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Dynamic Recognition Model of Driving Propensity Based on BPTT and Naive Bayes

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Abstract The driver's driving propensity will change dynamically in the short term due to the influence of emotion during the driving process, and the driving propensity will vary with the intensity of emotion in driving. In this paper, we propose a driving propensity dynamic recognition model based on BPTT and Naive Bayes, which can predict the driving data with drivers' emotion in a short time and identify the driving propensity in real time. The results show that the model can effectively identify driving propensity categories under angry driving emotions, and the accuracy of the driving propensity identification is 88.10%, which can intuitively reflect the change of driving propensity with the change of external environment, and it is helpful to improve the personalized driving assistance system.

Keywords Driving mood; BPTT algorithm; Naive Bayes; Driving propensity; Dynamic identification

1. Introduction

In recent years, more and more traffic accidents are closely related to the driver's personalized driving behavior, and the driver's emotion and the driving propensity can affect the data of driving behavior. Therefore, the research on emotion in driving and driving propensity have gradually become a research hotspot in the field of transportation. Wang Xiaoyuan et al. [1] took the driver's driving propensity as the research object, analyzed the influence of the driver's physiological and psychological parameters on the driving behavior, and obtained the characteristic parameter that can characterize the driving propensity. Xu Ting et al. [2] used AdaBoost to establish a classification model, and divided the truck drivers' propensity into radical type and conservative type. The average recognition accuracy can reach 98.74%. Zheng Yifang [3] proposed a strategy of driving pattern recognition, which can distinguish the driver's style and intention of driving in real time. Cordero Jorge et al. [4] built a hierarchical model to identify the driving style of advanced driver assistance system (ADAS), which considers the driver's emotion, state and driving style itself, and has a high recognition rate. Weilong Liu [5] proposed a method of driving style recognition, which uses Catboost as the basic classifier and semi supervised learning mechanism to reduce the dependence on data labels and improve the ability of recognition. Qun Wang et al. [6] put forward a model of driving style recognition based on random forest is proposed,, which shows that the recognition model based on random forest can effectively identify the different driving modes of mining trucks under heavy load and no-load operation, and the overall accuracy of the model is 95.39% and 90.74% respectively. Hamid Reza Eftekhari [7] uses a multi-layer perceptron to detect all the driver's action types in the process of driving, and gives three fuzzy numbers to the driver's lane change, turn and engine, and then evaluates the score of safe driving and aggressive driving by determining the similarity between the three fuzzy numbers and fuzzy modes, with an accuracy of 87%. Wu Zhenxin [8] used K-means clustering method and D-S evidence theory decision fusion method for clustering analysis to identify driving propensity, and the recognition rate reached 80%. Zhao Han et al. [9] put forward a multi-level recognition method of driving style considering traffic flow density. Under the influence of different traffic flow density, this method has high recognition accuracy for driving style. Wan Yu [10] used the improved DBSCAN algorithm to identify the driving style in order to avoid the problem of missing information and inaccurate recognition when identifying the driving style. According to the driving style score, the driving style was divided into five categories, and the influence of the collection period on the recognition results was discussed. Li Lizhi [11] designed a road test about driving style and established the driving style database, proposed a scheme for driving style recognition and objectification, and verified it with test samples to obtain high recognition accuracy.

To sum up, at present, the research on identification of driving propensity has been more in-depth, and the identification accuracy has reached a high level. However, in the previous research results, the time series of driving data and the real-time dynamic changes of driving propensity are rarely considered. In this paper, the BPTT and Naive Bayes identification model is used to identify the driving propensity of multi index driving data, the prediction of driving propensity changes with the change of the external environment, and then the information of prediction can be fed back to the driver in time, which is helpful to improve the safety early warning function of vehicle drive-assisted system.

2. Experiment and Data

2.1. Experiment of inducing emotion

The emotion-inducing material used in this experiment comes from the Chinese Emotional Stimulation Material Library of Beijing Normal University. According to the different sensory channels presented by the materials, the emotional materials in this experiment include visual (picture), auditory (music) and multi-channel stimulus materials (video). Each driver was asked to watch anger videos or related pictures for 3 ~ 5 minutes. After watching, the subjects were evaluated by self-report and behavior observation. If anger was successfully stimulated, then fill in the anger maintenance time scale; if the effect of emotion stimulation was not good, the experiment of emotion induction was repeated. The intensity of anger was recorded every minute. In view of the difference between the time of emotion induction and maintenance in the laboratory and the actual process of emotion generation, only 9 minutes were selected for specific analysis. The emotional activation metric is shown in Figure 1.

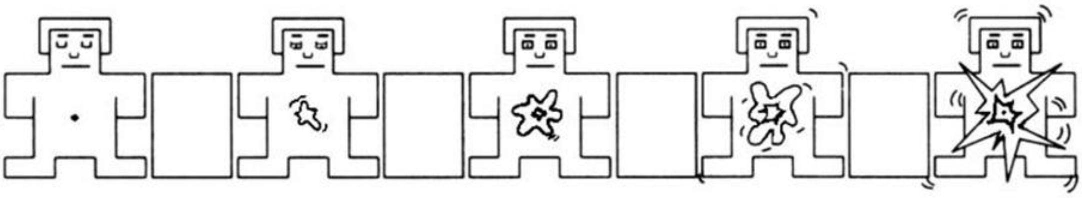

Figure 1: Emotional activation scale

In the above activation scale values, the scores of five human images are 1, 3, 5, 7 and 9 respectively. If the driver's feeling is between two small people, the scores are 2, 4, 6 and 8. Each driver evaluates his or her emotional intensity according to the corresponding score under the emotional activation scale, once every minute, for a total of 9 minutes. The design of the emotional maintenance time recording scale for these 9 minutes is shown in Table 1, and P-score is the value of emotional activation.

Table 1: Design of emotional maintenance time recording scale

Time	**1st minute**			**2nd minute**			**3rd minute**		
	1	2	3	1	2	3	1	2	3
P	4	5	6	4	5	6	4	5	6
	7	8	9	7	8	9	7	8	9
Time	**4th minute**			**5th minute**			**6th minute**		
	1	2	3	1	2	3	1	2	3
P	4	5	6	4	5	6	4	5	6
	7	8	9	7	8	9	7	8	9
Time	**7th minute**			**8th minute**			**9th minute**		
	1	2	3	1	2	3	1	2	3
P	4	5	6	4	5	6	4	5	6
	7	8	9	7	8	9	7	8	9

2.2. Simulated driving experiment

The driving simulation experiment is mainly based on the human, vehicle, environment comprehensive simulation experimental platform and the interactive automobile driving simulation experiment platform of multi person and multi machine. The driving simulation scene is a multi-lane highway with proper traffic flow and the weather is good. Before the start of the experiment: introduce the relevant operation and precautions of the driving simulator to the driver, so that each driver can drive for 10 minutes to adapt to the operation method and sports performance of the driving simulator, and eliminate the driving tension or discomfort.

Formal experiment: first of all, drivers are asked to watch the same emotional stimulus materials and time as the emotional induction experiment to ensure that the emotional induction effect is roughly the same. After the emotional induction, the simulation experiment of driving is carried out, including straight driving, turning, lane changing, acceleration and deceleration and other driving behaviors. Each experiment lasted for 9 minutes. During driving, the driver kept his concentration and could not talk with others. The experiment was repeated three times in anger with an interval of 5 minutes. Each driving simulation experiment was taken as a group of data, which was recorded by the recorder.

After the experiment number the driver and save the driving data.

2.3. Data statistics of emotional activation scale

In the process of driving, the intensity of anger will weaken with time, and the driving state will also change dynamically under the influence of emotion. Through the change of P-score per minute, we can know the performance state of emotion at the current moment. According to the degree of emotional activation within 9 minutes of self-evaluation, we can further calculate the time that emotion can be maintained in the driving process, and then consider the influence of different emotional intensity on the change of driving data. The activation degree of anger emotion in driving is shown in Table 2. According to the analysis of the emotional activation measurement table under anger, it can be seen that the driver's emotional activation degree is obviously strong in the first few minutes. As time goes on, the emotional intensity of 15 drivers gradually decreases.

Table 2: Data statistics of anger activation scale

Driver \ Time(min)	1	2	3	4	5	6	7	8	9
1	2	3	3	4	5	6	8	8	8
2	1	1	3	5	6	6	7	8	8
3	1	2	3	5	5	6	8	8	9
4	2	2	3	4	4	5	6	6	8
5	2	3	3	3	5	5	6	7	9
…	…								
14	2	2	3	3	4	5	6	7	8
15	1	2	2	4	4	4	6	7	7

2.4. Data of simulated driving experiments

Table 3: Changes of some driving index data of driver No.1

Time	RPM (r/minute)	Speed (km/h)	Steering (ratio)	Throttle (ratio)	Accel (m^2/s)	Distance to left border(meter)
1st minute	3090	66.8657	-0.0009	0.6560	0.10158	8.13085
	3190	69.4059	0.00245	0.6560	0.70561	8.35302
	3098	68.5266	0.00015	0.6560	-0.24425	8.31255
2nd minute	3019	86.6956	-0.0183	0.6786	0.28211	5.09375
	2729	87.8779	-0.0101	0.6616	0.32842	5.05566
	2986	87.0255	-0.0115	0.6689	-0.23678	5.062589
…				…		
9th minute	1387	53.1126	0	0	-0.54650	8.31652
	1476	52.3557	0.00128	0.0830	-0.21025	8.57263
	1398	52.3649	0.00154	0.0216	0.00256	8.50026

According to the simulation driving experiment, the driving data in the 9 minutes were counted, and several indicators such as speed, rpm value, steering angle, throttle, accel, distance left border, acceleration frequency and braking frequency were selected to express the changes of driving data under anger, the data changes of some indicators of driving are shown in Table 3 (limited to 3 seconds per minute).

3. Dynamic identification model of driving propensity

Driving propensity is a relatively stable driving habit formed by drivers in the long-term driving process, which cannot be measured directly and can only be shown through external performance such as driving data. The BPTT algorithm can predict driving data in steps based on time series during the dissipation of driving emotions, use fuzzy C-mean clustering to classify the driving propensity of every second of driving data, and take into account that the change of driving tendency is increasing or decreasing, and the accuracy of driving propensity recognition using BPTT algorithm only is not high, and the combination of plain Bayesian model to classify and identify the driving data that predicted by BPTT algorithm can achieve both the identification of driving propensity type in the process of gradually decreasing driving emotion intensity and the purpose of improving the accuracy of driving propensity recognition.

3.1. Fuzzy c-means clustering

With the help of fuzzy c-means clustering, the driver's driving data including time series is divided into driving propensity, so as to train and verify the dynamic identification model of driving propensity.

The fuzzy C partition space is shown by equation (1).

$$M=\left\{U\in R^{c\times N}\left|u_{ik}\in[0,1],\forall i,k;\sum_{i=1}^{c}u_{ik}=1,\forall k;0<\sum_{i=1}^{N}u_{ik}<N,\forall i\right.\right\} \tag{1}$$

There are C classes, a total of N data (samples), for a sample, its membership value sum in all classes is 1, for a class, the membership value sum of all data is less than N.

In the objective function, the distance between the sample and each prototype is weighted by membership value.

$$J(U,V)=\sum_{k=1}^{N}\sum_{i=1}^{c}u_{ik}^{m}(d_{ik})^2,m\in[1,+\infty) \tag{2}$$

Euclidean distance is used in this study.

$$d_{ik}^2=\left\|x_k-v_i\right\|_A^2=(x_k-v_i)^T A(x_k-v_i) \tag{3}$$

The elements of fuzzy partition matrix are:

$$u_{ik}=\frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}} \tag{4}$$

The cluster centers are as follows:

$$v_i=\frac{\sum_{k=1}^{N}(u_{ik})^m x_k}{\sum_{k=1}^{N}(u_{ik})^m} \tag{5}$$

To some extent, fuzzy clustering is to find the cluster center. According to the previous research, the driving propensity is divided into conservative type, ordinary type and radical type, which are expressed by 1, 2 and 3 respectively. Considering the engine speed, speed, acceleration, steering wheel angle, accelerator pedal strength, Lane centerline offset distance, acceleration frequency, braking frequency and other characteristic parameters in the driving process, the driving propensity is divided according to the driver's driving data, and the driving propensity label is shown in Table 4.

Table 4: Driving propensity label

Driving propensity	**Conservative type**	**Conventional type**	**Aggressive type**
Label	1	2	3

3.2. BPTT

BPTT algorithm is a commonly used method to train RNN, also known as back propagation over time. The core idea of BPTT is the same as BP algorithm, which continuously searches for better points along the negative gradient direction of the parameters to be optimized until convergence. Considering the timing of driving data in the driving process, BPTT algorithm can be used for short-term prediction. The specific prediction process is shown in Figure 2.

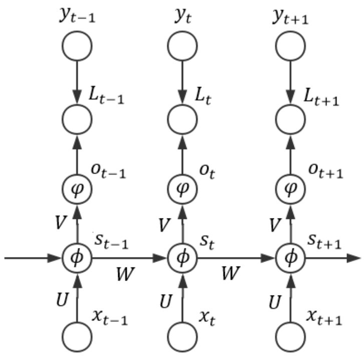

Figure 2: The algorithm expansion diagram of BPTT

In Figure 2, ϕ is the activation function of the hidden layer, φ is the transformation function of the output layer, $L_t = L_t(o_t, y_t)$ is the loss function of the model, the total loss of the model (the length of the model input sequence is n) is $L = \sum_{t=1}^{n} L_t$, and $o_t = \varphi(V_{st}) = \varphi(V\varphi(Ux_t + Ws_{t-1}))$ is obtained, and $s_0 = 0 = (0, 0, \ldots, 0)^T$. Let $o_t^* = V_{st}, s_t^* = Ux_t + Ws_{t-1}$, then $o_t = \varphi(o_t^*), s_t = \phi(s_t^*)$, get equations (6) and (7).

$$\frac{\partial L_t}{\partial o_t^*} = \frac{\partial L_t}{\partial o_t} * \frac{\partial o_t}{\partial o_t^*} = \frac{\partial L_t}{\partial o_t} * \varphi'(o_t^*) \tag{6}$$

$$\frac{\partial L_t}{\partial V} = \frac{\partial L_t}{\partial V_{st}} \times \frac{\partial V_{st}}{\partial V} = (\frac{\partial L_t}{\partial o_t} * \varphi'(o_t^*)) \times s_t^T \tag{7}$$

It can be seen from $L = \sum_{t=1}^{n} L_t$ that its total gradient can be expressed by equation (8).

$$\frac{\partial L}{\partial V} = \sum_{t=1}^{n} (\frac{\partial L_t}{\partial o_t} * \varphi'(o_t^*)) \times s_t^T \tag{8}$$

Since it is a back-propagation algorithm, t should be cycled in descending order from n to 1, during which the "local gradient" on the time channel is calculated:

$$\frac{\partial L_t}{\partial s_t^*} = \frac{\partial s_t}{\partial s_t^*} * (\frac{\partial s_t^T V^T}{\partial s_t} \times \frac{\partial L_t}{\partial V_{st}}) = \phi'(s_t^*) * [V^T \times (\frac{\partial L_t}{\partial o_t} * \varphi'(o_t^*))] \tag{9}$$

$$\frac{\partial L_t}{\partial s_{k-1}^*} = \frac{\partial s_k}{\partial s_{k-1}^*} \times \frac{\partial L_t}{\partial s_k^*} = \phi'(s_{k-1}^*) * (\mathrm{W}^{\mathrm{T}} \times \frac{\partial L_t}{\partial s_k^*}), (k = 1, \ldots, t) \tag{10}$$

Calculate the gradient of U and W using the "local gradient" on the time channel:

$$\frac{\partial L_t}{\partial U} = \sum_{k=1}^{t} \frac{\partial L_t}{\partial s_k^{\ *}} \times \frac{\partial s_k^{\ *}}{\partial U} = \sum_{k=1}^{t} \frac{\partial L_t}{\partial s_k^{\ *}} \times x_k^{\ T} \quad (11)$$

$$\frac{\partial L_t}{\partial W} = \sum_{k=1}^{t} \frac{\partial L_t}{\partial s_k^{\ *}} \times \frac{\partial s_k^{\ *}}{\partial W} = \sum_{k=1}^{t} \frac{\partial L_t}{\partial s_k^{\ *}} \times s_{k-1}^{\ T} \quad (12)$$

In order to verify the prediction performance of BPTT algorithm, take the driving data of subject 1 under anger as an example to predict the driving data in real time. The comparison results between some standardized test data and the corresponding data that predicted are shown in Table 5 and Table 6.

Table 5: Partial test data

Time(s)	RPM	Speed	Steering	Throttle	Accel	Distanced
			…			
206	0.9998	0.0214	-4.567e-06	2.191e-04	5.065e-05	0.0027
207	0.9998	0.0216	-3.031e-07	2.123e-04	-7.376e-05	0.0026
208	0.9998	0.0218	7.7e-07	2.056e-04	-7.376e-05	0.0026
			…			

Table 6: Corresponding forecast data

Time(s)	RPM	speed	steering	throttle	speedVect	distanced
			…			
206	0.9998	0.0214	-4.567e-06	2.191e-04	5.065e-05	0.0027
207	0.9998	0.0216	-3.031e-07	2.123e-04	-7.376e-05	0.0026
208	0.9998	0.0218	7.7e-07	2.056e-04	-7.376e-05	0.0026
			…			

In the process of algorithm training, in order to observe the similarity between the test data and the prediction data, the error value can be calculated and expressed by the error cost curve. The error cost curve is shown in Figure 3. With the increase of the number of iterations, the error value gradually decreases. When the error value is less than 1×10^{-4}, stop the iteration and get the prediction data.

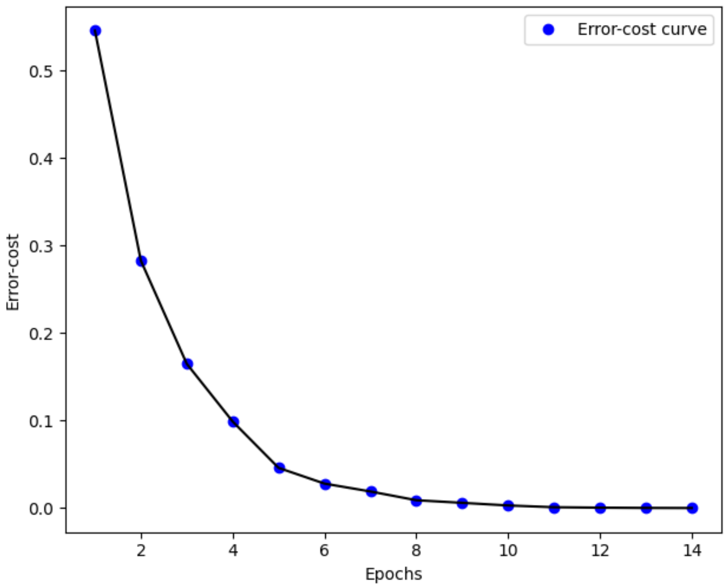

Figure 3: Error-cost curve

3.3. Naive Bayes

Naive Bayes is a classification method based on Bayes theorem and independent assumption of feature conditions. According to the fuzzy C-means (FCM) clustering, the driving data output per second can be mapped into three types of driving propensity: common type, conservative type and radical type. Some of the classified driving data are input into the naive Bayesian classification model for training, and then the driving propensity of the predicted driving data is identified. The specific steps are as follows:

①Let $x=\{a_1,a_2,\dots,a_6\}$ be an item to be classified, and each a is a characteristic attribute of x.

②Category set $C=\{y_1,y_2,y_3\}$.

③Solve $P(y_1 \mid x), P(y_2 \mid x), P(y_3 \mid x)$

a.Find a set of items to be classified, which is called training sample set.

b.The conditional probability estimation of each characteristic attribute under each category is obtained statistically.

c.If each feature attribute is conditionally independent, the derivation according to Bayesian theorem is shown in equation (13).

$$P(y_i \mid x)=\frac{P(x \mid y_i)P(y_i)}{P(x)} \tag{13}$$

Since the denominator is constant for all categories, we only need to maximize the numerator, and because each characteristic attribute is conditionally independent, there is formula (14).

$$P(x \mid y_i)P(y_i)=P(a_1 \mid y_i)P(a_2 \mid y_i)\dots P(a_m \mid y_i)P(y_i)=P(y_i)\prod_{j=1}^{m}P(a_j \mid y_i) \tag{14}$$

④ If $P(y_k \mid x)=\max\{P(y_1 \mid x), P(y_2 \mid x),\dots, P(y_n \mid x)\}$, then $x \in y_k$.

3.4. Dynamic recognition model of driving propensity based on BPTT and naive Bayes

BPTT algorithm can predict the driving data with time series according to the principle of error back propagation, and naive Bayes can identify the driving propensity of the predicted driving data. Therefore, the dynamic identification model of driving propensity based on BPTT naive Bayes can identify the transient changes of driving propensity affected by the external environment in real time. The flow chart of the identification model algorithm is shown in Figure 4.

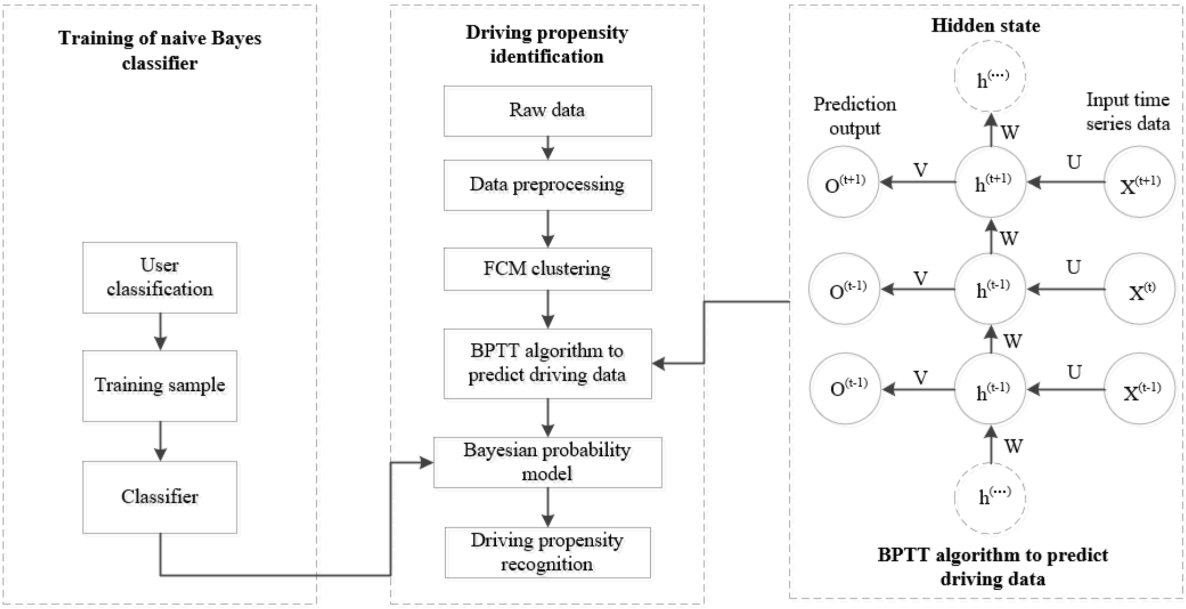

Figure 4: Algorithm flow chart

4. Results

The simulated driving data is used as the input of the model, and the driving propensity category is used as the output of the model for training. The confusion matrix of the output of naive Bayesian model in the process of model training is shown in Figure 5, and the identification accuracy is 91%, which indicates that the algorithm has obvious effect on the classification and identification of driving propensity.

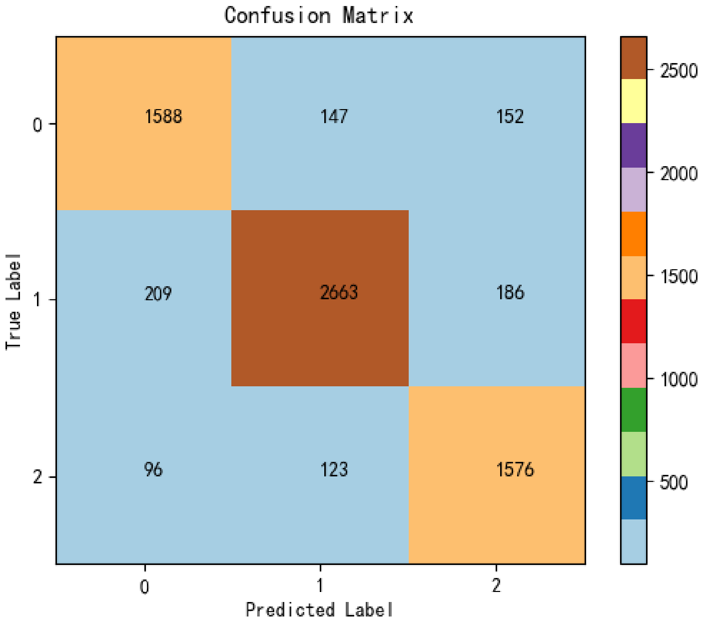

Figure 5: Confusion matrix of naive Bayesian model

The driving propensity dynamic identification model based on BPTT naive Bayes is used to identify the driving propensity in real time. In the process of driving, the driving data of the next second can be predicted in seconds according to the driver's driving state of nearly 30 seconds. The newly predicted driving data is used as input for continuous prediction, and the corresponding driving propensity is output. According to the driving propensity within one minute, the driving propensity with high probability is output as the driver's driving propensity in that minute, the stepwise dynamic identification prediction output of the model is shown in Figure 6.

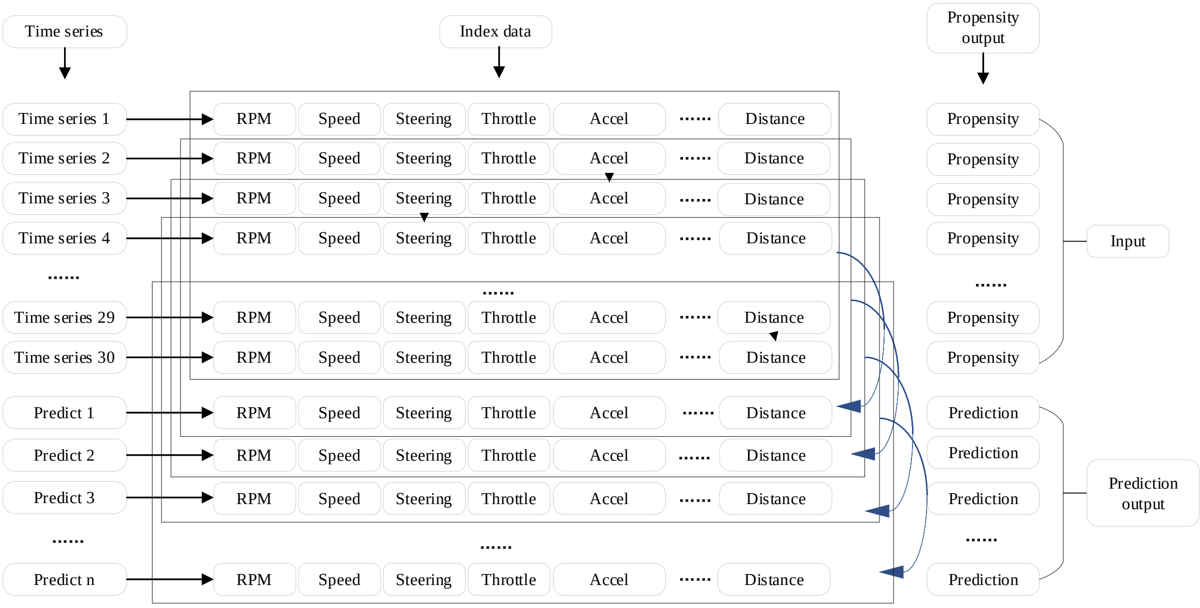

Figure 6: Model dynamic identification and prediction process

The driving data of 15 experimental objects is 540 seconds in 9 minutes. The driving propensity dynamic identification analysis is conducted for the driving data of 15 experimental objects respectively. The prediction and identification of driving data of each driver starts from the 31st second, with a frequency of 1 second / time, and the number of identification data per capita is 510. The identification accuracy is shown in Table 7, and the identification results of some experimental objects are shown in Figure 7.

Table 7: Dynamic identification accuracy of driving data

Subjects	Number of positive examples	Accuracy	Subjects	Number of positive examples	Accuracy
No.1	452	88.63%	**No.9**	420	82.35%
No.2	439	86.08%	**No.10**	456	89.41%
No.3	449	88.04%	**No.11**	465	91.18%
No.4	459	90.00%	**No.12**	460	90.20%
No.5	428	83.92%	**No.13**	458	89.80%
No.6	430	84.31%	**No.14**	443	86.86%
No.7	458	89.80%	**No.15**	468	91.76%
No.8	455	89.22%	**Total**	6740	88.10%

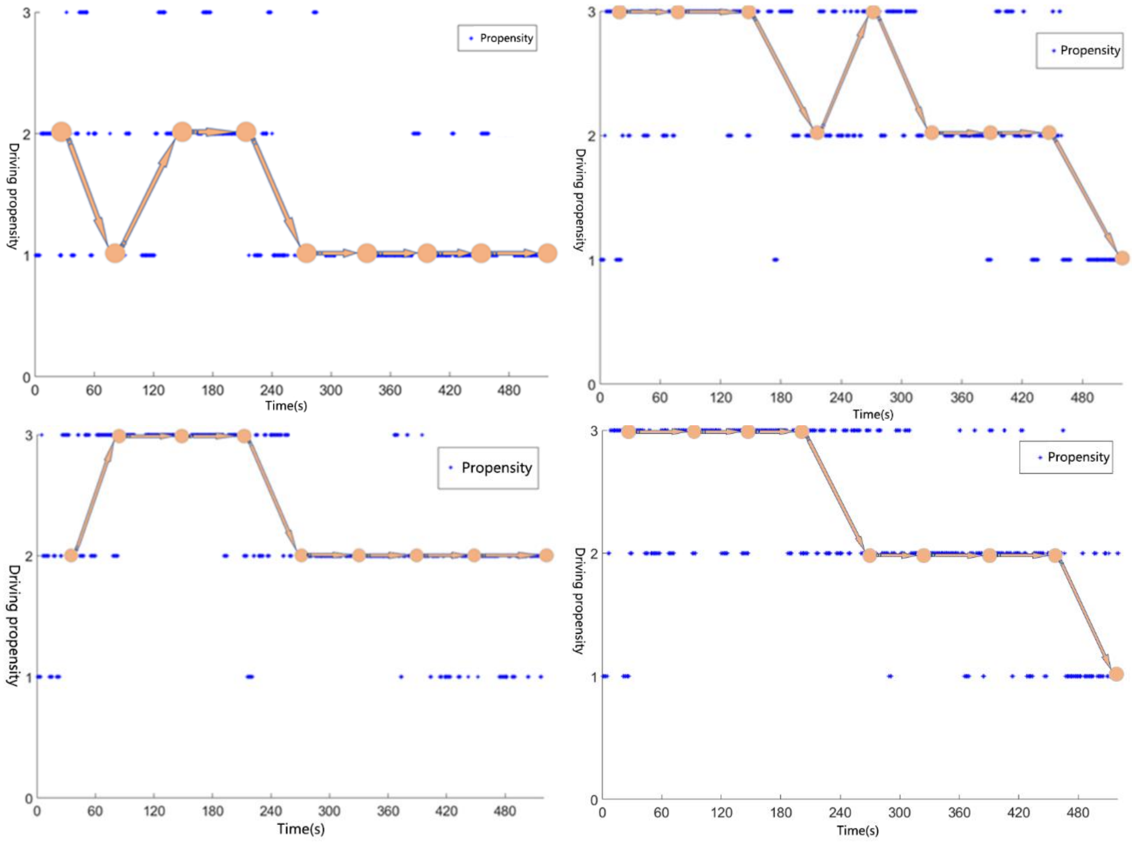

Figure 7: Identification results of driving propensity of No. 1, No. 4, No. 8 and No. 11 subjects

It can be seen from table 7 that the comprehensive accuracy of the algorithm is 88.10%, which indicates that the model can effectively predict the driving data and identify the driving propensity. The driving propensity value with the highest frequency of driving propensity in each minute predicted is taken as the driving propensity in that minute, and the dynamic change of driving propensity is represented by the dynamic line graph of driving propensity in Figure 7. With the decrease of the intensity of anger, the driving propensity moves from radical to conservative, it can directly show the relationship between driving propensity and dynamic changes of driving emotion.

5. Conclusion

Driver's driving propensity will change with the change of external environment. This paper establishes a dynamic identification model of driving propensity based on BPTT and Naive Bayes, which is used to identify the driving propensity of angry drivers in real time. The BPTT algorithm is used to complete the short-term prediction of driving data in the driving process, and then the driving propensity is identified by naive Bayes. It has been verified that with the decreasing intensity of anger, the driving propensity also shifts from radical to conservative. The accuracy of driving propensity output by the model is 88.10%, which can be used in automobile auxiliary driving system to further improve driving safety.

References

[1]. Xiaoyuan Wang, Yaqi Liu, Jianqiang Wang, Jinglei Zhang. Study on influencing factors selection of driver's propensity [J]. Transportation Research Part D, 2018(66):36-48.
[2]. Xu Ting, Zhang Xiang, Zhang Ya-kun, Wang Jian. Truck driver safety tendency classification based on the Ada Boost algorithm [J]. Journal of Safety and Environment, 2019, 19(04):1273-1281.
[3]. Zheng Yifang, Lu Ping. Strategy for Intelligent Drive Mode Detection Based on Driver's Intension
[4]. and Driving Scenario Estimation [J]. Automobile Applied Technology, 2020(09):53-57.
[5]. Cordero Jorge, Aguilar Jose, Aguilar Kristell, Chávez Danilo, Puerto Eduard. Recognition of the Driving Style in Vehicle Drivers. [J]. Sensors (Basel, Switzerland), 2020, 20(9):2597.
[6]. Liu W, Deng K, Zhang X, et al. A Semi-Supervised Tri-Cat Boost Method for Driving Style Recognition [J]. Symmetry, 2020, 12(3):336-354.
[7]. Qun Wang, Ruixin Zhang, Yangting Wang, et al. Machine Learning-Based Driving Style Identification of Truck Drivers in Open-Pit Mines. 2019, 9(1):19-42.
[8]. Hamid Reza Eftekhari, Mehdi Ghatee. A similarity-based neuro-fuzzy modeling for driving behavior recognition applying fusion of smartphone sensors [J]. Journal of Intelligent Transportation Systems, 2019, 23(1):72-83.
[9]. Wu Zhenxin, He Yunting, Yu Lijiao, Fu Lei, Chen Pan. Research on Driving Style Recognition Algorithm Based on Dig Data [J]. Automobile Technology, 2018(10):10-15.
[10]. Zhao Han, Liu Hao, Qiu Mingming, Cao Longkai, Zhang Yilei, Yu Wei. Research on the Driving Style Identification Method Considering the Influence of Traffic Density [J]. Automotive Engineering, 2020,42(12):1718-1727.
[11]. Wan Yu, Huang Miaohua, Wang Sichu. Research on a driving style recognition method based on improved DBSCAN algorithm [J]. Journal of Hefei University of Technology (Natural Science), 2020, 43(10): 313-1320.
[12]. Li Lizhi,Yang Jianjun, Liu Shangxi, Zhang Xianfeng, Guo Wencui, Li Ping. Research on Classification and Recognition of Driving Style of Domestic Crowds [J]. Journal of Chongqing University of Technology (Natural Science), 2019, 33(11):33-40.