Fig. 8 Process of emotion induction and enhancement

Table 1 Experimental variables and symbols

| Variable         | Symbol | Variable      | Symbol         | Variable    | Symbol |
|------------------|--------|---------------|----------------|-------------|--------|
| gender           | G      | Driving propensity | D_a            | Ave. acceleration of target veh. (m/s²) | a     |
| age              | A      | Ave. depth on accelerator pedal (cm) | T_a          | Ave. lateral distance between target veh. centerline & lane centerline (m) | d₁   |
| driving distance | D_A    | Ave. depth on brake pedal (cm) | T_b          | Ave. speed of surrounding veh. i (km/h) | v_i   |
| emotion          | Em     | Ave. speed of target veh. (km/h) | v             | Ave. acceleration of surrounding veh. i (m/s²) | a_i   |
| intention        | It     | Ave. angle of steering wheel (°) | w             | Ave. vertical distance between target veh. & surrounding veh. i (m) | d_c−i |
| emotional level  | Em     | Ave. force of steering wheel (N) | f_m          | —           | —     |

Table 2 Example of experimental data set

| L-(1) | G  | A  | D_A | Em    | It     | E     | D_a  | v | a  |
|-------|----|----|-----|-------|--------|-------|------|---|----|
| female | 28 | 18,165 | fear | lane-keeping & decel. | middle | middle-type | 36.74 | −1.58 |
| 4.8    | 1.58 | 29.1 | 17.6 | 0.49 | 15.2  | 16.3  | 7.1   | 10.2 |
| 40.32  | 36.43 | 32.14 | 35.11 | 1.13 | 1.32  | 0.12  | −1.25 |

| L-(2) | G  | A  | D_A | Em    | It     | E     | D_a  | v | a  |
|-------|----|----|-----|-------|--------|-------|------|---|----|
| female | 28 | 18,165 | helplessness | lane-keeping & decel. | high  | middle-type | 31.52 | −2.32 |
| 4.5    | 1.78 | 26.8 | 17.3 | 0.42 | 17.3  | 18.5  | 7.0   | 8.6  |
| 39.68  | 37.03 | 30.41 | 31.56 | 0.09 | 1.27  | 0.08  | −1.59 |

| L-(n) | G  | A  | D_A | Em    | It     | E     | D_a  | v | a  |
|-------|----|----|-----|-------|--------|-------|------|---|----|
| female | 28 | 18,165 | anxiety | lane-changing & accel. | middle | middle-type | 39.87 | 3.73 |
| 5.1    | 0.89 | 34.7 | 19.1 | 0.72 | 10.4  | 12.3  | 11.9  | 15.8 |
| 42.65  | 39.87 | 33.56 | 36.41 | 1.53 | 1.46  | 0.9   | 0.07 |

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The results show that the dynamic evolution of driver's emotion has a time-variant effect on driver's intentions and decisions. The effects were analyzed in terms of emotional states as follows.

- Drivers are more likely to increase driving speed and get engaged in aggressive driving behavior with the emotion evolution to contempt and anger. In the state of contempt, drivers tend to accelerate in the same lane at this moment if they went straight at the last moment (e.g. $p = 0.409$, fear → contempt, steady speed & lane-keeping → acceleration & lane-keeping), and drivers tend to speed up with changing lane at this moment if they changed lane at the last moment (e.g. $p = 0.511$, helplessness → contempt, steady speed & lane-changing → acceleration & lane-changing). In the state of anger, drivers tend to accelerate with changing lane at this moment if they changed lane at the last moment (e.g. $p = 0.430$, helplessness → anger, steady speed & lane-changing → acceleration & lane-changing), as well as drivers speed up with or without changing lane at this moment if they went straight at the last moment (e.g. $p = 0.619$, anxiety → anger, steady speed & lane-keeping → acceleration & lane-changing).

- Drivers are more likely to increase driving speed and get engaged in aggressive driving behavior with the emotion evolution to contempt and anger. In the state of contempt, drivers tend to accelerate in the same lane at this moment if they went straight at the last moment (e.g. $p = 0.409$, fear → contempt, steady speed & lane-keeping → acceleration & lane-keeping), and drivers tend to speed up with changing lane at this moment if they changed lane at the last moment (e.g. $p = 0.511$, helplessness → contempt, steady speed & lane-changing → acceleration & lane-changing). In the state of anger, drivers tend to accelerate with changing lane at this moment if they changed lane at the last moment (e.g. $p = 0.430$, helplessness → anger, steady speed & lane-changing → acceleration & lane-changing), as well as drivers speed up with or without changing lane at this moment if they went straight at the last moment (e.g. $p = 0.619$, anxiety → anger, steady speed & lane-keeping → acceleration & lane-changing).

- Drivers are more likely to increase driving speed and get engaged in aggressive driving behavior with the emotion evolution to contempt and anger. In the state of contempt, drivers tend to accelerate in the same lane at this moment if they went straight at the last moment (e.g. $p = 0.409$, fear → contempt, steady speed & lane-keeping → acceleration & lane-keeping), and drivers tend to speed up with changing lane at this moment if they changed lane at the last moment (e.g. $p = 0.511$, helplessness → contempt, steady speed & lane-changing → acceleration & lane-changing). In the state of anger, drivers tend to accelerate with changing lane at this moment if they changed lane at the last moment (e.g. $p = 0.430$, helplessness → anger, steady speed & lane-changing → acceleration & lane-changing), as well as drivers speed up with or without changing lane at this moment if they went straight at the last moment (e.g. $p = 0.619$, anxiety → anger, steady speed & lane-keeping → acceleration & lane-changing).
Table 3  Verification results of real vehicle driving experiment

| Data Group No. | Predict times | Comparison of prediction and recognition results | Accuracy |
|---------------|---------------|--------------------------------------------------|----------|
|               | Agree times   | Disagree times                                  |          |
| 1             | 80            | 66                                               | 14       |
| 2             | 80            | 69                                               | 11       |
| 3             | 80            | 65                                               | 15       |
| 4             | 80            | 69                                               | 11       |
| 5             | 80            | 65                                               | 15       |
| 6             | 80            | 67                                               | 13       |
|               |              |                                                  |          |
|               |              |                                                  |          |
| 4000          | 80            | 64                                               | 16       |
| Ave.          | 80            | 66.625                                           | 13.375   |

"p<sub>525</sub> = 0.553, fear → surprise, deceleration & lane-keeping→acceleration & lane-changing). Under the anxious state, it is highly possible that drivers accelerate in the current lane or adjacent lane (e.g. "p<sub>max</sub> = 0.487, pleasure → anxiety, deceleration & lane-changing→acceleration & lane-changing)."

Drivers are more likely to keep smooth driving with the evolution of emotion to relief and pleasure. Relief is a very stable emotional state, in which drivers could remain the speed unchanged substantially completely (e.g. "p<sub>511</sub> = 0.479 , anxiety → relief, deceleration & lane-keeping→steady speed & lane-keeping). Compared to the relief state, fluctuations in mood seem to be slightly more obvious in the pleasure state. In this state, drivers could keep the speed unchanged in most scenarios and keep it up occasionally (e.g. "p<sub>511</sub> = 0.422 , fear → pleasure, deceleration & lane-keeping→steady speed & lane-keeping)."

Moreover, drivers tend to run in a conservative manner with the emotion evolution to fear and helplessness. In the emotional state of helplessness, drivers might well be involuntary in slowing down in the current lane (e.g. "p<sub>511</sub> = 0.471 , contempt→helplessness, acceleration & lane-changing→deceleration & lane-keeping). When drivers feel fear, they are highly likely to decelerate in the current lane (e.g. "p<sub>511</sub> = 0.425 , pleasure → fear, steady speed & lane-keeping→deceleration & lane-keeping). Also, and they may change to another lane and slow down, as feeling less safe in the current lane (e.g. "p<sub>256</sub> = 0.388 , surprise → fear, steady speed & lane-changing→deceleration & lane-changing)."

5 Discussion

5.1 of real driving experiment

Four thousand effective data groups were randomly selected from the experimental data of the real vehicle driving. The transition probabilities of driver's intentions were obtained by the developed prediction model. The final predicted results (the maximum transition probability) were compared to the actual recognition results, shown in Table 3. It was observed that the model can achieve an average accuracy of 83.28% on identifying driver's intention under emotion.

5.2 Verification of virtual driving experiment

Four thousand effective data groups were randomly selected from the experimental data of the virtual driving experiment. The transition probabilities of driver's intentions were obtained by the developed prediction model. The final predicted results (the maximum transition probability) were compared to the actual recognition results, shown in Table 4. It was observed that the model can achieve an average accuracy of 83.91% on identifying driver's intention under emotion.

In summary, it was found that the developed model can achieve prediction accuracies of over 83%. The results indicate that the model can reach a high accuracy in predicting driver's intention transition with the evolution of driving emotion.

6 Conclusions

This paper proposed a dual-state transition model of driver's emotion and intention to predict driver's intention evolution. Real and virtual driving experiments were conducted to collect dynamic data of driver's intentions and emotions. The model was verified using the data of the real driving and virtual driving. The results showed that the developed model can achieve high accuracy and reliability in estimating driver's intention evolution (>83%). Our findings of this study suggest that the prediction accuracy of driver's intention can be improved by considering driver's emotion evolution. 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 exploring the transformation mechanism of driver's intention in more complex traffic environments.

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