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Influence of Non-driving Related Tasks on Driving Takeover Safety, A Study Based on Back Propagation Neural Network

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Abstract

As autonomous vehicles are developed and gradually applied, the driver with current technology is still a fallback level when the automated system reaches its limits. Autonomous vehicles still require a human driver to take over, and non-driving related tasks can affect the quality of the takeover and thus driving safety. In this paper, we collected data on driving takeover in two kinds of non-driving related tasks（NDRTs） and two takeover scenarios based on a fixed-base driving simulator, including vehicle driving data and driver eye movement data, and classified the takeover safety into safe and unsafe categories based on the mean gaze reaction time, and then used a back propagation neural network to predict the driver's takeover safety. The results showed that the prediction accuracy of the established network was good and the generalization ability was good. In addition, in the ranking of the importance of the predictors, it was found that the non-driving related tasks had an importance of 55.65% in the prediction, followed by the driving parameters during driving also had an important effect on the prediction of safety, while the driver's eye movement index did not show an important effect.

Keywords

Autonomous driving; Propagation neural network; Prediction; Model.

1. INTRODUCTION

A With the continuous technological breakthroughs in the field of intelligent vehicles and intelligent transportation in recent years, there has been a rapid development of vehicle-assisted driving technology. Autonomous driving has also become a research hotspot in the field of transportation vehicles. Since 2014, the Society of Automotive Engineers (SAE) has introduced a set of grading standards to distinguish the levels of self-driving vehicles. With the technological progress, SAE updated the standard in 2016, which is divided into six levels from L0-L5 according to the intelligence of the vehicle [1]. Due to the limitation of technology, most self-driving vehicles are basically below L3 level. Therefore, when an autonomous vehicle runs outside its operational design domain, the autonomous driving system reaches its limit, and the driver needs to remaneuver the vehicle quickly and accurately to ensure the safety of the vehicle, which is called takeover. Among the factors that influence the safety of takeover, non-driving related tasks are an important influence.

Non-driving-related tasks refer to the driver's involvement in driving irrelevant things during autonomous driving [2]. During autonomous driving, the driver may be involved in NDRTs, which can reduce the driver's perceptual understanding of the surrounding environment due to limited cognitive resources, especially after a long period of immersion in non-driving-

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related tasks, it will be challenging to return to the driving maneuver in the driving task where the driver is in the loop again. Distinguishing non-driving related tasks from task types can be mainly divided into standard tasks and daily tasks. The effect of three different realistic tasks on takeover performance was investigated. [3] used a driving simulator test to compare and analyze the takeover reaction time and takeover quality of the driver under different tasks. The experiments show that driver cognitive processing under different non-driving related tasks is impaired by distraction, which in turn seems to determine takeover quality. [4] found engaging in non-driving related tasks increases the difficulty of the driver when taking over. In visual non-driving tasks, the driver's takeover reaction time is affected. [5] wore vision tracking devices (HEDs) on the driver's head and collected data on the driver's pupil position and pupil diameter in different non-driving related task driving scenarios, based on which they analyzed the distraction status caused by different non-driving related task behaviors during driving. The results of the study showed that participation in non-driving-related tasks would have a smaller standard deviation of lateral position than normal driving, and that different types of driving non-driving-related tasks would have different degrees of influence on driving safety. [6] analyzed the variation patterns of various driving parameters, established a model about non-driving-related tasks, and used a supervised feedforward artificial neural network (ANN) structure to describe the effect of intrinsic nonlinearity between driving behavior and non-driving related tasks, and the results showed that the selected driving performance metrics can effectively detect relevant non-driving related task operations. In conclusion, driver involvement in non-driving related tasks can cause driver distraction and have a significant impact on driving safety. It is even more likely that driver distraction in non-driving related tasks occurs during autonomous driving. Therefore, it is necessary to explore the automatic driving takeover safety under non-driving related tasks. In this paper, we establish a BP neural network model to predict the driver's takeover safety based on the driver's takeover performance and visual risk perception data under different non-driving related tasks.

2. EXPERIMENTAL METHODOLOGY AND DATA SOURCES

2.1. NDRTs

The more mature the autonomous driving technology, the greater the opportunity for the driver to engage in non-driving related tasks. In Level 3 autonomous driving, drivers may be involved in a variety of NDRTs. different NDRTs differ depending on the sensory channels that occupy the driver's hands, eyes, and brain. Common non-driving-related tasks can be classified in terms of distraction types as visual distractions, cognitive distractions, operational distractions, and a combination of them, each causing a different degree of impact. In order to distinguish different levels and types of distractions and to take into account the actual non-driving-related tasks that may be involved, the non-driving-related tasks in this paper were chosen as everyday non-driving tasks. The settings are visual distractions (watching videos) and operational distractions (editing emails), all of which can exert relatively high visual and cognitive demands. In addition, a distraction-free task that only needs to monitor driving is set as a pair group, and only the road needs to be monitored during autonomous driving.

2.2. Takeover scenarios

The test road was a highway with a standard lane width of 3.75 m. Some other free traffic flows were randomly set up in each section with a speed limit of 100 km/h. However, in the takeover section, no other traffic flows were set up to avoid any influence on the driver's braking or steering operation during the takeover. The combination of dynamic scenes and static scenes as well as the ability to simulate the limits of the automated driving system is considered. The feasibility and reasonableness of the scenario selection features were integrated, and two takeover scenarios were set in this study, namely, a faulty vehicle in front and a missing road

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marking, causing the automatic driving system to be unable to recognize and thus send a takeover request.

2.3. Driving Simulator

The instrumentation used in this paper consists of the OKTAL high-fidelity driving simulator and the Tobii Glasses 2 eye-movement tracker. The driving simulator is a high-fidelity driving simulator developed by OKTAL, a French company, which consists of hardware and software components. Including the main control computer sound and light system, steering wheel and pedal force feedback system. The cockpit mainly includes a 14-size passenger car, steering wheel, instrument panel, transmission shift lever and sensors, etc. The software part is based on the control software SCANeR studio, including the scene drawing module, vehicle control module, and analysis module.

2.4. Back Propagation neural network prediction model

Back Propagation neural network is a multilayer feedforward network trained by error back propagation algorithm, and is one of the most widely used neural network models. Its working principle is to back-propagate the error between the actual value and the predicted value, and optimize the weights between modified individual neurons in an iterative way until the error meets the expected requirements and the iteration ends.

In the network structure, the number of nodes should be determined first. In this paper, the output layer results in two evaluation indicators of safe takeover and dangerous takeover, so there is only one node in the output layer, and the output results in safe takeover or dangerous takeover. Regarding the selection of nodes in the input layer in this paper, first of all the non-driving related task qualitative indicators should be included in the independent variables of the prediction process. All dependent variables except for the gaze reaction time should be taken into consideration. So the continuous variables selected in this paper for the prediction process are maximum lateral acceleration, maximum longitudinal deceleration, gaze road time, number of sweeps, and pupil diameter. So the number of nodes in the input layer is 6. For the hidden layer, a large amount of existing practice shows that the three-layer network does not easily enter the local minimum previous research results show that the BP neural network with a single hidden layer can approximate any one continuous function in the closed interval, so it is possible to map the input layer with nine data dimensions to a single output layer, so a single hidden layer is used. For the selection of the number of nodes of the hidden layer to be considered comprehensively the computational complexity also to consider the prediction performance of the model, the number of hidden nodes is generally between the number of input nodes and the number of output nodes, tentatively set at 5, gradually adjusted to the number under the optimal prediction accuracy.

The performance of the model mainly refers to the generalization ability of the model. The prediction in this study is essentially a dichotomous task, and the evaluation model of the dichotomous task is based on the confusion matrix, and the evaluation metrics mainly include Accuracy (A), which is the ratio of all correct predictions to all numbers. The accuracy Precision (P), is the number of samples with positive predictions that also have positive values. Recall (R) is the ratio of all positive labeled samples in which the predicted value is also positive. In addition, this study also uses ROC curves to measure the generalization ability of the prediction model.

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3. RESULTS AND ANALYSIS

3.1. Collected data

Before building the prediction model, it is important to first consider which indicators to use for prediction, and the data collected in the experiments are shown in Table 1.

Table 1. Indicators

Dependent measure	Unit	Definition
Gaze reaction time	s	Time interval between TOR and first gaze on the road
Maximum longitudinal deceleration	m/s^2	Maximum longitudinal deceleration in the manual driving period after the TOR
Maximum lateral acceleration	m/s^2	Maximum lateral acceleration in the manual driving period after the TOR
Focus on road time	s	Watching road time during takeover
Number of sweeps	times	Number of sweeps during takeover
Pupil diameter	mm	Pupil diameter of the eye during the receivership

3.2. Analysis of prediction results

In this study, predictions were made for ten participants in the safety of takeover, and based on the prediction results, we can obtain an accuracy of 70%, a check accuracy of 80%, and a recall rate of 66.7% for this model. The prediction results are shown in Table 2, where the prediction accuracy was 66.7% among drivers classified as safe, and 75% among drivers classified as dangerous takeover, with a better overall performance of the model. To evaluate the generalization ability of the model, the ROC curve was plotted with the false positive rate as the horizontal axis and the true positive rate as the vertical axis, as shown in Figure 1. It can be seen that although there is a crossover of the curves between danger takeover and safety takeover, and it cannot be stated for the time being which of the constructed prediction models is better in terms of the performance of danger takeover prediction and safety takeover prediction, the area enclosed by both curves and the straight line of the model output is over 70%, and the model has better generalization ability.

Table 2. Prediction results

Observed value	Predicted value		
	Safety	Danger	Correct percentage
Safety	6	4	66.7%
Danger	4	1	75.0%
Overall percentage		70%	

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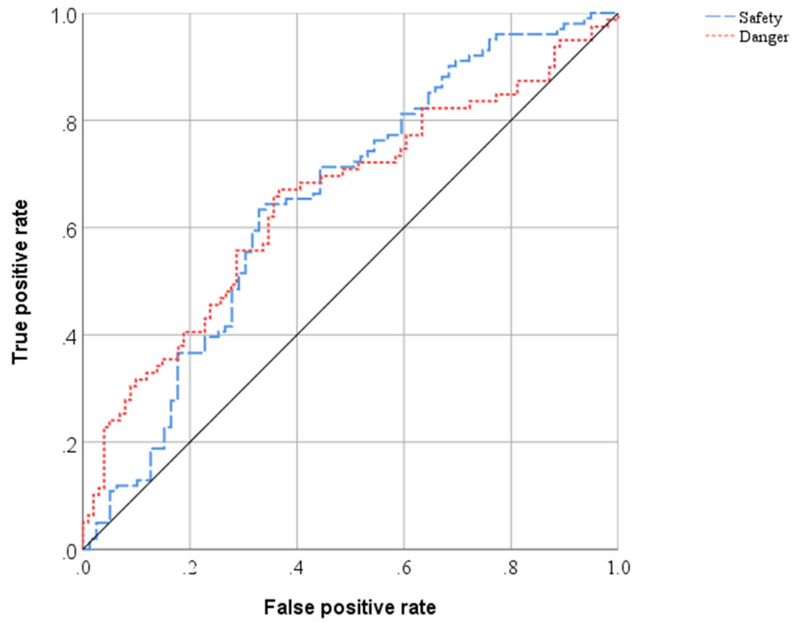

Figure 1. ROC Curves

In addition to the evaluation of the model performance, attention was paid to the importance of the selected input metrics in the prediction process. As shown in Figure 2, the importance of non-driving related tasks is the highest for driving performance metrics, and it can be seen that driver involvement in non-driving appointments can have a significant impact on driving takeover safety. Therefore, the current autonomous driving domain has to specify task boundary thresholds for non-driving related tasks. The next important thing is the maximum longitudinal deceleration, although the operation of taking over in different scenarios is not consistent, but basically can be divided into two categories of braking and steering, and this indicator belongs to the longitudinal performance of the vehicle movement process, small longitudinal deceleration may lead to collisions, large longitudinal deceleration is a kind of unstable driving. For the driver's eye movement indicators pupil diameter and number of sweeping glances and road gaze time, the effect of these two is not obvious, the possible explanation is that the variability between the driver's eye movements itself is not large, and may also be related to the light conditions during the experiment.

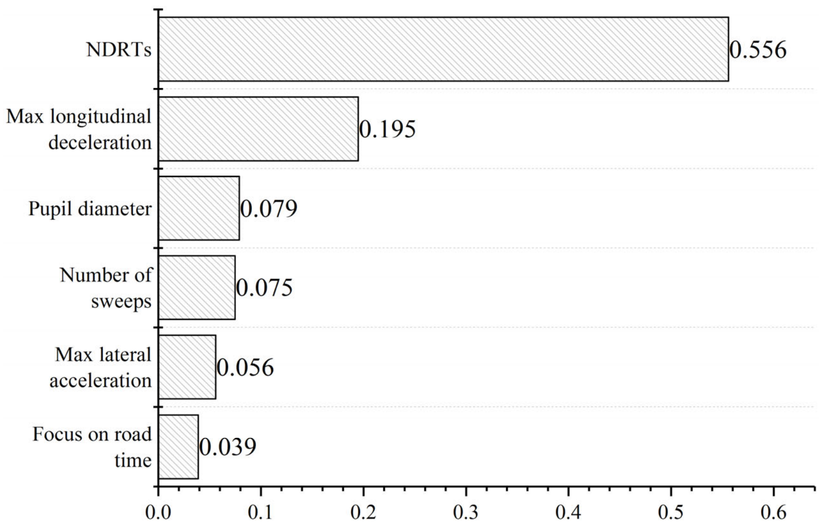

Figure 2. Importance of normalization

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4. CONCLUSION

In this study, we found that non-driving related tasks have a significant impact on the safety of the takeover process by designing a driving simulation takeover experiment and building a neural network prediction model. In the established neural network prediction model, the non-driving related tasks and the driving takeover performance occupy the most important level among all the predictors, compared to the driver's eye movement index, which is not significant in the prediction process and needs to be further investigated. In conclusion, this study can provide a theoretical basis for setting the boundaries of non-driving related tasks in the future autonomous driving process, and provide suggestions for vehicle product design.

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