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Research on Driving Performance under the influence of Voice Navigation Information

Zhengwen Cai[1, *]

[1]Hefei University of Technology, Hefei, 230009, China

[*]caizhengwen1997@163.com

Abstract

Voice navigation information can provide various functions and convenience for drivers, but the unreasonable design of the level of voice navigation information may have a negative impact on driver behavior and even cause safety hazards. This study investigated the driving performance of drivers under the influence of voice navigation information through driving simulation experiments. Four indicators, including standard deviation of lateral and longitudinal speed, lateral position, and standard deviation of lateral position, were collected, and the driving performance level was divided into high and low categories using the k-means algorithm. The driving performance level recognition model was established using random forest and gradient boosting tree algorithms, and the model performance was evaluated by accuracy, precision, recall, F1-score, and AUC value. The results showed that the gradient boosting tree model had better performance with an accuracy of 82.19%, and age and information level had the greatest importance in predicting the results. This study provides new ideas for researching the impact of voice navigation information on drivers.

Keywords

Level of information, Voice navigation information, Driving performance, Machine learning.

1. INTRODUCTION

Drivers need to obtain traffic information during the driving process, and make judgments, decisions, and actions based on the information obtained. Driving a vehicle is a complex task that requires the coordination of multiple sensory channels of the driver. The voice navigation system is the most widely used driving assistance system, which can provide various navigation information such as path guidance, real-time traffic conditions, and safety reminders to drivers, greatly facilitating the driver's access to information. Compared with visual navigation information, the use of voice navigation information has lower interference to drivers [1], and drivers have more reaction time [2]. However, some studies have found that the unreasonable design of navigation information can affect the behavior of drivers and create safety hazards. Excessive information can make drivers overwhelmed and even lead them to information overload [3]. As the available information increases, drivers may be overwhelmed by too much information, which may reduce performance, hinder normal activities, and affect decision-making [4]. When too much information occupies the driver's cognitive resources, it may lead to cognitive distraction and affect driving performance [5] [6]. Therefore, the amount of navigation information must be carefully designed to minimize interference with drivers and driving tasks [7]. In addition to the impact of voice navigation information, the driver's driving

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performance may also be affected by personal factors, such as age [8], gender [9], driving experience [10], etc., and these factors need to be considered.

This study obtained driving performance data through driving simulation experiments, evaluated driving performance, and established a driving performance recognition model through the random forest algorithm and gradient boosting algorithm. When establishing the model, SMOTE oversampling was used to balance the samples to improve the model's recognition ability.

2. METHOD

2.1. Experimental Design

In this experiment, the amount of voice navigation information was divided into three levels: low information level only included basic route guidance information, medium information level included distance information and route guidance information, and high information level included road condition information, distance information and route guidance information. The voice navigation information was randomly distributed at certain intervals along the experimental route. Each voice navigation information was only broadcasted once. In this experiment, manual driving was used, and the driver was required to follow the guidance of the voice information to complete the driving task. The driver could not engage in any activities unrelated to driving during the process.

2.2. Equipment

The experiment was conducted using an OKTAL driving simulator (Figure 1) which was fully equipped with a vehicle driving environment. The display system consisted of three independent high-definition displays with a resolution of 1080P. The audio system was able to output necessary sounds, including those of the vehicle, environment and voice navigation.

Figure 1. OKTAL Driving Simulator

2.3. Simulation Environment

The simulated driving environment is a city road with a road type of two-way six-lane road, separated by double yellow lines in the center. Each lane is 3.75 meters wide, and the speed limit is 70km/h. No road signs were set on the road to eliminate the influence of sign information, and no conflict scenarios were set. A small amount of traffic flow and pedestrians were set on the roadside in the simulation environment.

2.4. Data Collection

The data indicators analyzed in the study include speed standard deviation, lateral speed standard deviation, mean lateral position, and lateral position standard deviation. These indicators have been used in previous studies to measure driving performance. Lateral and longitudinal speed standard deviations are used to characterize the stability of the driver's

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longitudinal speed control [11]; lateral position deviation [12] and lateral position standard deviation [13] are commonly used to characterize the stability of vehicle lateral control.

3. ANALYSIS AND RESULT

3.1. Evaluation of driving performance levels

To classify drivers' driving performance, k-means clustering was used to divide driving performance data into two categories. The average value of each clustering index in each category was calculated as the clustering center point, as shown in Table 1. Overall, the performance indicators of Category 1 are better than those of Category 2. Therefore, Category 1 is classified as high driving performance, while Category 2 is classified as low driving performance.

Table 1. Cluster center feature values

clustering indicators	Cluster category labels	
	1 (n = 121)	2 (n = 59)
mean lateral position	0.209	0.385
speed standard deviation	1.134	1.815
lateral speed standard deviation	0.003	0.012
lateral position standard deviation	0.049	0.136

3.2. Establishment of driving performance level identification model

Compared to traditional statistical models, machine learning algorithms have a wider range of applicable conditions and better abilities in analyzing data. They can handle linear or nonlinear relationships between variables. Two algorithms were selected to build models and compare their performance.

(1) Random Forest

The Random Forest algorithm (RF)[14] is an improved version of the ensemble learning Bagging strategy, which introduces random attribute selection, making Random Forest less prone to overfitting and has certain noise resistance and strong adaptability to the dataset. In addition, Random Forest has good generalization ability.

(2) Gradient Boosting Decision Tree

Gradient Boosting Decision Tree (GBDT) is a gradient algorithm model [15] based on decision tree. GBDT moves in the negative gradient direction of the loss function to make the loss function smaller and continuously improve the model performance. The GBDT model has fast calculation speed and can flexibly handle various types of data.

3.3. Factor selection

Due to the fact that the driving performance of drivers is easily influenced by multiple factors, this study selected the influencing factors of driving performance level based on driver characteristics and voice navigation information characteristics. Four influencing factors were selected as input features for the model, as shown in Table 2. Using the selected influencing factors as independent variables and driving performance level as the dependent variable, a model for identifying drivers' driving performance level was established.

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Table 2. Model input features

Features	Category	Proportion	
		Low	High
Level of information (IL)	Low	0.50	0.50
	Medium	0.33	0.67
	High	0.15	0.85
Age	20-29	0.25	0.75
	30-39	0.22	0.78
	Over 40	0.54	0.46
Gender	Male	0.30	0.70
	Female	0.39	0.61
Driving age (years)	2-5	0.39	0.61
	Over 5	0.31	0.69

3.4. Model training

(1) Sample balance:

Due to the imbalance of different levels of driving performance obtained by clustering, in order to solve the problem of sample imbalance and improve model performance, this study used the SMOTE algorithm [16] to balance the samples before constructing the model.

(2) Data split:

When the sample size is not large, using a model trained only once may not perform well on the test set, and the model results may have some randomness. Therefore, the K-fold cross-validation method [17] is used to reduce the impact of data partition on the model results. This study divided the dataset into three parts: training set, validation set, and test set. 70% of the samples were used as the training set and validation set, and five-fold cross-validation was used for model training and parameter adjustment. 30% of the samples were used as the test set to evaluate the performance of the model.

3.5. Model performance measurement and results.

The performance of a machine learning model refers to its performance on an unknown dataset, also known as generalization performance. In machine learning, metrics based on a confusion matrix are generally used to evaluate a model's generalization ability, which can yield indicators such as accuracy, precision, and recall. This article selects the following performance indicators to measure the generalization performance of the model:

(1) Accuracy: The proportion of correctly predicted samples among all samples.

(2) Precision: The proportion of samples that are actually true among all samples predicted as true.

(3) Recall: The proportion of samples predicted as true among all samples labeled as true.

(4) F1-score: F1-score is a measure of model precision that takes into account both precision and recall.

(5) AUC value: The AUC value is defined as the area under the ROC curve, with a range usually between 0.5 and 1. A larger AUC value indicates better generalization performance of the model.

After multiple training, the final results of the model on the test set are shown in Table 3. The ROC curve corresponding to each model is shown in Figure 2.

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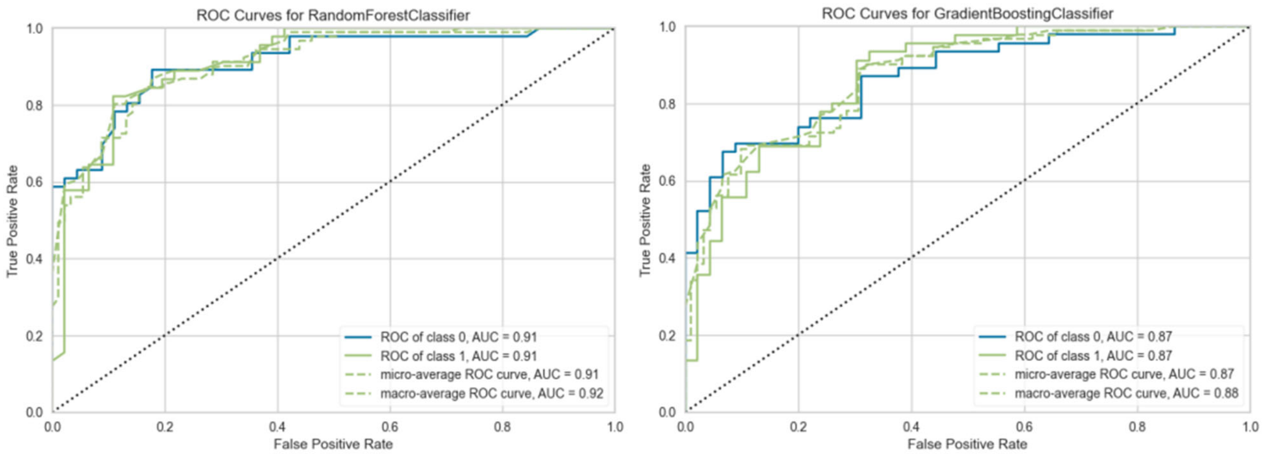
Table 3. Model performance metrics

Model	Model performance metrics				
	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
RF	83.52	80.39	89.13	84.54	0.92
GBDT	73.63	72.92	76.09	74.47	0.88



(a) RF (b) GBDT

Figure 2. ROC curve of models

According to the model results, the GBDT model performed the best among all the models, achieving better performance on all metrics. In order to analyze the impact of predictive features, the importance of predictive features in the GBDT model was analyzed, as shown in Figure 3, where the importance of the age and information amount features was higher.

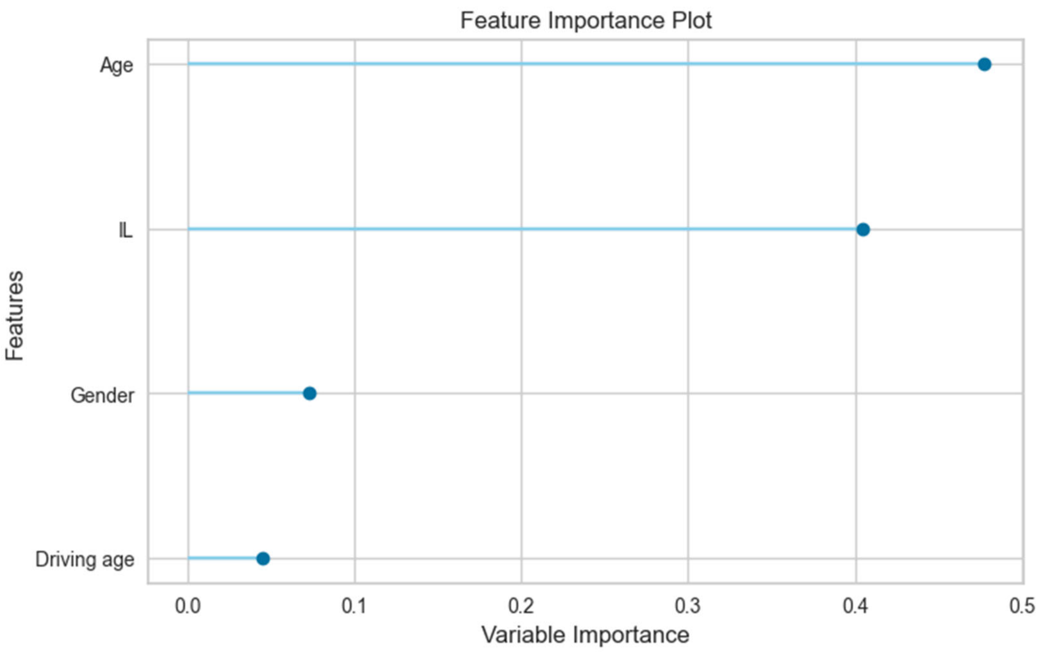


Figure 3. Feature importance plot

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4. CONCLUSION

This study collected driving behavior data from simulated driving experiments, and used k-means clustering to classify drivers' driving performance. Random forest and gradient boosting tree algorithms were selected to build a driving performance recognition model, with the gradient boosting tree model performing better. Age and the information content of voice navigation were found to be more important predictors of drivers' driving performance.

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