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Research Article

Dynamic Recognition Model of Driver's Propensity under Multilane Traffic Environments

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Driver's propensity intends to change along with driving environment. In this paper, the situation factors (vehicle groups) that affect directly the driver's affection among environment factors are considered under two-lane conditions. Then dynamic recognition model of driver's propensity can be established in time-varying environment through Dynamic Bayesian Network (DBN). Physiology-psychology experiments and real vehicle tests are designed to collect characteristic data of driver's propensity in different situations. Results show that the model is adaptable to realize the dynamic recognition of driver's propensity type in multilane conditions, and it provides a theoretical basis for the realization of human-centered and personalized automobile active safety systems.

1. Introduction

With the rapid development of China economy, vehicle quantity, especially private vehicle, is increasing rapidly, and the contradiction among people, vehicle, and environment is increasing outstandingly in road traffic system. Above 90% of traffic accidents are caused by person, and above 70% of traffic accidents are caused by drivers. The reduction of traffic accidents not only needs to solve the problems of vehicle safety, road safety, and environment and climate impacts, but what is also more important is to research the influence of drivers on safe driving. Driver's propensity is a dynamic measurement of controller's affection, predilection, and others during driving. It is a core parameter to compute driver's intention and consciousness in safety driving assist systems, especially vehicle collision warning systems. Vehicle, as a mean of modern transportation, is convenient to people's traveling; at the same time, it also brings some traffic safety problems. Automatic driving and driving assistant are vigorous and effective measures to reduce accidents and improve traffic safety. Driver's psychological and affective states are represented as driver's tendency [1] that is an important part of the driver-assistance systems, especially for the active security warning systems. Previous research about the driver's tendency focused mostly on the influence on traffic safety and the driver's psychological characteristics from relative static and macroscopic perspective [1–6]. Wang et al. [7–10] had researched preliminarily driver's tendency on special traffic scenes, such as free flow and car following; Feng and Fang et al. had researched cluster analysis of drivers' characteristics evaluation [11]; Chen et al. had researched subjective judgment of driving tenseness and control of vehicle motion [12]; Wang et al. had researched reliability and safety analysis methodology for identification of drivers' erroneous actions [13]; Cai and Lin had researched modeling of operators' emotion and task performance in a virtual driving environment [14]. However, they could not consider completely the influences of environment. In this paper, physiology-psychology experiments and real vehicle tests are designed to collect characteristic data of driver's propensity considering situation (vehicle group) that affects directly driver's affection among environment factors in different situations. Then dynamic recognition model of driver's propensity can be established in time-varying environment through Dynamic Bayesian Network. Results show that the model and relative experiment scheme are feasible. They can realize the dynamic recognition in multilane conditions.

2. Analysis of Traffic Situation Complexity

Vehicle group is crucial which consists of dynamic transport entity and its influence on driver's behaviors. Obviously, different vehicle position has different influence on target vehicle's driver. Within areas of influence, the front vehicle on the same lane has the largest effect on driver, then the around vehicles on the adjacent lanes, and rear vehicle on the same lane. The model can be simplified taking roads with two lanes in the same direction as an example and ignoring the influence from rear vehicle. The division of vehicle groups is shown in Figures 1 and 2.

Through simplifying the model further, the position of vehicles in left front, left side, left rear, right front, right side, and right rear can be represented into two types, limiting vehicles of left and right. When there is more than one limiting vehicle on target vehicle's left or right and the distance between them meets the minimum gap acceptance conditions, the vehicle whose spatial distance (distance between target and that vehicle along the direction of speed) is minimum can restrict target vehicle. If the distance does not meet the minimum gap acceptance conditions, then the two vehicles will be combined into one interference vehicle. So the complicated group is simplified as in Figure 3. Characteristics of driver's propensity for eight vehicle groups are shown in Table 1.

3. Dynamic Recognition Model of Driver's Propensity

3.1. Dynamic Bayesian Network

Dynamic Bayesian Network is also named Temporal Bayesian Network. It is static Bayesian Network developing with time. Every time slice corresponds to a Static Bayesian Network

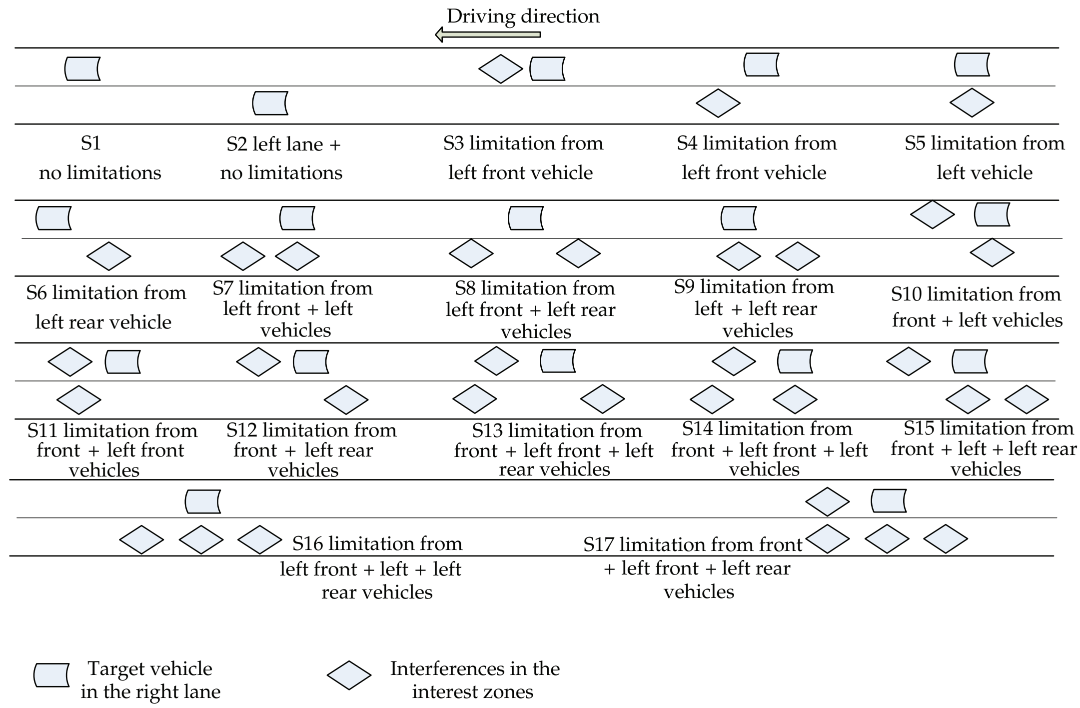

Figure 1: Vehicle group (A).

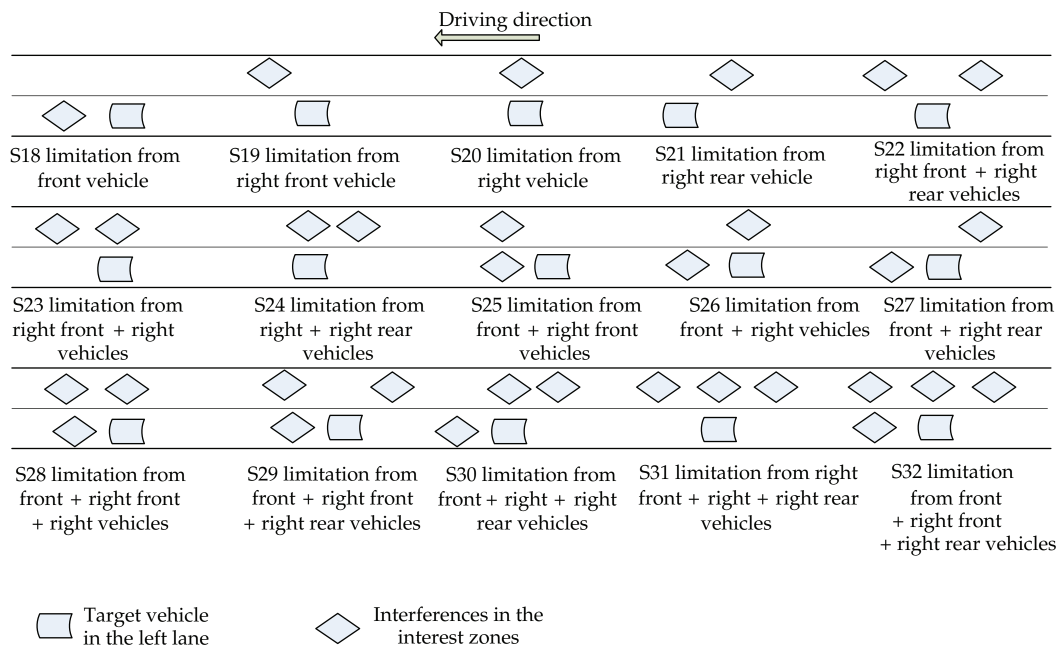

Figure 2: Vehicle group (B).

Table 1: Characteristics of driver's propensity for different groups.

Group	Characteristics of driver's propensity
T1 and T2	Speed of target vehicle; acceleration frequency; deceleration frequency; performance reaction time
T3 and T4	Speed of target vehicle; acceleration of target vehicle; headway; relative speed; relative acceleration; acceleration frequency; deceleration frequency; performance reaction time
T5 and T6	Speed of target vehicle; acceleration of target vehicle; acceleration frequency; deceleration frequency; risky lane-changing frequency; conservative lane-changing frequency; performance reaction time
T7 and T8	Headway; relative speed; acceleration frequency; deceleration frequency; risky lane-changing frequency; conservative lane-changing frequency; performance reaction time

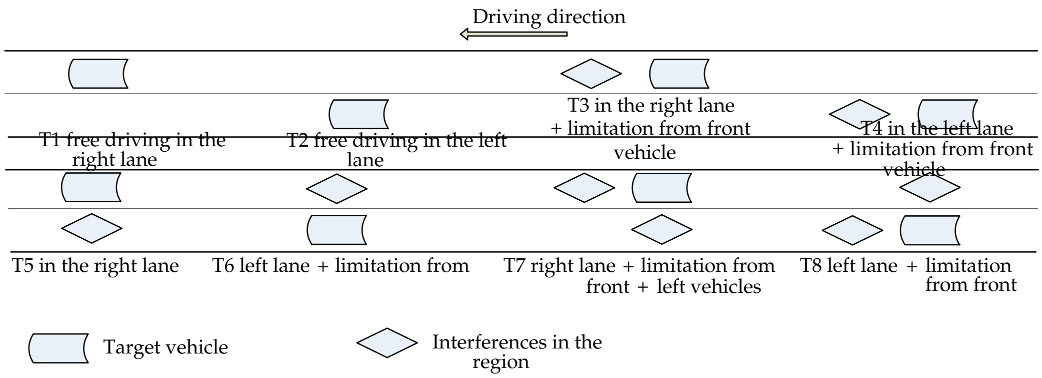

Figure 3: Simplified vehicle group under two-lane conditions.

with identical structure and parameters. Two adjacent time slices are jointed by arc, which represents dependencies between adjacent time slices [15, 16].

Figure 4 shows a simple Dynamic Bayesian Network with three time slices, where, A_1, A_2, and A_3 are hide nodes; B_1, B_2, and B_3 are observed nodes. Each node is a variable. Variables have many states. Inference basis of Dynamic Bayesian Network is Bayes formula:

$$P(x \mid y) = \frac{P(yx)}{P(y)} = \frac{P(yx)}{\sum_x P(yx)}, \tag{3.1}$$

With n hide nodes and m observed nodes, inference essence of Static Bayesian Network is to calculate the following formula:

$$P(x_1, x_2, \ldots, x_n \mid y_1, y_2, \ldots, y_n) = \frac{\prod_j P(y_j \mid \mathrm{Pare}(Y_j)) \prod_i P(x_i \mid \mathrm{Pare}(X_i))}{\sum_{x_1, x_2, \ldots, x_n} \prod_j P(y_j \mid \mathrm{Pare}(Y_j)) \prod_i P(x_i \mid \mathrm{Pare}(X_i))}, \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, m, \tag{3.2}$$

where x_i is a valued state of X_i, $\mathrm{Pare}(Y_j)$ is parent node sets of Y_j, $x_1, x_2, \ldots, x_n$ located in below the $\sum$ in the denominator is combination state of hide nodes, and $\sum$ is the sum for

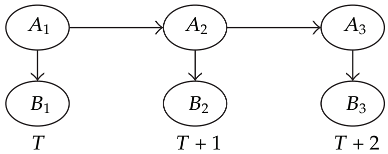

Figure 4: Simple Dynamic Bayesian Network.

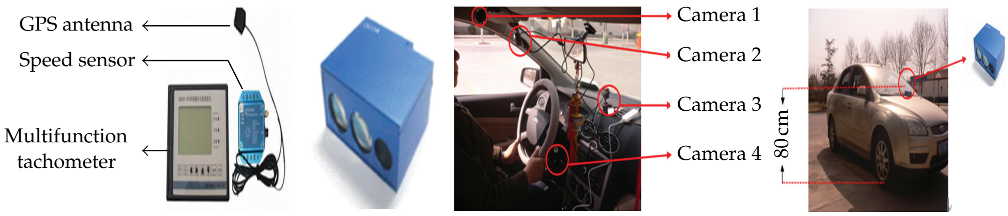

Figure 5: Dynamic human-vehicle-environment information acquisition systems.

joint distribution of observed variables and hidden variables combination state. In fact, it is to compute definite distribution of observed variables combination state.

Dynamic Bayesian Network consisted by T time slices can be obtained from Static Bayesian Network with time. Each time slice has n hide nodes and m observed nodes. Then inference of network can be expressed as follows:

$$\begin{aligned}
&P(x_{11}, x_{12}, \ldots, x_{1n}, \ldots, x_{Tn} \mid y_{110}, y_{120}, \ldots, y_{T10}, \ldots, y_{Tm0}) \\
&\quad = \sum_{y_{11}y_{12}\cdots y_{1m}\cdots y_{T1}\cdots y_{Tm}} \frac{\prod_{i,j} P(y_{ij} \mid \mathrm{Pare}(Y_{ij})) \prod_{ik} P(x_{ik} \mid \mathrm{Pare}(X_{ik}))}{\sum_{x_{11}x_{12}\cdots x_{1n}\cdots x_{T1}\cdots x_{Tm}} \prod_{i,j} P(y_{ij} \mid \mathrm{Pare}(Y_{ij})) \prod_{i,k} P(x_{ik} \mid \mathrm{Pare}(X_{ik}))} \\
&\qquad \times \prod_{i,j} P(Y_{ij0} = y_{ij}), \quad i = 1, 2, \ldots, T;\ j = 1, 2, \ldots, m;\ k = 1, 2, \ldots, n,
\end{aligned} \tag{3.3}$$

where x_{ij} is a valued state of X_{ij}, i is the time slice of i, j is the hide node of j during the time slice of i, y_{ij} is the value of observed variable of Y_{ij}, $\mathrm{Pare}(Y_{ij})$ is parent node sets of y_{ij}, Y_{ij0} is observed state of observed node j during time slice of i, and $P(Y_{ij0} = y_{ij})$ is the membership degree that continuous measurements of Y_{ij} belong to state y_{ij}.

3.2. Experiment Design

3.2.1. Experiment Equipment

The experiments designed in urban road environment collect data using dynamic human-vehicle-environment information acquisition systems (shown in Figure 5, including noncontact multifunction speedometer of SG299-GPS; laser range finder sensor of BTM300-905-200; high definition cameras; Minivap monitoring systems; HDTV camera; notebook computer.). Then driver's tendency can be extracted using the above data. In addition, the softwares used in the experiments include SPSS17.0 and Ulead VideoStudio10.0.

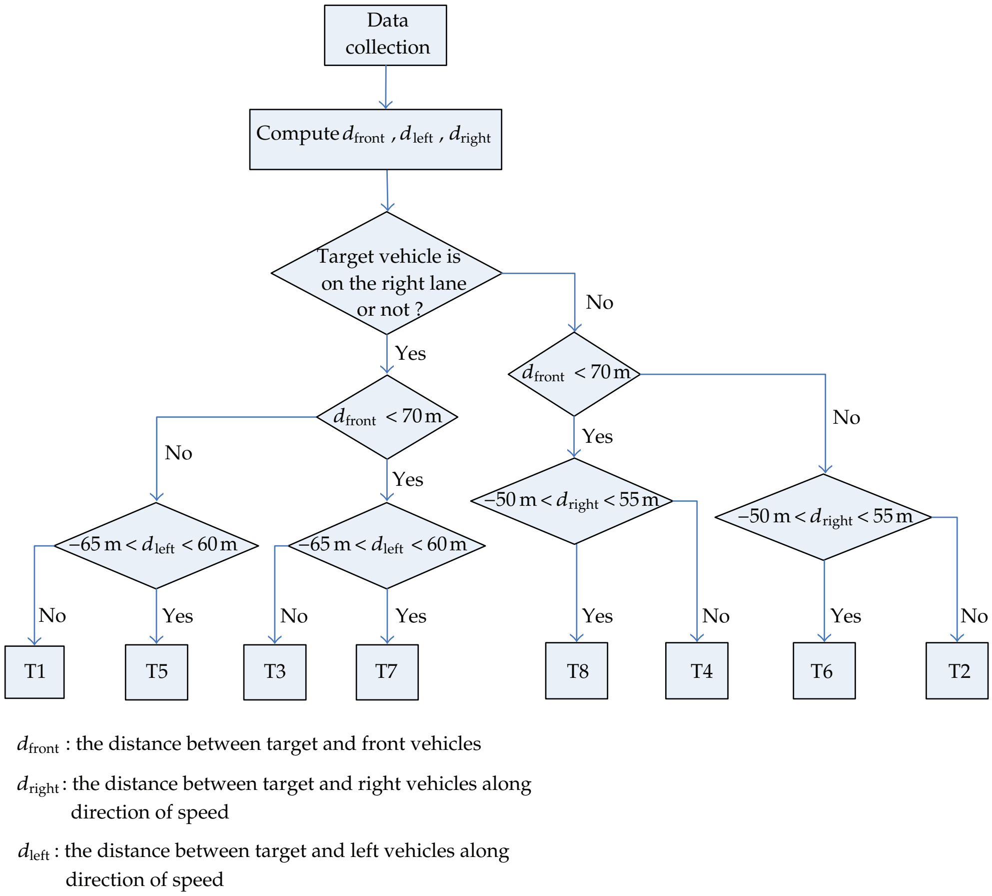

Figure 6: Recognition and identification model.

3.2.2. Experiment Conditions and Subjects

The experiments arranged in shiny days are taken from 8 : 00 am to 10 : 30 am on dry pavement, working day. Traffic is heavy, but there is no congestion. Sample capacity of experiment objects is 50, including 41 males and 9 females. Their ages range from 27 to 58 years old, average with 34.6 years. Driving years range from 3 to 22 years, with average 8.16 years.

3.2.3. Experiment Data

When human-vehicle-environment dynamic information is obtained, state division for the data is necessary to compute the membership degree in different states and to dynamically recognize driver’s tendency. Computing model of state division and membership degree shown in chapter 2.3. Part of transited data is shown in Table 2.

Table 2: Typical data of drivers.

Type	Time	d_6	d_7	d_1	d_2	d_5	d_4	d_3
	1	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.5, 0.3, 0.2)	(0.7, 0.2, 0.1)	(0.6, 0.2, 0.2)	(0.9, 0.1, 0.0)	(0.7, 0.2, 0.1)
	2	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.2, 0.2)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.9, 0.1, 0.0)	(0.7, 0.2, 0.1)
Ty1	3	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.9, 0.1, 0.0)	(0.7, 0.2, 0.1)
	...	...	...	...	...	...	...	...
	10	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.2, 0.2)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.7, 0.2, 0.1)
	1	(0.4, 0.4, 0.2)	(0.6, 0.3, 0.1)	(0.4, 0.5, 0.1)	(0.5, 0.3, 0.2)	(0.5, 0.5, 0.0)	(0.4, 0.4, 0.2)	(0.5, 0.4, 0.1)
	2	(0.4, 0.4, 0.2)	(0.6, 0.3, 0.1)	(0.4, 0.5, 0.1)	(0.5, 0.3, 0.2)	(0.5, 0.5, 0.0)	(0.4, 0.4, 0.2)	(0.5, 0.4, 0.1)
Ty2	3	(0.4, 0.4, 0.2)	(0.6, 0.3, 0.1)	(0.4, 0.5, 0.1)	(0.5, 0.3, 0.2)	(0.5, 0.4, 0.1)	(0.4, 0.4, 0.2)	(0.5, 0.4, 0.1)
	...	...	...	...	...	...	...	...
	10	(0.5, 0.4, 0.1)	(0.4, 0.4, 0.2)	(0.4, 0.5, 0.1)	(0.5, 0.3, 0.2)	(0.4, 0.4, 0.2)	(0.4, 0.4, 0.2)	(0.5, 0.4, 0.1)
	1	(0.2, 0.7, 0.1)	(0.2, 0.6, 0.2)	(0.2, 0.7, 0.1)	(0.2, 0.6, 0.2)	(0.2, 0.7, 0.1)	(0.1, 0.8, 0.1)	(0.2, 0.6, 0.2)
	2	(0.2, 0.6, 0.2)	(0.1, 0.7, 0.2)	(0.2, 0.7, 0.1)	(0.2, 0.7, 0.1)	(0.2, 0.7, 0.1)	(0.1, 0.8, 0.1)	(0.2, 0.6, 0.2)
Ty3	3	(0.2, 0.6, 0.2)	(0.2, 0.6, 0.2)	(0.2, 0.7, 0.1)	(0.2, 0.7, 0.1)	(0.2, 0.7, 0.1)	(0.1, 0.8, 0.1)	(0.2, 0.6, 0.2)
	...	...	...	...	...	...	...	...
	10	(0.2, 0.7, 0.1)	(0.1, 0.8, 0.1)	(0.1, 0.6, 0.3)	(0.2, 0.6, 0.2)	(0.1, 0.7, 0.2)	(0.2, 0.7, 0.1)	(0.2, 0.6, 0.2)
	1	(0.1, 0.5, 0.4)	(0.2, 0.4, 0.4)	(0.1, 0.4, 0.5)	(0.1, 0.3, 0.6)	(0.2, 0.4, 0.4)	(0.1, 0.4, 0.5)	(0.2, 0.4, 0.4)
	2	(0.1, 0.5, 0.4)	(0.2, 0.4, 0.4)	(0.1, 0.4, 0.5)	(0.2, 0.4, 0.4)	(0.2, 0.4, 0.4)	(0.1, 0.4, 0.5)	(0.2, 0.4, 0.4)
Ty4	3	(0.1, 0.5, 0.4)	(0.2, 0.4, 0.4)	(0.1, 0.4, 0.5)	(0.2, 0.4, 0.4)	(0.1, 0.4, 0.5)	(0.1, 0.4, 0.5)	(0.2, 0.4, 0.4)
	...	...	...	...	...	...	...	...
	10	(0.1, 0.4, 0.5)	(0.1, 0.4, 0.5)	(0.1, 0.4, 0.5)	(0.1, 0.4, 0.5)	(0.1, 0.4, 0.5)	(0.1, 0.4, 0.5)	(0.2, 0.4, 0.4)
	1	(0.1, 0.2, 0.7)	(0.1, 0.1, 0.8)	(0.2, 0.2, 0.6)	(0.1, 0.2, 0.7)	(0.1, 0.1, 0.8)	(0.2, 0.2, 0.6)	(0.1, 0.2, 0.7)
	2	(0.1, 0.2, 0.7)	(0.1, 0.1, 0.8)	(0.2, 0.2, 0.6)	(0.1, 0.2, 0.7)	(0.1, 0.1, 0.8)	(0.2, 0.2, 0.6)	(0.1, 0.2, 0.7)
Ty5	3	(0.1, 0.2, 0.7)	(0.1, 0.1, 0.8)	(0.2, 0.2, 0.6)	(0.1, 0.2, 0.7)	(0.1, 0.1, 0.8)	(0.2, 0.2, 0.6)	(0.1, 0.2, 0.7)
	...	...	...	...	...	...	...	...
	10	(0.1, 0.2, 0.7)	(0.0, 0.2, 0.8)	(0.1, 0.2, 0.7)	(0.1, 0.1, 0.8)	(0.1, 0.1, 0.8)	(0.2, 0.2, 0.6)	(0.1, 0.2, 0.7)

Note: Ty1 is conservative type; Ty2 is common-conservative type; Ty3 is common type. Ty4 is common-radical type; Ty5 is radical type. d_1 is acceleration frequency, d_2 is deceleration frequency, d_3 is performance reaction time, d_4 is risky lane-changing frequency, d_5 is conservative lane-changing frequency, d_6 is headway, and d_7 is relative speed.

Table 3: Conditional probability matrices of driver's characteristics under T7 conditions.

Type	Conditional probability matrices of driver's characteristics														
	P (d_1 | human) (small, medium, and large)			P (d_2 | human) (large, medium, and small)			P (d_3 | human) (slow, moderate, and fast)			P (d_4 | human) (high, medium, and low)			P (d_5 | human) (low, medium, and high)		
Ty1	0.75	0.15	0.10	0.85	0.10	0.05	0.80	0.10	0.10	0.90	0.05	0.05	0.80	0.10	0.10
Ty2	0.45	0.45	0.10	0.40	0.45	0.15	0.50	0.40	0.10	0.60	0.30	0.10	0.10	0.30	0.10
Ty3	0.15	0.75	0.10	0.10	0.80	0.10	0.10	0.80	0.10	0.15	0.70	0.15	0.10	0.80	0.10
Ty4	0.10	0.40	0.50	0.10	0.45	0.45	0.10	0.45	0.45	0.15	0.25	0.60	0.10	0.40	0.50
Ty5	0.10	0.10	0.80	0.10	0.15	0.75	0.10	0.10	0.80	0.10	0.15	0.75	0.05	0.15	0.80

Notes: The above table shows the corresponding probability when driver's characteristics are conservative type, common-conservative type, common type, common-radical type and radical type. For example, when driver's characteristics are conservative type, the small probability of d_{12} is 75%, the medium probability is 15%, and the large probability is 10%.

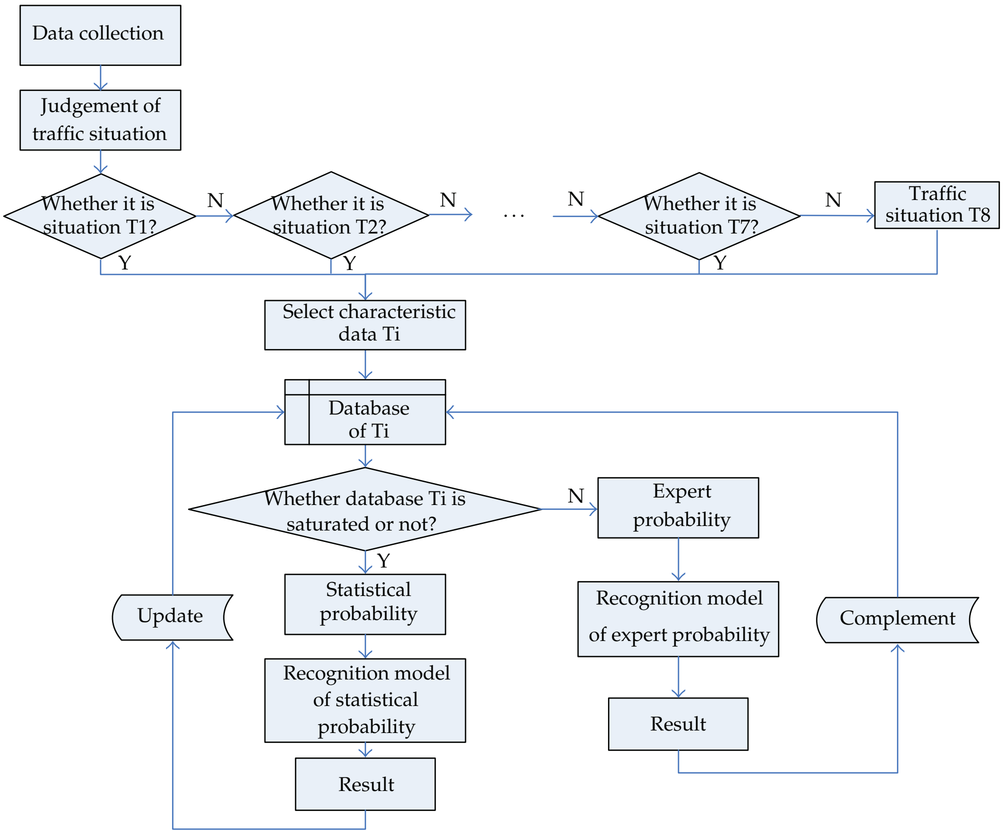

Figure 7: Flow chart of the model.

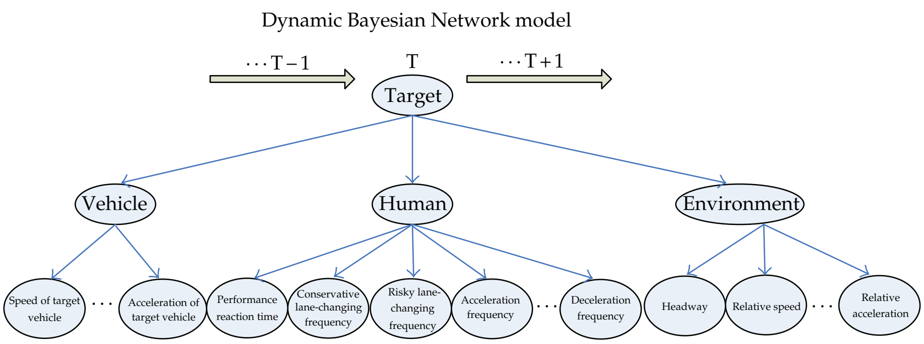

Figure 8: Model of Dynamic Bayesian Network (union of characteristic data).

3.3. Recognition of Driver's Propensity Based on Dynamic Bayesian Network

Vehicle group recognition depends on a group of different space location and distance along with direction of speed. Amounts of experiments show that when d_{left} or d_{right} (d_{left} is space line distance between target vehicle and vehicles in the left lane along with direction of target vehicle's speed, and d_{right} is space line distance between target vehicle and vehicles in the right lane along with direction of target vehicle's speed) are less than (or equal to) one

Table 4: Conditional probability matrices of environmental characteristics under T7 conditions.

Type	Conditional probability matrices of environmental characteristics					
	P (d_6 | environment) (large, medium, and small)			P (d_7 | environment) (small, medium, and large)		
Ty1	0.80	0.10	0.10	0.75	0.15	0.10
Ty2	0.50	0.40	0.10	0.50	0.45	0.05
Ty3	0.10	0.80	0.10	0.10	0.80	0.10
Ty4	0.10	0.45	0.45	0.10	0.40	0.50
Ty5	0.05	0.10	0.85	0.05	0.15	0.80

Table 5: Conditional probability matrices of tendency type under T7 conditions.

Type	Conditional probability matrices of driver's propensity type									
	P (human factor | propensity) (Ty1, Ty2, Ty3, Ty4, and Ty5)					P (environment | propensity) (Ty1, Ty2, Ty3, Ty4, and Ty5)				
Ty1	0.75	0.10	0.05	0.05	0.05	0.65	0.15	0.10	0.05	0.05
Ty2	0.15	0.65	0.10	0.05	0.05	0.10	0.70	0.10	0.05	0.05
Ty3	0.05	0.10	0.70	0.10	0.05	0.05	0.10	0.70	0.10	0.05
Ty4	0.05	0.05	0.10	0.70	0.10	0.05	0.05	0.10	0.65	0.15
Ty5	0.05	0.05	0.10	0.15	0.65	0.05	0.10	0.10	0.15	0.60

Notes: the above table shows the corresponding probability when driver's or environment characteristics are conservative type, common-conservative type, common type, common-radical type, and radical type. For example, when driver's propensity is conservative type, the probability that driver's characteristics belong to conservative type is 75%, belong to common and conservative type is 10%, belong to common type is 5%, belongs to common and radical type is 5%, and belong to radical type is 5%.

threshold value, it will affect the target vehicle. Amounts of data for different drivers show that the interval of d_{left} is (−65 m, 60 m) and interval of d_{right} is (−50 m, 55 m). Recognition and identification model of vehicle group is shown in Figure 6. Flow chart of the model for Dynamic Bayesian Network is shown in Figure 7. Model of Dynamic Bayesian Network is shown in Figure 8.

Figure 8 contains all characteristic data in different groups. According to different environments and corresponding characteristic data, computing can be made in the process of recognition and identification. Variable state sets in Dynamic Bayesian Network are shown as follows.

Driver's propensity includes conservative type, common-conservative type, common type, common-radical type, and radical type; speed of target vehicle includes small, medium, and large; acceleration of target vehicle includes small, medium, and large; headway includes large, medium, and small; relative speed includes slow, moderate, and fast; relative acceleration includes small, medium, and large; deceleration frequency includes high, middle, and low; acceleration frequency includes high, middle, and low; performance reaction time includes long, medium, and short; conservative lane-changing frequency includes high, middle, and low; risky lane-changing frequency includes low, middle, and high.

Variable states are fuzzy set. Definition of state is derived from relative change of data during driving. If states are divided uniformly, then the differences of driver's characters cannot be represented truly. State thresholds of drivers are different. The data of inputting model is expressed with probability. In this paper, membership degree is to express the probability of certain characteristic data. If sample data x contains N characteristic data, it

Table 6: State transition probability of Dynamic Bayesian Network under T7 conditions.

New/old node	State transition probability of Dynamic Bayesian Network				
	Ty1 (old)	Ty2 (old)	Ty3 (old)	Ty4 (old)	Ty5 (old)
Ty1 (new)	0.60	0.20	0.10	0.05	0.05
Ty2 (new)	0.15	0.60	0.15	0.05	0.05
Ty3 (new)	0.05	0.10	0.70	0.10	0.05
Ty4 (new)	0.05	0.05	0.15	0.60	0.15
Ty5 (new)	0.05	0.05	0.10	0.15	0.65

Table 7: Initial probability of different driver's propensity.

Calibration result	Initial probability				
	P (Ty1)	P (Ty2)	P (Ty3)	P (Ty4)	P (Ty5)
Ty1	0.75	0.10	0.05	0.05	0.05
Ty2	0.10	0.70	0.10	0.05	0.05
Ty3	0.05	0.10	0.70	0.10	0.05
Ty4	0.05	0.05	0.10	0.70	0.10
Ty5	0.05	0.05	0.05	0.10	0.70

will be expressed with the value of membership degree. P_i is probability that characteristic component is subordinate to i. There are three kinds of eigenvector state. Calculation formula of membership degree is shown as follows:

$$\begin{gathered} P_1 = \left(1 + \left|\frac{a_i - a_{i\ \min}}{a_{i\ \max} - a_i}\right|\right)^{-4}, \\ P_2 = \left(1 + \left|\frac{a_i - \overline{a_i}}{a_{i\ \max} - a_i}\right|\right)^{-1}, \\ P_3 = 1 - \mathrm{P}_1 - \mathrm{P}_2, \end{gathered} \tag{3.4}$$

where $\overline{a_i}$ is mean value of known sample data, a_i is observed value of characteristic data, and $a_{i\ \min}$ and $a_{i\ \max}$ are minimum and maximum of observed values.

3.3.1. Prophase Parameter Setting

Conditional probability matrix is a kind of expert knowledge, which represents an opinion of causality between correlative nodes in network. According to expert experience, characteristic data of driver's propensity includes headway, relative speed, deceleration frequency, acceleration frequency, performance reaction time, conservative lane-changing frequency, and risky lane-changing frequency during stable driving under vehicle group of T7. So its inference rule is probabilistic manner. Initial conditional probability is got by expert experiences. When the number of data in database reaches to a certain capacity, probability will be got by computing.

According to the above inference rule, conditional probability matrices of driver's characteristics are gained and shown in Tables 3, 4, 5, and 6. d_1 is acceleration frequency, d_2 is

Table 8: Recognition and identification result of driver's propensity (expert probability).

Type	Time	Recognition and identification result (expert probability)				
		Ty1	Ty2	Ty3	Ty4	Ty5
Ty1	1	0.63067	0.14054	0.10462	0.06543	0.05874
	2	0.66285	0.15179	0.09091	0.04815	0.0463
	3	0.68018	0.14084	0.11021	0.01992	0.04984
	...	...	...	...	...	...
	10	0.85191	0.06092	0.03991	0.03909	0.00817
Ty2	1	0.14124	0.61423	0.12424	0.07676	0.04353
	2	0.12077	0.64089	0.13091	0.05914	0.04829
	3	0.13541	0.65434	0.11333	0.05559	0.04133
	...	...	...	...	...	...
	10	0.05357	0.84156	0.06255	0.01744	0.02488
Ty3	1	0.04137	0.15113	0.61122	0.12872	0.06756
	2	0.05448	0.14411	0.64415	0.13575	0.02151
	3	0.05333	0.12483	0.68329	0.10621	0.03234
	...	...	...	...	...	...
	10	0.04184	0.05131	0.84024	0.05879	0.00782
Ty4	1	0.01266	0.06271	0.11206	0.64751	0.16506
	2	0.03132	0.03185	0.12166	0.65865	0.15652
	3	0.03257	0.06239	0.10242	0.66757	0.13505
	...	...	...	...	...	...
	10	0.02226	0.02633	0.04422	0.85572	0.05147
Ty5	1	0.06148	0.06211	0.09043	0.17782	0.60816
	2	0.04468	0.07452	0.08471	0.15531	0.64078
	3	0.04462	0.03474	0.09399	0.14577	0.68088
	...	...	...	...	...	...
	10	0.02312	0.02257	0.05262	0.04704	0.85465

deceleration frequency, d_3 is performance reaction time, d_4 is risky lane-changing frequency, d_5 is conservative lane-changing frequency, d_6 is headway, and d_7 is relative speed.

It is noticed that conditional probability matrix is a kind of expert knowledge, so it has certain subjectivity. Sample data can be debugged repeatedly. Matrix data can be adjusted reasonably to improve the creditability of assessment result.

Due to the limited space in this paper, prophase parameter setting of other groups is not amplified any more.

3.3.2. Anaphase Parameter Setting

When the number of data reaches to a certain capacity, the database of driver's propensity can be established. According to driver's psychology test results, the data is classified to five types: conservative type, common-conservative type, common type, common-radical type, and radical type. Data of each type consist of characteristic data extracted and the recognition result of driver's propensity in prophase stage. In the same results of psychology tests, statistical analysis for data is to determine the proportion of characteristic data from

Table 9: Recognition and identification result of driver's propensity (statistical probability).

Type	Time	Recognition and identification result (statistical probability)				
		Ty1	Ty2	Ty3	Ty4	Ty5
Ty1	1	0.73461	0.15486	0.06825	0.03038	0.01190
	2	0.77525	0.11735	0.05814	0.03394	0.01532
	3	0.81994	0.11206	0.01064	0.04224	0.01513
	...	...	...	...	...	...
	10	0.93704	0.02811	0.01651	0.01004	0.00829
Ty2	1	0.10751	0.71301	0.11708	0.02018	0.04223
	2	0.09211	0.72634	0.09094	0.04531	0.04530
	3	0.07130	0.81076	0.08220	0.02817	0.00758
	...	...	...	...	...	...
	10	0.02198	0.94139	0.02289	0.01247	0.00128
Ty3	1	0.06365	0.11161	0.70473	0.11451	0.00550
	2	0.02781	0.11532	0.70561	0.11371	0.03755
	3	0.03796	0.10864	0.74603	0.10353	0.00384
	...	...	...	...	...	...
	10	0.00302	0.03251	0.94079	0.02103	0.00264
Ty4	1	0.01647	0.05396	0.09593	0.73192	0.10172
	2	0.00506	0.02362	0.10056	0.76312	0.10764
	3	0.01482	0.03376	0.08892	0.79106	0.07145
	...	...	...	...	...	...
	10	0.00227	0.01161	0.02368	0.93504	0.02741
Ty5	1	0.02530	0.03231	0.07193	0.16028	0.71018
	2	0.02938	0.02224	0.07548	0.14080	0.73210
	3	0.01952	0.02803	0.06931	0.11413	0.76901
	...	...	...	...	...	...
	10	0.00022	0.00671	0.01712	0.03149	0.94446

driver's propensity in different traffic environments in order to determine the conditional probabilities in Dynamic Bayesian Network. The determination of state transition probability of Dynamic Bayesian Network is similar to that of conditional probability, so the process is not amplified any longer.

3.4. Model Verification

There are two parts of recognition and identification model. Firstly, recognition can be taken with data from expert experiences. Secondly, recognition of driver's tendency can be taken with statistical data. In the situation of absence of another evidence, initial states depend on initial value set with driver's propensity, which is shown in Table 7.

According to the above several circumstances, initial values of different drivers are taken as a rational starting point. Evidence in different nodes can be collected (assuming independent). Vast characteristic data and recognition results for several drivers can be collected in this paper. The data of five typical driver's propensity (initial calibration) is

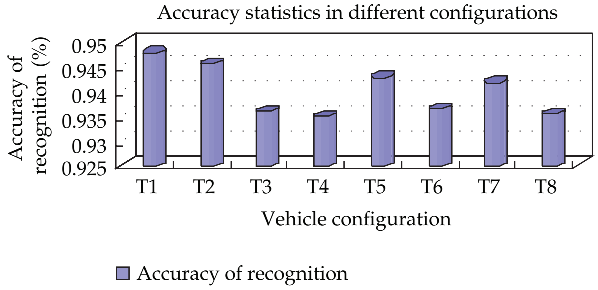

Figure 9: Accuracy of recognition in different situations.

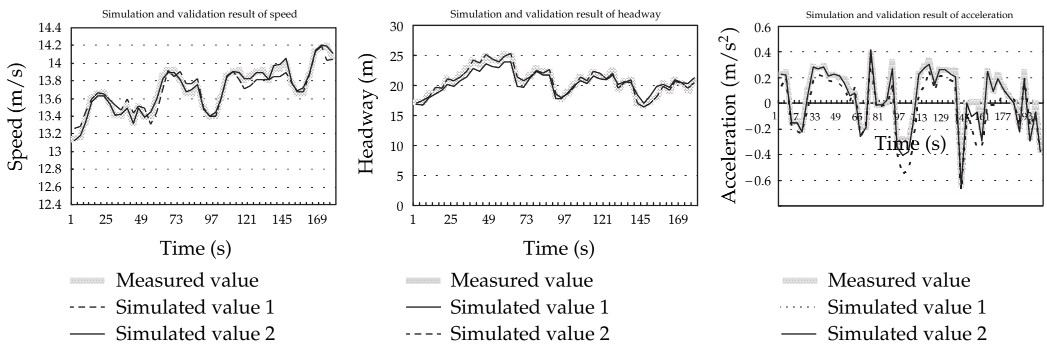

Figure 10: Verification results of speed, headway, and acceleration.

amplified under T7 conditions. Tables 8 and 9 are recognition and identification results of driver's propensity (includes expert probability and statistical probability).

The same method is used to verify accuracy of recognition for driver's propensity in different groups. The result is shown in Figure 9.

Verification results are shown in Figure 10. Curve 1 is the result without considering the change of driver's propensity in the simulation process. Curve 2 shows the situation process with considering driver's propensity in real time.

Microscopic models considering differences of driver's propensity are more precise to simulate driver's behaviors. Meanwhile, scope of application is very broad.

Accuracy of recognition and identification model is relatively higher under multilane environments. It also can meet the need of dynamic recognition for driver's propensity under multilane conditions.

4. Conclusion

Driver's propensity can represent their affection states in the process of vehicle operation and movement. It can change along with environment and affect profoundly drivers' cognition and process procedure on environment information. Therefore, the real-time identification of driver's state is the key to realize the driver-assistance systems and the active security warning systems. In this paper, situation factors (vehicle group) that affect directly driver's affection among environment factors are considered under two-lane conditions. Then dynamic recognition and identification model of driver's propensity can be established in time-varying environment through Dynamic Bayesian Network. It also can provide a theoretical basis for the realization of human-centered and personalized automobile active safety systems. For three-lane or more complicated environments, recognition and computing of driver's affection need further research.

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