Differentiation Analysis Between Driving Demand Based on Driving Atlas and Road Supply

Guoqing Liu(✉)

Institute of Logistics and Science, Shanghai Maritime University, Shanghai 201306, China
gqlliu@163.com

Abstract. In order to reduce traffic accidents on special sections of mountainous highways and optimize individual driving behaviors, a behavioral map for studying individual driving behaviors is proposed. Based on simulated driving behavior data of individual drivers on mountainous highways, the statistical characteristics of driving behaviors are studied. The acceleration, deceleration, and steering wheel angle of the vehicle are selected as the feature indicators to describe individual driving behaviors, and a graph-based individual driving behavior feature expression method is constructed to study the supply-demand differences between different driving behaviors and road conditions. The results show that the driving behavior map can not only accurately and intuitively express the relationship between driving behavior and driving safety, but also clearly display the conflicts between road condition supply and driving behavior demand. The research results provide reasonable suggestions and solutions for alleviating supply-demand conflicts and behavior control, and improve the safety and operational efficiency of road traffic.

Keywords: driving behavior · graph representation · feature classification · supply-demand difference analysis

1 Introduction

During the driving process, driving behavior data is continuous numerical data with characteristics such as a large amount of data, poor stability, and high noise. Moreover, multiple driving operations often occur simultaneously at a given moment, making it difficult to use traditional statistical analysis and data charting methods to accurately reflect the changes in driving behavior. Therefore, new methods are needed to achieve an accurate description of driving behavior characteristics. Due to its significant advantages in information visualization, graphing has gradually become an important means of displaying the characteristics of complex, multi-dimensional, uncertain, incomplete, and internally related data. Knowledge graphs can intuitively display complex knowledge fields, revealing the development process of knowledge and structural relationships. By encoding data and establishing association rules, graphing can accurately describe the characteristics and interrelationships of driving behavior data in the form of nodes and connecting lines, intuitively expressing the changes in driving behavior.

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In recent years, significant research progress has been made in the study of driving behavior parameters and modeling of driving behavior characteristics, which have been applied to the identification and prediction of driving behavior features. Some researchers have attempted to use neural network methods to model driving behavior and have achieved acceptable model accuracy in driving behavior recognition and prediction [1–3]. Other researchers have used mathematical models to recognize driving styles, but these models cannot visually express driving behavior characteristics [4]. These research results cannot explain where inappropriate driving behavior occurs and cannot visually reflect the differences in driving behavior characteristics [5, 6]. Therefore, leveraging the advantages of graphing and visualization, Chen et al. [7] proposed a graphical driving behavior modeling method that extracts and sorts typical driving patterns of drivers to construct a behavioral graph, which can directly describe a driver's driving habits and distinguish driving characteristics. Scholars such as Faria et al. [8] analyzed the waveforms of different driver activities and compared the standard feature extraction and classification methods with angle-based image transformation-based transfer learning methods, and the results showed that the feature extraction method can better distinguish different driving behaviors with fewer computing resources. Wang et al. [9] constructed the DHG (Driving Habit Graph) driving behavior habit graph model. As DHG can simulate driving styles, it can be used to predict driving behavior and estimate the degree of danger in the upcoming driving situation.

In summary, current research mainly extracts driving behavior features from the time dimension and does not consider the spatial distribution characteristics of driving behavior. At the same time, current research on driving behavior spectra lacks consideration of traffic scene elements. There are certain differences in the driving behavior performance of individuals in different driving scenarios. Based on this, on the basis of selecting the driving environment, a time-distance driving behavior graph method is proposed, which not only can recognize and classify driving behavior characteristics but also can analyze the conflicts between road supply and driving demand, providing a reference for optimizing driving behavior and road safety design and evaluation.

2 Driving Data Acquisition

2.1 Experimental Setting and Design of the Plan

Considering the practical significance of the study, an automatic transmission vehicle was selected as the driver simulator. The driving simulator can simulate driving scenarios, reproduce and record operational parameters of driving behavior (such as the depth of acceleration and braking pedal depression, steering wheel angle) and vehicle running state parameters (such as speed, engine speed, lateral displacement, etc.). The experimental simulation scenario in this study was based on a section of the G78 mountainous highway, with a total length of 2000m, a single lane width of 3.75m, and a two-way four-lane design. Due to the influence of terrain and geology, the design speed of this road section is 60km/h. The road facilities, including lane markings, shoulder lines, traffic signs, and other road facilities, are complete, with various line shapes such as straight lines and curves.

Table 1. Driving behavior indicators.

Number	Name	Symbol	Variation range
1	Acceleration Pedal	A	[0,1]
2	Brake Pedal	B	[0,1]
3	Steering wheel angle	S	[-1,1]

2.2 Experimental Data Collection

Compared to manual transmission vehicles, automatic transmission vehicles have simpler driving operations, lower operating intensity, and higher driving safety. When the road conditions are not too complex (such as flat road surfaces), the vehicle operates smoothly, and the driving operations are relatively simple, with little difference in individual driver behavior characteristics. When the road conditions are more complex, the driving operations will also increase, and it becomes a typical representative of driver behavior characteristics, which can reflect the driving level and style of different drivers. Therefore, studying the driving behavior generated by the vehicle during the entire experimental route can clearly reflect the differences in operational behavior characteristics among different types of drivers. At the same time, complex road conditions have a higher danger coefficient, and the probability of traffic accidents significantly increases, making this type of road scene of significant practical research significance.

During the experiment, the vehicle entered the experimental route at a certain speed, and the experimental scene was composed of different line combinations, requiring various driving behaviors to generate multiple operation combinations. Compared to other road scenes (such as flat roads in cities), it can better represent the driving style of drivers. The experimental vehicle was an automatic transmission vehicle, and the main research indicators, symbols, and ranges of driving operation behaviors are shown in Table 1.

3 Graph Construction

The original driving behavior data has characteristics such as strong real-time performance, poor stability, and continuous changes, making it difficult to reflect driving proficiency and style [10]. It is necessary to screen, extract, and process the raw data, and convert it into intuitive graphical numerical data. The driving behavior graph mainly includes the following steps.

3.1 Driving Behavior Extraction

Driving operation behavior is extracted by moving time windows to transform the raw data into numerical data based on the time axis. According to the results of the simulation experiment, the completion time range for the driver is between 102s and 158s. Due to the relatively long completion time for driving, the operation behavior does not change significantly within a short period of time. Therefore, a time window length of one

Table 2. Encoding scheme.

f(n + 1) − f(n) Driving behavior	**0–25%**	**25%–50%**	**50%–75%**	**75%–100%**
A				
B				
S				

second can not only fully record driving operation behavior, but also avoid redundant data recording. The driving simulator records 60 instances of driving operation behavior every 1s, and formula (1) indicates that recording of operation behavior is conducted every second.

$$f(n) = \frac{1}{60}\sum\nolimits_{i=60(n-1)+1}^{60n} f(x_i) \tag{1}$$

3.2 Behavioral Data Coding

After extracting the operational behavior data on a per-second basis based on time windows, numerical data was transformed into abstract symbols specific to graph theory, a process known as data encoding. As the degree of pedal depression affects vehicle status and driver perception, encoding was conducted under the following conditions: pedal depression was categorized into five levels, including no depression (0%), light depression (1–25%), moderate depression (26–50%), deep depression (51–75%), and full depression (76–100%). When the change in driver behavior at a given moment exceeded 25% compared to the previous moment, it was recorded and encoded. Therefore, the range of driver behavior data was divided into four equal parts, with node size representing the degree of driver behavior, such as the degree of pedal depression. Similarly, during driving at a speed of 60km/h, the steering wheel angle also showed significant differences when the car was changing lanes or turning. Node division is shown in Table 2.

3.3 Construction of Driving Behavior Map

During actual driving, changes in driving state may be caused by a single driving behavior or the combined effects of multiple driving behaviors. Therefore, after completing the extraction of driving behaviors and the encoding of behavior data, not only is it necessary to plot the temporal changes of individual driving behaviors, but also to design the combination of multiple driving behaviors.

The purpose of map drawing is to observe the degree of variation in indicator parameters throughout the entire driving process. The rules for drawing the map are as follows:

(1) Start drawing when the behavior first changes. (2) Record and draw when the degree of change in operation is greater than 1/4 compared to the previous moment.

Construct a coordinate system with time series on the X-axis and mileage on the Y-axis. At the time of operation occurrence, determine the position and attributes of each operation behavior on the coordinate axis based on the encoding rules. When drawing maps of multiple operation behaviors, the following should be considered: The coding records of different operation behaviors at the same moment, and the mutual influences between various operations at different moments.

4 Differentiation Analysis

Using the method of constructing a driving behavior graph, a driving behavior graph was drawn to compare the differences in driving operation characteristics among different drivers. Firstly, the driving behavior was preliminarily classified according to the driving time. According to the road safety driving regulations, it takes about 120s to complete the experimental section of the road. Considering the linear characteristics of the experimental section and the road speed limit regulations, it is considered that driving times between 110s and 133s are all in compliance with road safety driving regulations. Therefore, the driving behavior characteristics were preliminarily divided into three categories based on driving time, as shown in Table 3.

Random samples were selected from different groups, and driving behavior graphs were plotted as shown in Fig. 1.

4.1 Analysis of Driving Behavior Graphs

Type I drivers show a significant change in driving operation behavior after leaving the initial straight road section, with a clear increase in the frequency and degree of stepping on the accelerator and brake pedals, indicating a more aggressive driving behavior on this road segment. Before entering the curved road section, drivers deepen the degree of stepping on the brake pedal and then continuously step on the accelerator pedal with large amplitude after entering the straight road section for acceleration. There are certain differences in driving behaviors among different drivers, including but not limited to the specific position and degree of vehicle acceleration operation on the same road section.

Vehicles driven by Type II drivers remain in a stable state, with less frequent occurrences of aggressive driving behavior. Before entering the curved road section, vehicles slow down in advance and adopt appropriate turning and braking operations to ensure

Table 3. Classification of driving behavior sample data

Type	Driving behavior characteristics	Temporal range	Sample size
I	Fast	[102,110]	14
II	Moderate	(110,133)	28
III	Slow	[133,158]	8

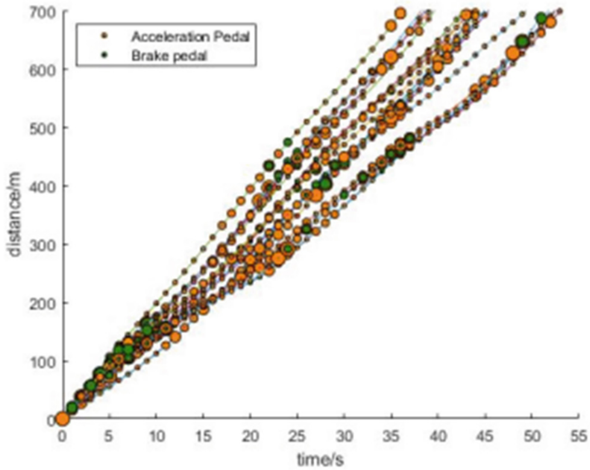

Fig. 1. Driving Behavior Graphs

that the vehicle enters the curved road at an appropriate speed, avoiding loss of control due to excessive speed. After leaving the curved road, the driver repeatedly and slightly steps on the accelerator pedal to maintain a certain speed range and ensure safe driving while keeping the road smooth. There is a certain similarity between these driving behavior graphs, which also provide a reference standard for other drivers to better grasp safe driving skills and driving habits.

Type III driving behavior is relatively stable on straight road segments, but emergency braking and other stress operations occur when entering the curved road section. Due to the low speed when leaving the curved road section, there is a significant acceleration by stepping on the accelerator pedal after leaving the curve. There is also a certain similarity between the driving behavior graphs of this type, but due to the low operating speed, it has a certain impact on the smoothness of the road and conflicts with driving behaviors of other styles, leading to road safety hazards.

5 Conclusion

In this study, we utilized typical driving behavior data and leveraged the unique advantages of graph theory in information representation to construct individual driving behavior graphs, achieving the visualization of driving behavior. The driving behavior graphs can clearly and accurately demonstrate the behavioral characteristics of individual drivers. By classifying driving behavior based on current road standards, we discovered significant differences in the driving behavior graphs of different categories. Similarities among driving behavior characteristics of the same category were also observed, validating the rationality and accuracy of graph construction theory. Moreover, through the comparison of road supply graphs and driving behavior graphs, conflicts between road supply capacity and driving demand were reflected, indicating whether road conditions and facilities meet current driving needs. By analyzing the differences and mechanisms, targeted driving training and regulation or road facility improvement can be implemented for individual drivers or road infrastructure, respectively.

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