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Research Article

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Recognition of Driver Cognitive Distraction Behavior based on Numerical Data

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Abstract In recent years, with the continuous development of the automotive industry, the number of motor vehicles has also been increasing, which has brought about worrying traffic safety issues. As an important factor in the road traffic system, drivers are a significant factor in causing traffic accidents. Dangerous driving behaviors such as distracted driving and angry driving seriously affect traffic safety. Among them, distracted driving can be divided into different types such as cognitive distracted driving, visual distracted driving, and operational distracted driving. This article mainly focuses on the research of cognitive distracted driving. Due to the certain risks of conducting real vehicle driving experiments, this article uses a driving simulator to simulate driving experiments. The driving state is following driving, and the vehicle operation information data and human factor data of the experimental vehicle are collected. Based on these two types of data, feature extraction is carried out, Establish a driving behavior dataset and establish a recognition model based on optimized GRU, with an accuracy rate of over 80%.

Keywords Driving behavior;Cognitive distracted driving; Dropout mechanism;Gate Recurrent Unit network model

1. Introduction

With the development of the economy and the improvement of residents' income levels, the number of cars is also continuously increasing, leading to road traffic problems. The incidence of road traffic accidents is high, and the road traffic system includes people, vehicles, roads, and the environment. As an important part of it, drivers play a great role in road traffic safety. According to data from the National Highway Traffic Administration (NATHA) in the United States[1], in 2020, the number of deaths from motor vehicle accidents caused by dangerous driving reached 38824, of which 8% were due to distracted driving.

According to the multi-channel resource theory[2], driver distraction is generally divided into the following four categories. Cognitive distraction causes the driver's mind to deviate from the road driving task; Visual distraction, causing the driver's gaze to deviate from the road; Operation distraction, the driver's manual or hand leaving the steering wheel to operate things unrelated to the driving task; Auditory distraction, where the driver's auditory channel is occupied by the sound of the car audio or radio program. With the continuous development of the automotive industry, the corresponding in car multimedia systems are also constantly enriched; The application of internet-based devices such as smartphones increases the likelihood of drivers being distracted due to external factors. As a result, the relationship between the driver's state of consciousness and safe driving becomes inseparable, that is, the essence of cognitive distraction driving is for the driver's mind to leave the road and turn towards activities unrelated to driving.

Shi Wen et al. [3] designed a real vehicle road experiment and collected vehicle operating parameters and driving operation parameters. The results showed that when cognitive distraction occurred, the driver's reaction slowed down, resulting in a decrease in the stability of changes in parameters such as steering wheel angle and angular velocity. Georgios et al. [4] found that when drivers are cognitively distracted while driving, the lane keeping performance of the vehicle improves, the driver's attention to the center of the road becomes more focused, and lateral handling indicators are reflected in the increase in steering wheel reversal rate and steering entropy. Wang Chang and Guo Yingshi et al. [5] found through actual vehicle experiments that when a driver is in a cognitive distraction state, the average steering wheel angular velocity significantly decreases when the driver's gaze leaves the front area compared to normal driving. The trend of the vehicle deviating from the lane centerline also becomes more pronounced with the increase of time the driver's gaze leaves the road ahead. Yuan Xin [6] studied the visual characteristics of driver cognitive distraction states, analyzed their changing patterns in different road environments, constructed three road scenes, set up two driving distraction sub tasks, collected driver performance data and eye movement data in different road environments and distraction states, and constructed a fuzzy discrimination model for driving safety risks. Cheng Wendong et al. [7] proposed a cognitive distraction image recognition method based on head and eye behavior characteristics to address the issue of drivers easily falling into cognitive distraction during mobile phone conversations during driving. They used D-S evidence theory to establish a fusion of head eye behavior characteristics, achieving a high recognition rate. This provides a certain basis for the research of intelligent driving assistance systems. Hua et al. [8] analyzed and studied the effects of cognitive distraction on driver's pupil diameter, blink frequency, vehicle speed, and steering wheel angle in both traditional and mixed traffic environments. They used repeated measures ANOVA to test the effects of cognitive distraction and traffic environment on these parameters, and the results showed a significant impact.

This article conducts driving simulation experiments using driving simulators and human factors devices, collects human factors data of drivers and vehicle operation information of experimental vehicles, extracts feature information, establishes a driver behavior dataset, optimizes the GRU neural network through the use of Adam optimizer and the introduction of Dropout mechanism, and establishes a cognitive distraction behavior recognition model for drivers in the following state, achieving a high model recognition rate.

2. Experiment Design and Data Processing

Experimental equipment

This study focuses on the recognition method of cognitive distraction behavior of drivers in a following state. Due to the need to induce drivers to engage in distracted driving during the experiment, conducting experiments on real roads may pose certain risks. Therefore, the experiment was conducted in a simulation laboratory. The hardware equipment adopts a multi person multi machine interactive driving simulator, equipped with a computer host and a Samsung curved display screen. The human factors equipment adopts the PsyLAB human factors engineering experimental system to obtain physiological signal data of the driver, including electrocardiogram (ECG), electrodermal (EDA), electromyography (EMG), etc. The software equipment adopts the 3D real-time virtual simulation software UC win/Load from FORUM8 company in Japan, as well as the PsyLAB software system that matches human factors equipment.

Selection of experimenters

From the initial recruitment to the final determination, the number of experimental personnel was 55, aged between 18 and 55, all of whom obtained national driving licenses. All drivers had not experienced any road traffic accidents in the past year, were in a healthy physical and psychological state, and had a visual acuity or corrected visual acuity of 1.0 or above, reaching the international standard level of vision.

Design and experimental process of distraction tasks

The experimental scenario for this experiment is a city road with a high traffic volume, with a total length of 10km and six lanes in both directions. The speed limit for urban roads is 60km/h, and the traffic flow state is set to free flow, guiding vehicles to drive steadily at a speed of 50km/h.

The cognitive distraction behaviors associated with distraction identified in the natural driving research database of The Second Strategic Highway Research Program (SHRP2) in the United States include using mobile phones, talking to passengers, and getting lost in thought.

This study sets different levels of cognitive distraction sub tasks, which are talking to passengers, thinking and answering questions, and difficult numerical calculations. These three different distraction tasks are used to simulate the driver's WeChat conversation and talking to passengers and other distraction states. As a control experiment, the driver performs a normal following driving.

(1) Non distracting task: The driver follows and guides the vehicle in a normal state for a period of time.

(2) Low load cognitive distraction task: experimenters chat with drivers. For example, do you usually fasten your seat belt while driving?

(3) Medium load cognitive distraction task: This stage simulates the driver entering contemplation, and the inspiration for such problems comes from the listening perceptual attention training course for primary and secondary school students. For example, a set of words, flower shop, gymnasium, memorial hall, gymnasium, flower shop, gymnasium, memorial hall, flower shop. How many times have you read flower shop?

(4) High load cognitive distraction task: The experimenter verbally presents addition and subtraction operations of two or one digit three or four items, and the driver answers the answer as soon as possible. For example: 71-29+15=?

Each driver shall conduct a 24 minute driving experiment, which includes 12 minutes of normal driving and 1 minute of rest. After resting for 1 minute, the subjects shall enter a low load distraction task period as required by the experimenter. The driver shall drive with the vehicle for about 4 minutes and also have a brief conversation with the experimenter; After resting for about 1 minute, the driver listened to and answered questions from the experimenter during the middle load distraction task; After resting for about 1 minute, the driver enters a period of high load distraction tasks. They listen to the numerical calculations asked by the experimental staff and complete the answers as soon as possible.

3. Data collection and preprocessing

Based on the vehicle operation information data collected from 55 drivers in the simulation driving experiment, each driver conducted a total of 24 minutes of simulation experiments. The original data was output using the UC win/Load software provided by the driving simulator. According to previous research, the selected vehicle operation data in this article are vehicle speed (v), lateral acceleration (ax), longitudinal acceleration (ay), and vehicle following distance (s) The steering wheel rotation amplitude (R) and the vehicle position offset from the center of the driving lane. To ensure the validity of the experimental data, the data for the first 5 seconds and the last 5 seconds of each distraction task experiment were cut off. For the convenience of subsequent data processing, the data for the first and last 15 seconds of normal following driving were cut off. The final data obtained were 690 seconds of normal driving data, 230 seconds of low load distraction driving data, 230 seconds of medium load distraction driving data, and 230 seconds of high load distraction driving data. Each driver obtained a total of 1380 seconds of vehicle data. This article uses a total of 11 variables, including the mean and standard deviation of vehicle speed, mean and standard deviation of lateral acceleration, mean and standard deviation of longitudinal acceleration, mean and standard deviation of following distance, steering wheel rotation amplitude, and mean and standard deviation of vehicle position offset from the center of the driving lane. Each driver obtained a total of 1380 seconds of vehicle driving experiment data. According to one sample every 5 seconds, each driver had a total of 276 samples. Among 55 drivers, a total of 15180 samples were obtained, with 7590 samples for normal driving, 2530 samples for low load cognitive distraction, 2530 samples for medium load cognitive distraction, and 2530 samples for high load cognitive distraction. Equations 2.1 and 2.2 below are the formulas for calculating the mean and standard deviation of each indicator.

$$X = \frac{\sum_{i=1}^{n} x_i}{n} \tag{3.1}$$

X is the average value of a certain characteristic indicator, n is the driving time of each sample, and Xi is the specific value of the data during this driving process.

$$Y = \frac{1}{\mathrm{n}}\left(Y_i - X\right)^2 \tag{3.2}$$

Y is the standard deviation of a certain characteristic indicator, n is the driving time of each sample, and Y_i is the specific value of a certain characteristic data during this driving process.

Based on experimental data collected from human factors devices and previous research, a total of 6 characteristic variables were selected, including mean heart rate, mean heart interval, standard deviation of heart interval, mean skin electrical activity, and standard deviation of electromyography. To ensure consistency in time, the collection of vehicle operation data and human factors data remained completely consistent in time. The calculation of mean and standard deviation of the original data fully complied with equations 3.1 and 3.2, The division of samples is exactly the same as the vehicle operation information data, so it will not be repeated here.

After dividing the data into samples, this article uses Z-value normalization to process the data samples. Z-value normalization maps the sample values of a set of data to a standard distribution with a mean of 0 and a standard deviation of 1.

4. Model building process

Factor analysis for feature extraction

If a single data is used to establish a recognition model for feature extraction in factor analysis, the recognition rate of distraction behavior will be lower. Therefore, this chapter will integrate the obtained vehicle data and human factors data for information fusion. There are three methods for information fusion from the perspective of fusion hierarchy. This article selects the feature level fusion method to fuse the data. This article uses factor analysis to reduce the dimensionality of the data. Seventeen vehicle operation information data and human factors data parameters were selected and subjected to sufficiency testing using SPSS. KMO was used to check the partial correlation of variables. The value of KMO was between 0-1, and the closer it was to 1, the better the effect of factor analysis. After testing, the value of KMO was found to be 0.673>0.5, indicating that it is suitable for factor analysis. The next step is to conduct Bartlett's sphericity test to test whether each variable is independent. After testing, the P-value is less than 0.05, indicating that the variables are correlated and factor analysis can be performed. By using SPSS for analysis, it was found that the first 8 factors collectively explained a total variance of 96.176%, which can explain most of the original variables. The following figure 1 is a gravel plot about the initial eigenvalues. We will obtain 8 common factors that can be used as inputs for the improved gated recurrent unit neural network model in the future.

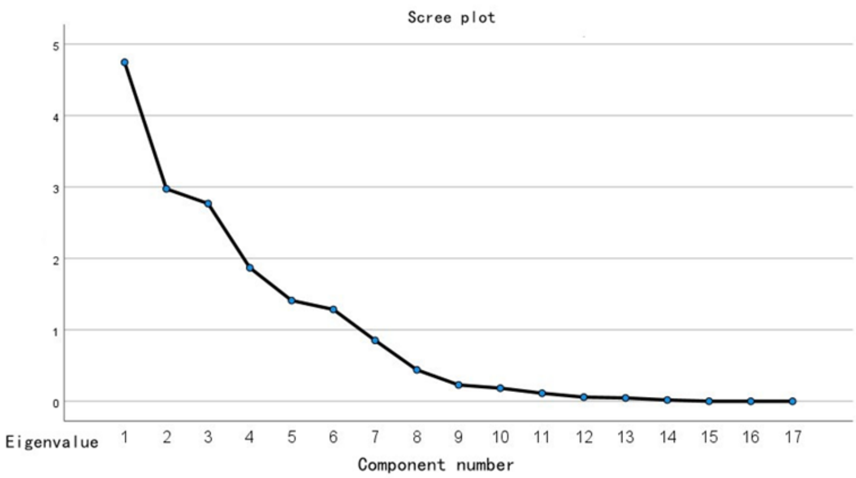

Figure 1: Scree plot

Improvement of Gate Recurrent Unit (GRU) network model establishment

After conducting factor analysis on the driver's vehicle operation information data and human factor feature data in the previous section to extract features, this paper establishes a recognition model by improving the gated recurrent unit neural network. Recurrent neural networks [9] have short-term memory ability, which can remember the information input earlier and apply it in the current output calculation. There are connections between nodes in the hidden layers, and the input to the hidden layer is not only the output of the input layer, but also the output of the previous hidden layer. However, recurrent neural networks are unable to learn longdistance dependencies in input sequences, which can cause gradient explosion or vanishing. To alleviate this problem, a GRU neural network based on recurrent neural networks has been developed, with an update gate used to calculate the output of the hidden state at the current time, and another gate used as a reset gate to reset memory information.This article selects GRU to establish a recognition model and further optimizes the relevant parameters to achieve better model recognition accuracy. The network structure diagram of GRU is shown in Figure 2.

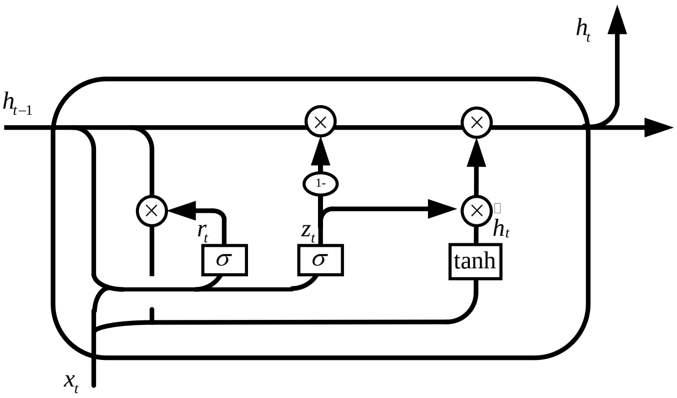

Figure 2: GRU network architecture diagram

In order to obtain more objective model accuracy, this paper will further optimize the GRU network. In the selection of optimizers, the Adam optimizer is used instead of the random gradient descent method. The Adam optimizer can automatically adjust the learning rate of parameters, quickly converge and reduce training time, and more accurately find the minimum value of the loss function, which is better than using a fixed learning rate for the random gradient descent method. In order to alleviate the overfitting phenomenon of the model and prevent the parameters from relying too much on the training data, this paper introduces the Dropout mechanism to increase the generalization ability of the parameters on the dataset.

This article constructs one input layer, three GRU layers, and one fully connected layer as the hidden layer, and finally serves as the output layer. In order to facilitate sample partitioning, this article selects 15000 data samples. According to the 8:2 partitioning ratio, the training set has 12000 data samples, and the test set has 3000 data samples. Among the 3000 data samples, there are 1500 normal driving samples, 500 low load cognitive distraction samples, and 500 medium load cognitive distraction samples, 500 high load cognitive distraction samples. After 25 iterations of training the model, the accuracy change curve is shown in Figure 3, and the loss value change curve is shown in Figure 4.

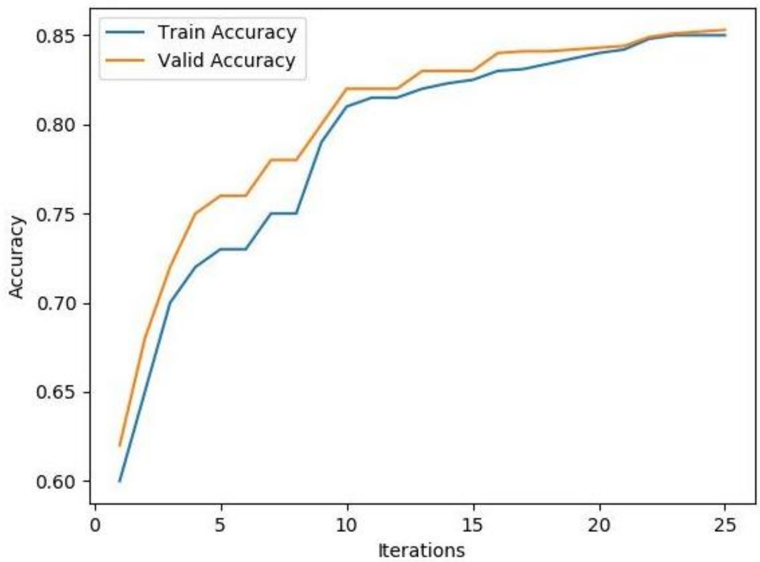

Figure 3: Improved GRU accuracy change curve

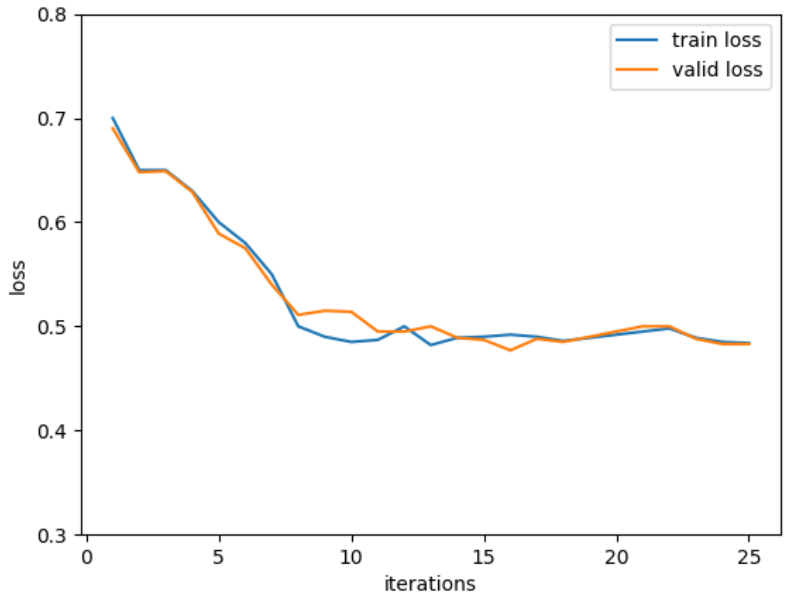

Figure 4: Improved GRU loss value variation curve

After 25 iterations of training the model, the loss value of the model remained around 0.483, and the recognition accuracy of the model was 84%, reaching over 80%. To evaluate the effectiveness of the model, it is usually necessary to use certain evaluation indicators to measure the quality of the model. For classification models, commonly used indicators include confusion matrix, accuracy, precision, and recall. Confusion Matrix, also known as error matrix, is mainly used in supervised learning to compare classification results with real information of instances.

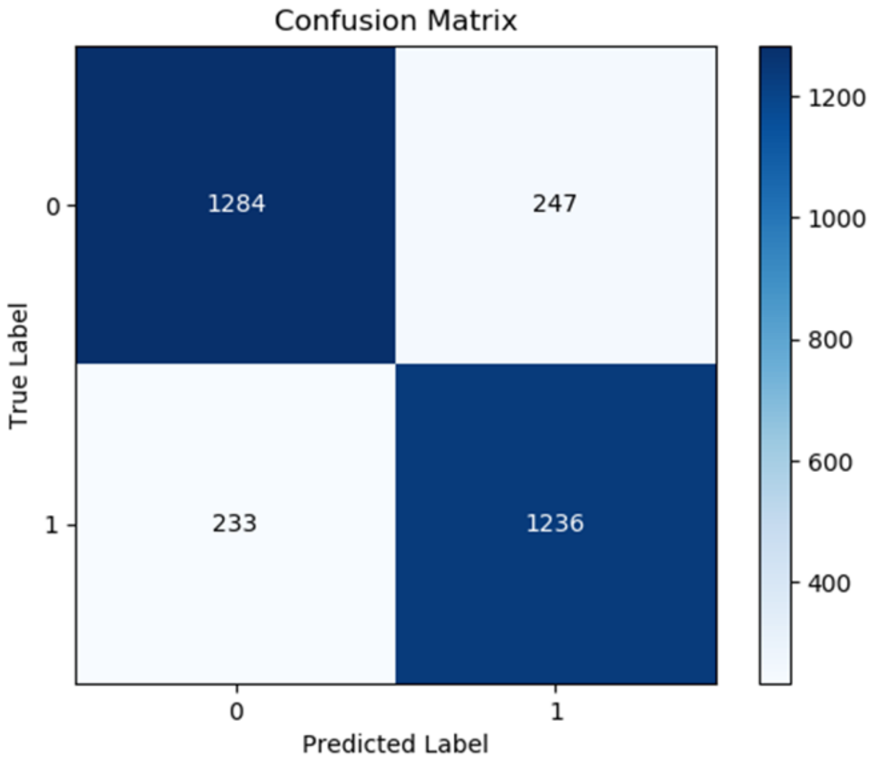

Figure 5: Improving the GRU confusion matrix

According to Figure 3.5, the classification accuracy of the model is 84%, Precision is 0.846, and Recall is 0.839. Overall, it can be seen that the recognition effect of the model is good and can provide a certain theoretical basis for advanced driving assistance systems.

5. Conclusion

This article simulates driving experiments, designs distracted driving sub tasks, obtains vehicle operation data and driver human factors data of experimental vehicles in a following state, extracts features through factor analysis, and establishes a driver cognitive distracted driving behavior recognition model based on improved GRU. The accuracy rate reaches 84%, achieving good recognition results. This model can provide a certain basis for dangerous driving recognition systems.

6. Acknowledgment

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