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A risky prediction model of driving behaviors: especially for cognitive distracted driving behaviors

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***Abstract*—The non-driving related operation behavior in driving process has a significant impact on road traffic status and driving safety, but there is less systematic study on the main characteristics and influence mechanism of such behaviors. Aiming at this problem, four types of typical behaviors of normal and abnormal driving are monitored and recorded by real vehicle test. The cognitive distracted driving behavior is taken as the research object, and the influence mechanism and prediction method of distracted driving are studied by using the driver's physiological state and vehicle running state. This paper focuses on the changes and statistical characteristics of driver's physiological state parameters and vehicle running state parameters during distracted driving, and then explores the influence mechanism of different types of distracted driving tasks with different loads on driver's state. This paper analyzes the influence mechanism from two aspects of human and vehicle. Based on the comparison of behavior criterion and load criterion, the parameter system of cognitive distracted driving behavior considering driving load is obtained after cross analysis. The prediction model is established as the training sample of LSTM model, and the model is tested with the data collected from real vehicle test After 100000 iterations, the training accuracy is 90.2% on the training set and 74% on the test set. The results showed that the cross-comparison method is scientific and reasonable, and the prediction model of distracted driving behavior based on physiological state and vehicle running state has good accuracy.**

Keywords—driving behavior analysis, human factors, risk prediction, cognitive distracted driving

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I. INTRODUCTION

Vehicle driving has been integrated into people's daily life and greatly improved the efficiency of transportation. However, frequent traffic accidents have proved that driving car is a high-risk project. During the driving process, besides the main driving behaviors such as vehicle control, lane keeping, and road condition monitoring, the driver also performs behaviors that are not or not directly related to driving like making phone calls, talking with passengers or thinking, etc., which lead driver to be distracted and posing a serious threat to driving safety [1,2]. The main feature of this type of behavior is that it takes up the driver's mental load, and rarely or almost does not occupy the action resources and visual range, so it is often called cognitive distracted driving behavior [3,4].

Relevant scholars generally combined the driver's physiological indicators, vehicle handling and stability and vehicle running state, and conducted research on cognitive distracted driving behavior from the two aspects of the driver's physiological state and vehicle operating state.

(1) The impact of distracted driving behavior on the physiological state of drivers. Cognitive load overloads the physiological resources of the driver, thereby opening the maneuvering feedback loop of the car driver. Research by Cooper et al. [5] showed that even if these stressors did not cause a car accident, they would still reduce traffic efficiency. Reference [6], [7] found that cognitive and visual distracted driving behaviors could prolong the reaction time of drivers in dealing with lateral and longitudinal conflicts.

(2) The impact of distracted driving behavior on the operating state of the vehicle. The impact of distracted driving behavior on the driver's manipulation behavior directly affects the operating state of the vehicle, which is mainly reflected in the differences in the indicators such as vehicle trajectory, following distance, and driving stability from normal driving. In related domestic research, Ma et al. [8] found that the vehicle operating state was different during normal driving and distracted driving, which was mainly manifested in the change law of the longitudinal and lateral control activities of the vehicle and the stability and other aspects of the vehicle operating state. Li et al. [9] found that the use of mobile phones would reduce the driver' s ability to use turn signals, gear shifts, and velocity maintenance to varying degrees. Similarly, Dozza et al. [10] found that using mobile phones during driving would cause the driver's control ability to be weakened. Jin and Wang et al. [11,12] used data mining methods to filter out the feature evaluation index set of distracted driving behavior, and established a high degree of mapping relationship between vehicle operating state parameters and distracted driving behavior. Stinchcombe [13] et al. found that as the load of cognitive distracted driving behavior increased, the vehicle lateral control parameters changed significantly. Kountouriotis [14] and Baldwin [15] et al. found that the steering wheel turning angle, when the driver was distracted, was generally significantly smaller than the value during normal driving, and the steering wheel angular acceleration and steering wheel turning rate were significantly

increased. The research results of Yoon [16] et al. showed that watching videos or using smartphones would affect the driving behavior of drivers to varying degrees.

In summary, cognitive distracted driving behavior has a non-negligible impact on driving safety, and its identification, prediction, and prevention are essential. Limited by the movement and visual resources it occupies, the main difficulty in recognizing or predicting such behaviors is that the features are not easy to obtain, and the direct impact of cognitive load on driving behavior is rarely considered, which makes it difficult to improve the accuracy of recognition or prediction. Take Mario et al. [17] using the driver's physiological signals and vehicle motion information to establish a driver's state prediction model as an example. The model could achieve 97.5% accuracy (for the driver in the training set) when predicting the driver's state. But when the model was extended to drivers outside the training set, the accuracy rate was only 46.9%.

This paper aims to select typical cognitive distracted driving behaviors as the research object and propose an improved subjective load measurement method as an assisted load analysis tool. The influence mechanism of cognitive load on the driving behavior state will be explored. After that, the difference in the representation parameters of cognitive distracted driving behavior under different load conditions could be obtained. And then so will the accurate representation parameter set of cognitive distracted driving behavior, which will be used as sample data to establish a prediction model based on LSTM. The multiple analysis and demonstration of the applicability of the model will eventually result in a cognitive distracted driving behavior prediction model with better accuracy under real vehicle test conditions.

II. DRIVING LOAD ASSESSMENT METHOD

A. Cognitive distracted driving behavior

Phone calls can distract drivers' attention. Due to the limited ability of the brain to perform two or more tasks at the same time, drivers will pay less attention to potential hazards on the road when performing secondary driving tasks. According to a survey in 2016, 84.1% of drivers use their mobile phones at least once a week [18]. Another literature [19] showed 52% of drivers had distraction during driving. The common types of distracted driving behaviors were: communication with passengers (15%), mobile phone calls (6%), using air conditioning and broadcasting systems (4%). Literature [20] shows that the quantity of driving risk events of young drivers will be increased when the co drivers ride with peers. After in-depth study, it was found that the main way is to make the driver in a state of distracted thinking or cause emotional fluctuations through conversation. The increase of driving task load brought by this way will significantly reduce driving performance. Pavlou et al. [21] designed the effect of conversation test on driver's driving ability, and found that talking with passengers has negative effect on driving behavior safety. Based on the above research and analysis results, in this paper, handheld cell phone calls, chatting and thinking are classified as cognitive distracted driving behaviors.

B. Driving behavior design and driving load application

After being familiar with the vehicle condition, the site condition and the experimental scheme, each subject started carring out the experiment. A total of 1 kind of focused driving behavior and 3 typical cognitive distracted driving behaviors (handheld cellphone calls, thinking and chatting) were selected. In order to quantitatively apply the load of distracted driving behaviors, the n-back paradigm is used as the driving load application method. N-back test is a common means of applying cognitive load in the field of psychology [22]. It mainly uses the way of thinking to occupy the auditory working memory of the subjects and exerts mental load. This paper represents the driving behavior of using mental load such as thinking. In a group of n-back tests, subjects will hear 10 randomly set 1-digit numbers (0-9) in turn. The pause interval between each number is 2 seconds. The subjects need to repeat the nth digit before the number after hearing a certain number.

(1) Focused driving (FD). The subjects were absorbed in driving the vehicle and required to devote all their energy to control and keep the vehicle running normally.

(2) Handheld cellphone calls (HCC). The subjects answered the call from the test assistant by a handheld cell phone, the test assistant began to ask questions to the driver, and the subjects answered them within the limited time. The questions were in the form of 1-back and 2-back tests.

(3) Thinking (THK). The subjects carried out the driving test in the test site. They listened to the questions given by the test assistant and got the answers by themselves. There was no need to answer the results of the questions which were in the form of 1-back and 2-back tests.

(4) Chatting (CHT). The test subjects conducted the driving in the test site, and answered the test assistant's questions throughout the 1-back and 2-back tests, and answered the results of the questions within 2 seconds.

C. Experimental conditions

The real vehicle test site is a national closed test park. All road construction of the site meets the national standards of China. The top view of the site is shown in Fig. 1 and the unnecessary parts in the map have been concealed. The pavement of the test site is made of cement concrete, with no potholes and clear marks. The main test sections 1 ~ 4 are two lanes, the design maximum speed is 70km/h, the road width is 6m, and the total length of the selected test section is about 3.6km.

Fig. 1. Schematic diagram of the test site

The HEX-NET hardware and VC-scope analysis software were combined to collect vehicle operating parameters through the OBD diagnostic interface of the test vehicle. The BIOPAC's MP160 physiological signal recorder with Acqknowledge 4.2 software were used to collect the driver's physiological signals by skin contact. The main software and hardware test equipment is shown in Fig. 2.

D. Experiment scheme

According to the data report of drivers released by the Road Traffic Safety Research Center of the Ministry of Public

Security in 2019, the ratio of male to female is about 7:3. Therefore, a total of 30 subjects (20 males, 10 females) were recruited in the whole trial. Due to equipment wearing, wire dropping and other problems, part of the stored data failed. The actual effective data came from 26 people (19 males and 7 females), whose average driver age were 2.6 years. Each subject was divided into three stages: familiar with the test process, practice driving and formal vehicle test. The modified NASA-TLX questionnaire was completed after each test.

Fig. 2. Vehicle running parameter acquisition equipment and physiological parameter recorder

III. Parameter Analysis of Cognitive Distracted Driving Behavior Based on Driving Load

A. Improved comprehensive evaluation method of driving load based on NASA-TLX

National aeronautics and space administration task load index (NASA-TLX) was proposed by Sandra in 1998, which is mainly used in the subjective evaluation of psychological load in the field of human efficacy [23,24], such as astronauts, pilots, who need to process a large amount of information and make correct decisions under various tasks or emergencies. The psychological load of such people will affect their work performance to a certain extent. NASA-TLX assumes that workload is affected by mental demand, physical demand, temporal demand, performance, frustration level and effort [25]. After assessing each 6 factors on the scale, individuals made pairwise comparisons of the six factors to determine the source of the higher workload factor for each pair of factors. A comprehensive evaluation method for quantifying workload level is established by using factor rating and relative weight calculated from the comparison stage.

Although NASA-TLX is considered to be superior to other methods in terms of sensitivity and is widely accepted and used by researchers, it was originally designed to assess pilots' workload during aviation flight, with the goal of developing a test that can better assess psychological load [26]. In order to apply this method to the driving load evaluation of this paper, a load assessment method suitable for automobile drivers is proposed. In NASA-TLX, one of the evaluation indexes is "physical demand", that is, "how much physical activity do you need? Such as: push, pull, rotate, control, etc. As the modern automobile is a highly automated vehicle, the physical expenditure of the driver is low, so it is not suitable for the mental load of vehicle drivers.

Based on the original version of NASA-TLX, the applicability of NASA-TLX in vehicle driving load assessment (especially in the study of distracted driving behaviors) was adjusted. First, the "physical demand" is replaced by "visual occupancy" to investigate the occupancy of sensory resources by various driving tasks. Second, "Operating performance" is equivalent to "driving performance". The subjective driving performance evaluation based on the self-report of the subjects is used to reflect their load. The two poles of the dimension are opposite to the other five indicators. The better the driving performance is, the lower the load is; otherwise, the lower the driving performance, the higher the load. To sum up, the six groups of drivers' load evaluation indicators are shown in Table I. After completing each single test, drivers fill in the psychological load questionnaire. The questionnaire adopts the 10 level Likert scale (indicating the load from "low" to "high").

TABLE I. EVALUATION INDEX OF DRIVER LOAD

Index	Poles	Description
Mental demand	low/high	The mental demand (including attention and mental load) needed to think, make decisions, choose and search during driving.
Visual occupancy	low/high	The occupation of visual resources by driving tasks during driving.
Driving performance	high/low	Drivers' satisfaction with their driving performance.
Temporal demand	low/high	The driver's pressure from the time constraint is forced to feel the rhythm (leisurely, flustered, etc.).
Effort	low/high	The degree of effort required to complete the driving test.
Frustration level	low/high	When a driver performs a driving task, it comes from frustration such as emotion and pressure, or the level of constraint and stress (fatigue, insecurity, annoyance, discouragement, etc.).

B. Load evaluation of distracted driving behaviors

After the completion of a single driving test, each subject was investigated using the above driving load assessment method. The weight of each driving task's corresponding load evaluation index was calculated, and each evaluation index was combined and paired with one by one comparison method. The subjects selected the evaluation index which contributed more to the load from each group, and determined the weight of the index to the driving load according to the selected times in each group, after normalization, the Table II is obtained. The overall driving load evaluation value of single driving task is the weighted average value of six evaluation indices multiplied by 10, the evaluation results are shown in Table III.

TABLE II. WEIGHTS OF LOAD EVALUATION INDICES CORRESPONDING TO DRIVING BEHAVIORS

Index	Mental demand	Visual occupancy	Driving performance	Temporal demand	Effort	Frustration level
FD	0.131	0.110	0.221	0.220	0.144	0.174
HCC-2B	0.142	0.172	0.223	0.204	0.132	0.126
HCC-1B	0.139	0.171	0.226	0.207	0.135	0.122
CHT-2B	0.221	0.146	0.226	0.167	0.111	0.129
CHT-1B	0.145	0.160	0.235	0.215	0.118	0.127
THK-2B	0.155	0.143	0.198	0.237	0.128	0.139
THK-1B	0.148	0.133	0.243	0.222	0.122	0.133

TABLE III. LOAD EVALUATION RESULTS

Driving behavior	Application mode	Load capacity	Relative grade
FD	-	3.07	low
HCC	2-back	6.82	high
	1-back	5.77	medium
CHT	2-back	5.67	medium
	1-back	4.90	medium
THK	2-back	5.78	medium
	1-back	5.09	medium

C. Characterization parameters of cognitive distracted driving behaviors

This paper mainly focuses on the driver's physiological state and vehicle running state. Analyzing the change law of the parameters in cognitive secondary-task driving process compared with normal driving process, and then deeply explore the influence of cognitive distracted driving behavior on normal driving state [27,28]. The characterization parameters of driving behavior are divided into vehicle running state parameters and driver physiological state parameters, as shown in Table IV. Vehicle running state parameters mainly include lateral (steering) and longitudinal (velocity, acceleration) running state parameters of the vehicle, and cover the driver's handling characteristic parameters of the vehicle. Moreover, the standard deviation is used as the derivative index of the original parameters, and the dispersion degree of vehicle operation parameters is used to reflect its volatility. In addition to individual and group differences in physiological status, the process of focused driving is also different from that of distracted driving. The physiological parameters of distracted driving state were reflected by the difference of heart state, respiratory state and skin signal of drivers, and their standard deviation was used to reflect the change degree.

TABLE IV. CHARACTERIZATION PARAMETERS OF DRIVER'S PHYSIOLOGICAL STATE AND VEHICLE RUNNING STATE

Type	Parameters
Physiological state	Heart rate (bmp)
	Standard deviation of heart rate (bmp)
	Skin electric signal (mV)
	Standard deviation of skin electric signal (mV)
	Breathing rate (bmp)
	Standard deviation of breathing rate (bmp)
	Perinasal electrical signal (μV)
	Standard deviation of perinasal electrical signal (μV)
Vehicle running status	Velocity (km/h)
	Standard deviation of velocity (km/h)
	Acceleration (m/s2)
	Standard deviation of acceleration (m/s2)
	Steering velocity (deg/s)
	Standard deviation of steering velocity (deg/s)

D. *Comparative analysis of characterization parameters based on behavior criterion*

Taking distracted driving behavior as the comparison criterion of differences, through the analysis of the data characteristics representing the parameters, the variables that can fully represent the characteristics of each behavior are selected. According to the distribution of physiological parameters (Fig.3) and vehicle running state parameters (Fig.4) of different driving behaviors, a total of 10 characterization parameters show significant differences between behaviors. Physiological parameters include heart rate, skin electrical signal, standard deviation of skin electrical signal, breathing rate, perinasal electric signal and standard deviation of perinasal electric signal. Vehicle running state parameters include velocity, standard deviation of velocity, acceleration, standard deviation of steering velocity.

E. *Comparative analysis of characterization parameters based on load criterion*

Taking the load evaluation level in Table III as the comparison criterion, and comprehensively referring to the comparison results of characterization parameters based on the behavior criteria, the cross-comparison results of the representation parameters of cognitive type driving behavior were obtained, which were used as the training samples of the prediction model in next section.

According to the distribution of physiological parameters (Fig. 5) and vehicle running state parameters (Fig. 6) based on load criterion, there are 9 characteristic parameters showing significant differences: heart rate, breathing rate, perinasal electrical signal, velocity, standard deviation of velocity, acceleration, steering velocity and standard deviation of steering velocity. Through the cross-comparison, the parameters for training LSTM model are obtained as follows: heartrate, breathing rate, perinasal electrical signal, velocity, standard deviation of velocity, acceleration, standard deviation of steering velocity.

IV. COGNITIVE DISTRACTED DRIVING BEHAVIOR PREDICTION METHOD BASED ON LSTM

A. *Long-short term memory network*

The traditional neural network is often used to deal with the classification and prediction problems. However, because it is not sensitive to the time series relationship, the accuracy of the model will be reduced when dealing with multiple input variables with time series relationship. Therefore, the recurrent neural network (RNN) was proposed, through the continuous operation of time information cycle, to ensure the existence of information, so as to solve the above problems. The classical RNN structure is shown in the Fig. 7 below.

Although RNN can deal with the time-sequence of input, each multiplication of the derivative of activation function will cause an attenuation when the gradient returns, then gradually accumulates into gradient disappearance or explosion when passing through the full connection layer. This make it difficult to express the input with long time sequence. As a special RNN, LSTM can make the gradient of back propagation remain or fade away by multiplying the activation function value every time through the introduction mechanism. The two hidden cells can go through the forgetting gate without passing through the full connection layer, so as to solve the problems of gradient disappearance and gradient explosion. The structure of LSTM is shown in the Fig.8.

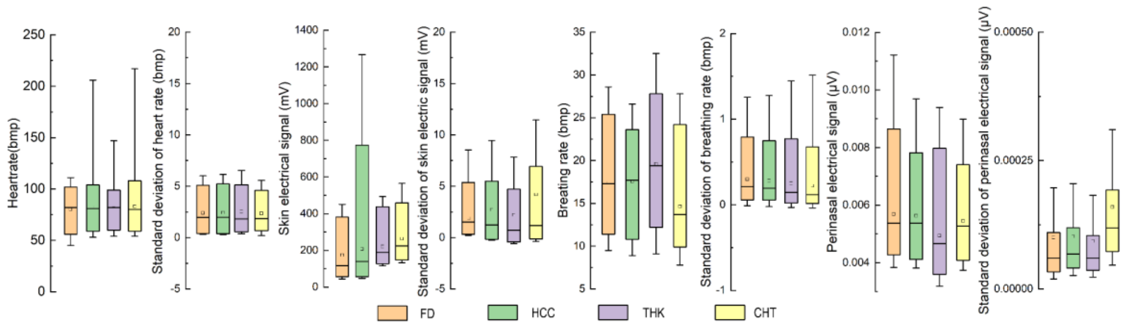

Fig. 3. Distribution of physiological parameters (behavior criterion)

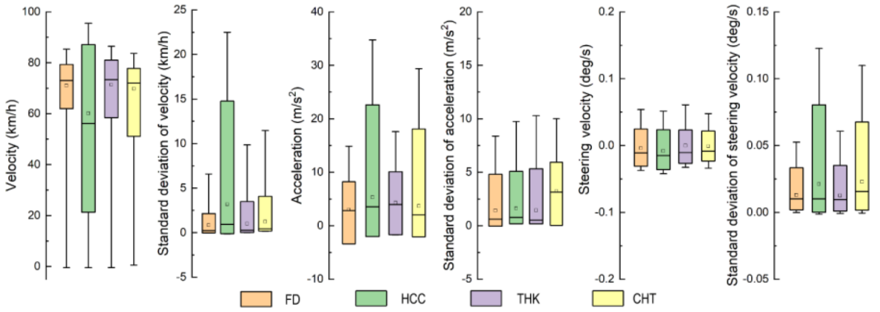

Fig. 4. Distribution of vehicle running parameters (behavior criterion)

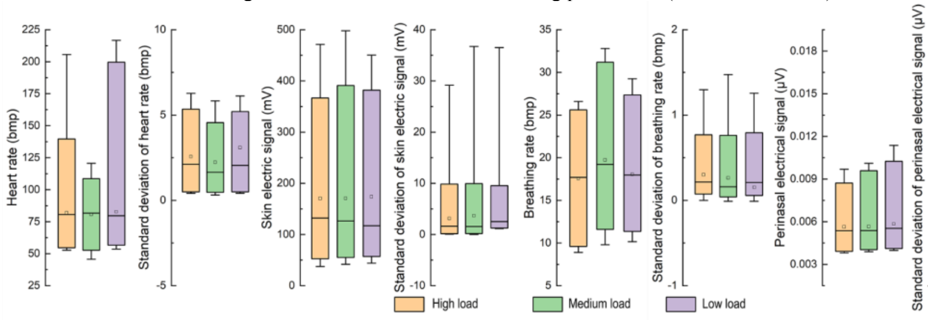

Fig. 5. Distribution of physiological parameters (load criterion)

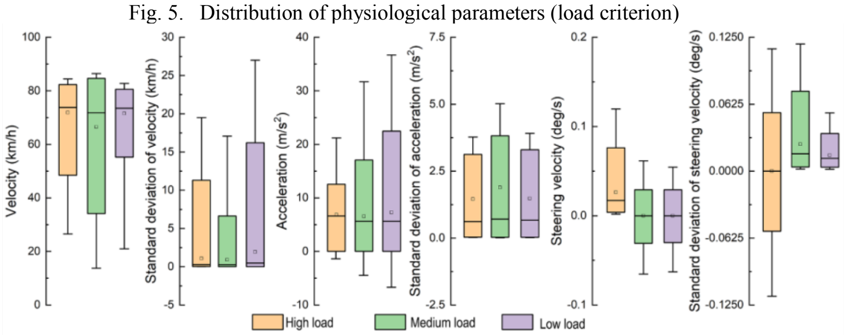

Fig. 6. Distribution of vehicle running parameters (load criterion)

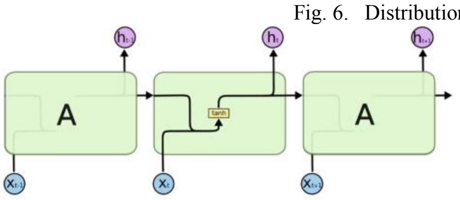

Fig. 7. Classical RNN structure

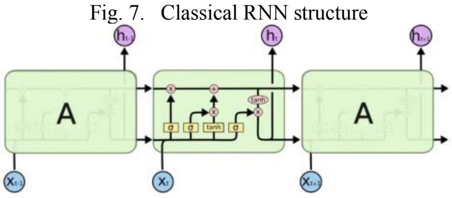

Fig. 8. Structure diagram of LSTM

The forward propagation formula of LSTM is as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Where f, i, C, o are forgetting gate, input gate, cell state and output gate respectively; σ, $tanh$ are sigmoid activation function and hyperbolic tangent activation function; W, b are weight and bias respectively.

B. The prediction network of cognitive distracted driving behavior based on LSTM

With 7 driving characterization parameters as input and 4 cognitive distracted driving behaviors as output, a cognitive distracted driving behavior prediction network based on LSTM was designed. The specific network structure is shown in Fig.9. The structure of cognitive distracted driving behavior prediction network based on LSTM is mainly composed of three layers of LSTM， and it is used to extract abstract features. At the same time, we embed two dropout layers in the middle of the three LSTM layers to avoid overfitting. The RNN network may boost noise, instead of allowing the dropout layer to operate on a single neuron, we put it between cells, that is, in the time step connection.

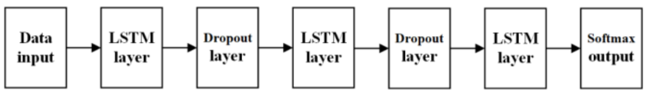

Fig. 9. The structure of LSTM prediction network

C. Experimental data preparation and experimental environment

A total of 81 groups of data were collected in the experiment. Each group of data contained 7 driving parameters of 4 cognitive distracted driving behaviors. Due to the equipment acquisition error, the data were cleaned. After cleaning, 56 groups of data were used for model training and 25 groups were used for model test. Each group of data contained 418-time steps. The experiment was carried out on the laboratory workstation with i7-7700k CPU, NVIDIA GTX 1080ti GPU and 16g memory. Python is chosen as the programming language and Tensorflow as the deep learning framework.

D. Results

Adam is used as the optimizer in the training of the model, and the number of hidden nodes in each layer of LSTM is set to 128. Through experiments, after 89600 iterations, the accuracy rate on the training set is gradually stable. After 100000 iterations, the accuracy rate on the training set is 90.2%, and the accuracy rate on the test set is 74%. In order to verify the real-time performance of the network prediction, seven driving characterization parameters of four cognitive driving tasks were synchronized into the network in real time, and the average prediction time under the experimental verification platform was 80ms.

Conclusions

Compared with previous studies, this paper has 3 contributions: (1) The NASA-TLX scale was improved and used to evaluate the driver's load, and different cognitive secondary tasks were ranked according to the quantitative load. (2) This paper put forward the behavior criterion and load criterion as the reference standards, and then explored the influence mechanism of typical cognitive distracted driving behaviors on driver's physiological state and vehicle running state. (3) The distracted driving behavior prediction model achieved good result under the test of naturalistic data, which is more meaningful than simulation driving. Consequently, the methods and results of this paper can effectively provide the reference but not limited to estimate cognitive and visual driving behaviors, and driving load analysis etc...

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