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A graphical modeling method for individual driving behavior and its application in driving safety analysis using GPS data

Chen Chen [a], Xiaohua Zhao [a,*], Yunlong Zhang [b], Jian Rong [a], Xiaoming Liu [a]

[a] Beijing Key Laboratory of Traffic Engineering, (Beijing University of Technology), Pingleyuan No. 100, Chaoyang District, Beijing 100124, PR China
[b] Zachry Department of Civil Engineering, Texas A&M University, 3136 TAMU, College Station, TX 77843, USA

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ABSTRACT

Due to differences in driving skills and personal characteristics among drivers, the behaviors of drivers when faced with various driving environments differ, causing different levels of driving safety concerns. In past research, the measurement of safety-related driving behavior mostly focused on classification, while few studies were concerned with individual driving behavior characteristics. However, it is important for drivers to recognize and correct their dangerous behaviors and optimize their driving. This paper presents a graphical method for modeling individual driving behaviors, and the results can be used in driving safety analysis. Based on the assumption that drivers have specific driving habits, typical driving patterns during driving are first detected and extracted. These typical driving patterns are then sorted according to their frequencies, forming a driving behavior graph that can directly illustrate each driver's behavior features. Furthermore, a quantitative analysis method for evaluating driving safety based on the behavior graph is provided. To verify the proposed method, a case study focusing on vehicles' longitudinal motion was conducted using GPS data collected from Beijing taxis. The results demonstrated that the graphical method can describe the individual features of a driver's longitudinal acceleration behavior and distinguish differences among drivers. The development of this method can help understand the individual features of driving behaviors and further support measures to optimize driving safety.

1. Introduction

Different drivers have different driving behaviors due to their personal characteristics and driving skills, leading to different accident risks. Some drivers prefer to drive aggressively, while others are more cautious. Therefore, an analysis of the driving behavior is useful in measuring drivers' driving safety and in helping to prevent traffic crashes.

In recent years, many studies have attempted to model driving behavior from the perspective of driving safety (Chen, Fang, Tien, & Wu, 2014; Constantinescu, Marinoiu, & Vladoiu, 2010; Dörr, Grabengiesser, & Gauterin, 2014; Eboli, Guido, Mazzulla, Pungillo, & Pungillo, 2017; Eren, Makinist, Akin, & Yilmaz, 2012; Hong, Margines, & Dey, 2014; Johnson & Trivedi, 2011; Li, Li, Cheng, & Green, 2017; Lu, Jiang, & Wang, 2013; Saiprasert, Pholprasit, & Pattara-Atikom, 2013; Van Ly, Martin, & Trivedi, 2013). The methods used in these studies include driving-event-based evaluation, fuzzy analysis,

* Corresponding author.
E-mail addresses: chen-chen@emails.bjut.edu.cn (C. Chen), xiaohuazhao618@gmail.com (X. Zhao), yzhang@civil.tamu.edu (Y. Zhang), jrong@bjut.edu.cn (J. Rong), liuxm@bjut.edu.cn (X. Liu).

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and machine learning. The goal of most of these studies was to classify drivers into several driving safety levels, such as safe, normal or dangerous, while few focused on individual driving behavior characteristics. However, in addition to classification, another important function of driving behavior modeling is to assist in driving behavior optimization, which is related to the drivers themselves. In other words, clear guidance with regard to the improvement of driving skills would be helpful for individual drivers. In addition, due to the differences in drivers' personalities and driving skills, the responses to a set of driving conditions may not be the same, so an evaluation based on predefined driving events is not proper for all drivers. Thus, it is necessary to find a way to describe an individual driver's driving behavior characteristics and to further analyze the relationship between these characteristics and driving safety to help improve the behavior and reduce accident risks.

Driving behavior can be seen as the reaction of a driver to external driving conditions. We assume that there are some fundamental patterns for each driver that can be regarded as the basic units that form driving behaviors upon arrangement in the time dimension. The fundamental patterns represent the internal features that can be seen as the integration of driving-related habits, skills and other characteristics, independent of the environment. These patterns ultimately result in the observed driving behaviors when drivers face specific driving conditions. This paper introduces our attempt to explore drivers' individual behavioral features. A graphical modeling method is used to directly demonstrate drivers' typical driving patterns. Compared with machine learning methods, such as the neural network and support vector machine techniques, graphs can provide an intuitive impression of drivers' driving features that is easy to understand and readily conveys information.

With the development of information and technology, various sensors have become embedded in many devices, such as smartphones and on-board diagnostic (OBD) devices, making it easier to obtain data on naturalistic driving behavior. In particular, the global positioning system (GPS) is the most widely used and has high precision. In this paper, the case study is based on GPS data from OBD devices mounted in Beijing taxis, and the longitudinal motion of the vehicle is used to verify the proposed method.

This paper is structured as follows: the next section reviews the previous literature on driving behavior modeling. Section 3 describes the proposed graphical modeling method, and a case study based on OBD data is performed in Section 4 to demonstrate the effectiveness of the method.

2. Literature review

In the field of the safety analysis of driving behavior, driving style detection is a hot topic that mainly involves the classification of driving styles, most commonly nonaggressive, neutral or aggressive. Because driving styles are thought to be tightly related to driving safety, the differentiation of driving styles is regarded as a way of evaluating driving safety.

Some driving style-related studies classified driving styles by applying statistical methods or machine learning algorithms using features of driving behavior parameters (Constantinescu et al., 2010; Dörr et al., 2014; Eboli et al., 2017; Hong et al., 2014). Constantinescu et al. (Constantinescu et al., 2010) modeled personal driving styles based on GPS data. The driving parameters used in their research included speeds over 60 km/h and acceleration (positive acceleration and braking). Utilizing cluster analysis and principal component analysis, the drivers were classified into different driving styles, including nonaggressive, somewhat nonaggressive, neutral, moderately aggressive and very aggressive. Eboli et al. (2017) investigated the traffic accident risk using parameters based on the travel speed as. The 50th and 80th percentile speeds and average speeds were calculated and used to classify the drivers into three types of driving behavior: safe, unsafe, and safe but potentially dangerous. Hong et al. (2014) constructed an in-vehicle sensing platform to evaluate drivers' driving styles. The sensors used in their study were an Android smartphone, an OBD and an inertial measurement unit (IMU). The driving behavior features, including the maximum, average, and standard deviation of the speed, speed change, longitudinal acceleration, lateral acceleration, RPM, and throttle position, were collected, and the features were discretized into five levels using thresholds that made the number of samples in each state equivalent. A naive Bayes classifier was applied to model the relationship between driving features and driving styles (determined by driving violations and questionnaire responses). The results showed that the proposed models exhibited good accuracy, and the driving feature distributions of the different driving styles were described. Some of these studies obtained a higher accuracy for the driving style classification. However, due to the features of the methods used, those studies cannot be directly used for diagnosing faults in an individual driver's behavior.

Another popular method of driving style classification is to detect safety-related driving events, such as sharp acceleration, sharp braking, and sharp turning (Bagdadi, 2013; Baldwin, Duncan, & West, 2004; Bergasa et al., 2014; Chen et al., 2014; Eren et al., 2012; Fazeen, Gozick, Dantu, Bhukhiya, & González, 2012; Johnson & Trivedi, 2011; Li et al., 2017; Lu et al., 2013; Musicant, Bar-Gera, & Schechtman, 2010; Paefgen, Kehr, Zhai, & Michahelles, 2012; Saiprasert et al., 2013; Van Ly et al., 2013) instead of using the abstract features of driving behavior data. In Johnson's (Johnson & Trivedi, 2011) research, data from smartphone sensors, including accelerometer values, gyroscope values and Euler angle rotation, were used to determine drivers' driving styles. The types of events that could be detected included right/left/U turns, aggressive right/left/U turns, and aggressive acceleration/deceleration/lane changes. Based on these data, the drivers' behaviors were determined to be typical or aggressive. The method used in their study was dynamic time warping (DTW), which mainly performs time series data matching. Thus, some predefined templates of the detected driving events were needed. In the research of Li et al. (2017), the driving behaviors on highways were categorized into 12 driving states, including emergency braking, free driving, constrained/free left/right lane changing, and near/middle/far following, which were defined based on thresholds from previous works. Then, a random forest algorithm was used to classify the driving style using the transitions between individual maneuvering states. The results showed that five maneuvering states were statistically significant for the classification: free driving, approaching, near following, and constrained left and right lane changing. The detection of the driving states in that study was very detailed, although many sensors were needed, including 7 cameras and CAN buses, and the states were manually identified frame-by-frame, making it infeasible for large-scale testing. Chen et al. (2014) proposed a method to predict dangerous driving events. In their study, dangerous driving events were translated into a dangerous attributed relational map (ARM), which is a map that illustrates time series-based driving maneuvers. Then, the translated driving behavior was compared with a template ARM using a two-way fuzzy attribute map matching technique to determine if it was a dangerous driving event. Van Ly et al. (2013) explored the method of using vehicle CAN bus data to construct driving profiles for drivers and then classified their driving styles. The driving events used in their studies included acceleration, braking and turning. A support vector machine and *k*-means clustering were used in the training algorithm, and the results showed an accuracy of 60–80%. In these studies, the use of predefined driving events was essential, but the thresholds used in the definition of these driving events were not consistent. In the research of Paefgen et al. (2012), the thresholds used were $\pm 0.1\, g \approx 1\ \mathrm{m/s^2}$ for sharp acceleration and deceleration. Baldwin et al. (2004) used $\pm 0.15\ \mathrm{g} \approx 1.5\ \mathrm{m/s^2}$, and Bergasa et al. (2014) used $\pm 0.4\ \mathrm{g} \approx 4\ \mathrm{m/s^2}$. In the research of Fazeen et al. (2012), the thresholds were $\pm 0.3\ \mathrm{g} \approx 3\ \mathrm{m/s^2}$. Bagdadi used $\pm 0.48\ \mathrm{g} \approx 4.8\ \mathrm{m/s^2}$ (Bagdadi, 2013).

In addition to the analysis of the driving style, some scholars have modeled the safety of driving behavior directly. Vaiana et al. (2014) developed an algorithm to evaluate the aggressiveness based on a *g-g* diagram, which was drawn using both the longitudinal and lateral accelerations. In their study, a ‘safe area’ was defined on the *g-g* diagram, and a driver’s aggressiveness was evaluated by counting the percentages of external points. Similarly, Joubert, de Beer, and de Koker (2016) defined three levels of risk space on a *g-g* diagram using three quantiles. By assigning different weights to the three risk spaces, the driving safety could be calculated. Another study (Eboli, Mazzulla, & Pungillo, 2016) also utilized the *g-g* diagram to analyze car users’ safe or unsafe driving behavior, taking the speed into consideration. Ellison, Greaves, and Bliemer (2015) introduced driver behavior profiles to evaluate the risk of driving behavior. The frequencies and magnitude of speeding events, aggressive acceleration events and aggressive braking events were taken as behavior measures, and their temporal and spatial features were also taken as factors. Based on these parameters, drivers’ behavior profiles were established, and total scores representing the driving risk were given. Although these studies directly evaluate the risk of driving behavior, the individual characteristics are still unclear.

To summarize, most of the driving safety-related studies focused on the classification of driving styles or the scoring of driving risk. However, these previous methods mainly considered the description of cluster characteristics. For individual drivers, the features of their individual driving behavior were still ambiguous. While event-based research can provide some information to drivers, such as the frequencies of dangerous driving events, most of the studies of this type needed a predefined and fixed threshold when defining dangerous driving events. In addition to the issue of such events’ inconsistent definitions, a fixed threshold might not be proper for all drivers due to drivers’ different levels of driving skill and knowledge of the driving environment.

In recent years, a graphical model that can provide a visual display of data features has been introduced in the modeling of driving behavior. Chen, Fang, and Tien (2013) proposed the use of a driving habit graph (DHG) to model driving behavior. A DHG can illustrate significant changes in behavior parameters in a sequence of driving data, providing an intuitive display of the driving style. However, the DHG may not be appropriate for huge datasets because it requires subjective judgment when drawing a driving map and manual work. Inspired by that study, this paper focuses on the general features of the driving behavior and proposes a different graphical method to model driving behaviors.

3. Method

3.1. Overview of the proposed method

As mentioned above, it is assumed that drivers have individual typical driving patterns. Driving behaviors are the arrangement of these patterns over time in response to driving situations. Our work is to identify these typical patterns, which are then used to evaluate the level of driving safety of the drivers.

The primary task in this method is to extract the typical patterns, which are part of the temporally continuous behavior data. During driving, the vehicle is controlled by the driver’s constant adjustments to arrive at a desired state. We consider three seconds to be a proper duration during which a driver is able to adjust the vehicle to some desired state. Thus, the patterns are defined as the driving behaviors (such as speed, acceleration, steering, etc.) during every three seconds.

As time series data, a reasonable simplification is needed for the extracted features to reduce the complexity. During the method exploration, we used the Symbolic Aggregate Approximation (SAX) method to translate data into simplified codes. The SAX algorithm was proposed by Lin, Keogh, Lonardi, and Chiu (2003) in 2003 and can transform an input time series into a string such as ‘aabcda’. Fig. 1 shows a detailed example of SAX results. The SAX process consists of two steps (Symbolic Aggregate approXimation, 2018): (i) transformation of the raw data to a piecewise aggregate approximation (PAA) representation (blue line to red dots) and (ii) translation from the PAA data to a string according to the positions of the red dots. In this

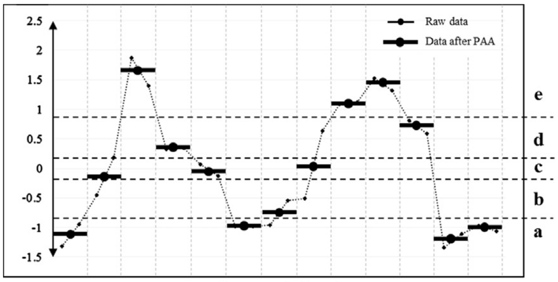


Fig. 1. Detail of SAX.

paper, the driving behavior data are converted to codes (such as '001123') instead of strings (such as 'aabbcd') to make it easier to read and compute by computers. PAA is applied with a frame duration of 1 s. In this case, every three consecutive codes are a unit and are identified as one driving pattern (like '012'), representing the driver's behavior during those three seconds.

There are five steps included in our method: data normalization, data grading and coding, pattern detection, typical pattern extraction, and graph drawing. Among the five steps, the first two steps are part of the SAX process. Fig. 2 shows the flow of the method. The data used in Fig. 2 are just a sample for illustration purposes. In the following description, acceleration data are used as an example to help understand the process.

(1) *Data normalization*

One driver's raw driving behavior data, such as the acceleration data, are normalized using the Z- standardization method to have the same dimension as the other drivers' data:

$$x^* = \frac{x - \mu}{\sigma} \tag{1}$$

Here, x is the raw data of a driver. μ and σ are the mean and standard deviation of x, respectively. x^* is the data after normalization, with a mean of 0 and a standard deviation of 1, as shown in Fig. 2b. This normalization is required in SAX in preparation for the data grading. Each driver's data are handled separately.

(2) *Data grading and coding*

Similar to SAX, the normalized data are first subjected to PAA to make each frame be 1 s and then graded into one of the seven grades, as shown in Fig. 2c (the sample frequency of the raw data is 2 Hz; thus, every two data points are combined into one PAA data frame). In fact, SAX can divide data into at most 20 grades and provides corresponding thresholds. The choice of seven grades is the result of several tests with different numbers of grades, i.e., 3, 5, 7, 9, and 11 grades. Only odd numbers of grades are tested so that the median grade always represents neutral behaviors (for acceleration data, the median grade corresponds to cruising).

As mentioned before, the data are converted to code with the numbers '0' to '6' (seven grades) instead of the letters 'a' to 'g (the seven grades in the SAX representation). Because the mean of the normalized data is zero, code '3' represents the neutral behaviors. Taking the acceleration data as an example, code '3' represents acceleration values close to 0 m/s^2, i.e., cruising. Codes '0', '1' and '2' represent negative data values, and the amplitude of the data values increases with decreases in the code value. Taking acceleration data as an example, codes '0', '1' and '2' represent negative acceleration values, i.e., deceleration. The deceleration becomes sharper as the code value decreases. In contrast, codes '4', '5', and '6' represent positive data values, and the amplitude of the behaviors increases with the increase in the code value. Taking acceleration data as an example, codes '4', '5' and '6' represent positive acceleration values, i.e., accelerating motion. The acceleration becomes sharper as the code value increases.

(3) *Pattern detection*

From the start of the data, every three codes are regarded as one driving pattern. Driving is a continuous process; thus, the patterns are detected using a moving window with a window size of 3 s, as shown in Fig. 2d. In that figure, the driving patterns are detected as '036', '364', '643' ... '501'. In this case, one continuous acceleration data set of length n can produce n-2 patterns.

(4) *Typical pattern extraction*

Due to the differences in drivers' levels of driving skill and individual characteristics, each driver has specific driving habits. Based on the driving patterns extracted in the previous step, the most frequent driving patterns (typical patterns) are used to represent drivers' driving habits.

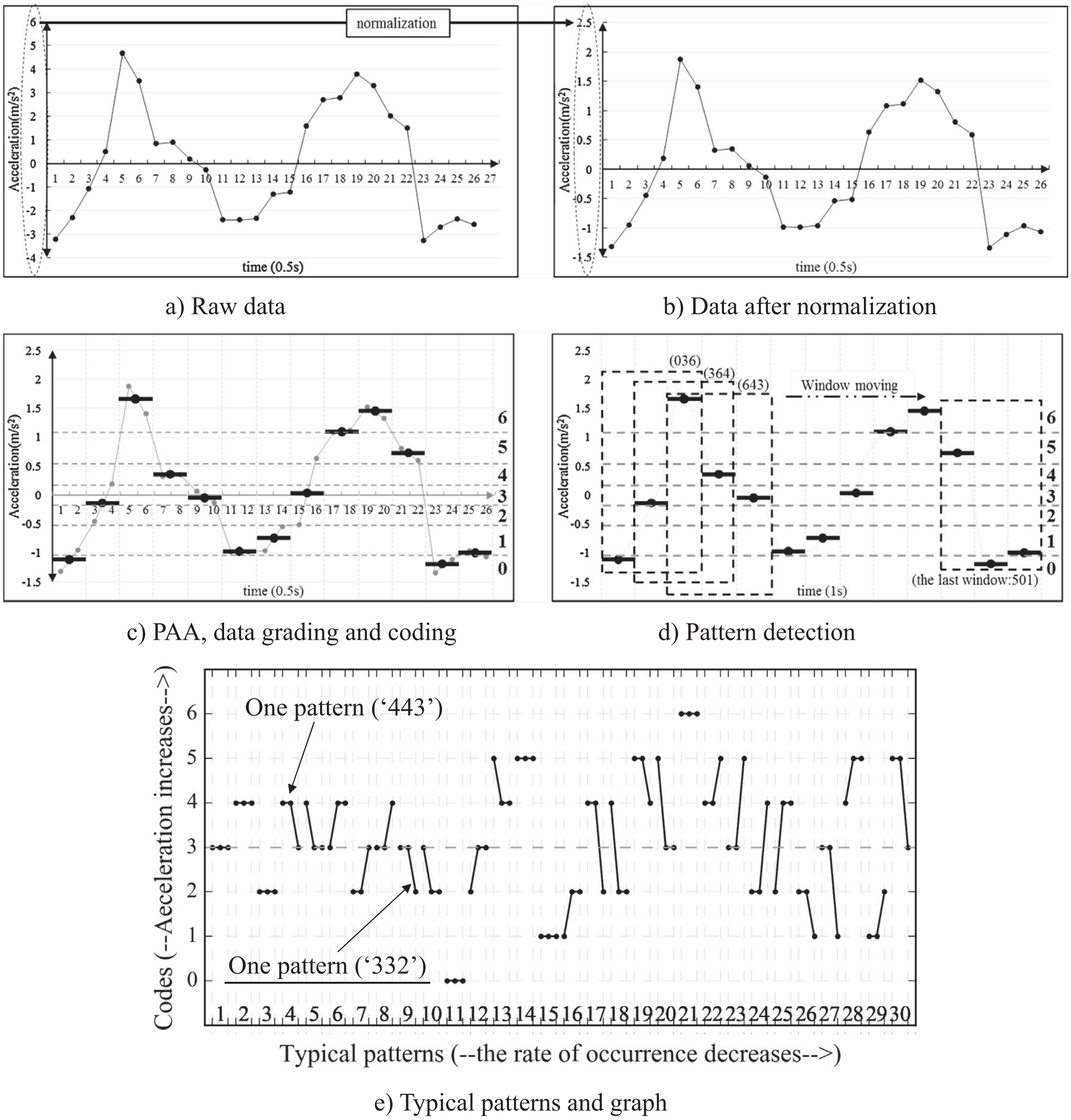


Fig. 2. Steps of the proposed method.

The driving patterns that have the same codes are naturally clustered into one group, and the number of patterns contained in each group is counted. Then, the rate of occurrence (%, ROO) of each type of driving pattern is calculated. For example, if the driving pattern '011' appears m times in one continuous acceleration data set of length n, then the ROO of the driving pattern '011' is $m/(n-2)$. For each driver, the thirty most frequent driving patterns are extracted and are regarded as his or her typical patterns. Under the premise that enough driving data are collected to cover various traffic conditions, road types and other external factors, these typical patterns can describe the driver's intrinsic driving habits. Obviously, these typical patterns are independent of the external driving conditions and instead reflect the driver's general driving preferences.

(5) *Graph drawing*

The typical driving patterns are plotted in the descending order of their ROOs, and the resulting plot is regarded as the driving behavior graph for one driver, as shown in Fig. 2e. Different drivers have different orders of typical patterns, indicating the individual characteristics of the different driving behaviors.

The driving behavior data can be transformed into graphs via the five steps described above. The driving environments are ignored, and the typical patterns are considered fundamental behavior modes, reflecting the general characteristics of drivers.

3.2. Quantitative analysis using the behavior graph

The driving behavior graph is a visual representation and a qualitative description of a driver's driving habits. However, the frequencies and rankings of the typical patterns and the coding of the patterns themselves provide the potential for quantitative analysis.

Here, taking the acceleration data as an example, a simple algorithm is proposed to provide an example of a quantitative analysis of driving safety.

$$SCORE = \sum_{i=1}^{30} freq_i * \{abs[mean(CODE) - 3] + 0.5 * std(CODE)\} \tag{2}$$

Here, *SCORE* is the score of driving behavior safety. *i* is the number of typical driving patterns. $freq_i$ is the ROO (%) of the i^{th} typical driving pattern. *CODE* is the code of a typical pattern, e.g., '123'. *mean* and *std* are functions used to calculate the mean and standard deviation of a *CODE*, respectively. For example, the mean of code '123' is (1 + 2 + 3)/3 = 2, and the standard deviation is 1. is the function used to calculate the absolute value.

This scoring method is based on the consideration that both the amplitude of the acceleration values and its variation, represented by the functions *mean* and *std*, respectively, can reflect driving behavior safety. Compared with the variation, the amplitude is thought to be more important; sharp acceleration behaviors are more dangerous than fluctuating moderate acceleration behaviors. Thus, the weight of the mean is determined as 1, while the weight of the standard is 0.5. The function '$abs[mean(CODE) - 3]$' is used to evaluate the amplitude of the acceleration for both acceleration and deceleration behaviors because code '3' represents cruising behavior. This quantitative analysis method can take both the amplitude (reflecting the change in the vehicle state) and the variation (reflecting the stability of vehicle control) of the acceleration into consideration. Clearly, a lower score indicates safer driving behaviors.

3.3. Capability of the method

In this method for modeling individual driving behavior, the most important question is whether it has enough capability to distinguish between different drivers. In other words, the behavior graphs need to have enough types of structures to describe the characteristics of thousands or millions of drivers. There are two dimensions to describe its capability.

(1) *The possible types of driving patterns*

The data are divided into seven grades, and every three seconds are identified as one driving pattern. Thus, the driving patterns have 7^3 = 343 potential types in theory. Focusing on the acceleration behavior, there are 4^3–1 = 63 potential types of driving patterns. Here, driving patterns that include temporary cruising are also regarded as acceleration behavior, such as the pattern '345' or '335', based on the consideration that these patterns indicate the desire for acceleration. The minus 1 in the above calculation of the potential types is the exception of the pattern '333', which represents a smooth cruising motion. The deceleration behavior has 63 types of driving patterns as well.

(2) *The possible types of behavior graphs*

A behavior graph consists of the first 30 frequent driving patterns. Thus, there are A_{343}^{30} types of graphs. Considering the acceleration or deceleration behaviors, A_{63}^{30} types of graphs are available.

Not all of the possible types of driving pattern and behavior graphs will emerge. However, the huge numbers of possible types of both driving patterns and graphs prove the capability of the proposed graphical method.

4. Case Study: Method application on the driving safety analysis

To verify the proposed method, we applied the method to a driving behavior safety analysis. The data used in this case study come from OBD devices. For illustration purposes, only the drivers' longitudinal acceleration was used in the safety analysis. The longitudinal acceleration is chosen as the example because the acceleration is a typical index that is closely related to driving safety, and changes in the acceleration also represent changes in vehicle speed, which is another important index of driving safety.

4.1. Data collection

The data used in this paper were collected using OBD devices mounted on Beijing taxis. The OBD device consists of one GPS module used to collect position data, one OBD module used to collect vehicle operation data, and one cellular network module used to upload the collected data to the server. The collected parameters include the time, device ID, longitude, latitude, GPS speed (km/h), instantaneous fuel consumption (L/h), cumulative travel distance (km), engine speed (rpm), and engine torque (N•m), etc., with a sampling frequency of 1 Hz.

A total of 124 taxis (Hyundai Elantra (1.6 L), all with vehicle ages of 2 years) were equipped with the device, and data on the driving behavior of the drivers of these 124 taxis were collected. These drivers were recruited from a taxi enterprise, and they are all professional drivers with more than 15 years of driving experience on average. The data were collected over approximately 115 days from January 2017 to April 2017. For each driver, approximately 480 h of driving data were collected.

The recruited taxi drivers did not have fixed working times or fixed rest days, and most of the drivers drove during the day, ranging from 7:00 AM to 12:00 PM in general. In addition, the driving routes depended on the needs of passengers, and the data collection time was sufficiently long. Thus, it was thought that the collected data cover almost all traffic conditions and road types.

4.2. Driving safety pre-evaluation

The aim of this case study is to verify the proposed method by applying it to the modeling of a driver's individual driving behavior and the analysis of the safety of the driving behavior. Thus, it is necessary to give the test data a label that indicates the driving safety of the drivers. The proposed method can be considered effective if the behavior graphs can describe the characteristics of the driving behavior and determine differences in driving safety among drivers. Unfortunately, neither the driving violation data nor traffic accident data for these professional drivers were obtained. As an alternative option, the driving safety was evaluated by identifying the frequencies of dangerous driving events. Because only the longitudinal speed was used, only two driving events, sharp acceleration and sharp deceleration, were taken into consideration. The acceleration data used (m/s^2) were calculated based on the collected GPS speed data.

Here, thresholds ($\pm 0.3\ g \approx 3\ m/s^2$) taken from the literature (Fazeen et al., 2012) were used to detect the two events. Utilizing these thresholds, a simplified scoring method was conducted to assign a driving safety label to each driver. First, the frequencies (%) of sharp acceleration (acceleration > $3\ m/s^2$) and sharp deceleration (acceleration < $-3\ m/s^2$) were counted. Then, the drivers were sorted according to the total frequency of sharp acceleration and sharp deceleration. Drivers who had a high total frequency were determined to be of low safety in terms of driving behavior. The evaluation results are shown in Fig. 3. The total frequency of dangerous driving events gives an integrated evaluation of the driving safety. The distinction between the frequencies of sharp deceleration is more obvious, while the acceleration behavior does not show such obvious differences.

Six drivers, including three safe drivers (numbers 1, 2, and 3) and three risky drivers (numbers 4, 5, and 6), were randomly selected as examples for the verification of the proposed graphical modeling method.

4.3. Driving behavior graph drawing

Applying the steps described in Section 3, six drivers' driving behavior graphs were drawn based on the acceleration data, as shown in Figs. 4–6. It should be kept in mind that as the driver's ID number increases, the driver's driving behavior safety decreases.

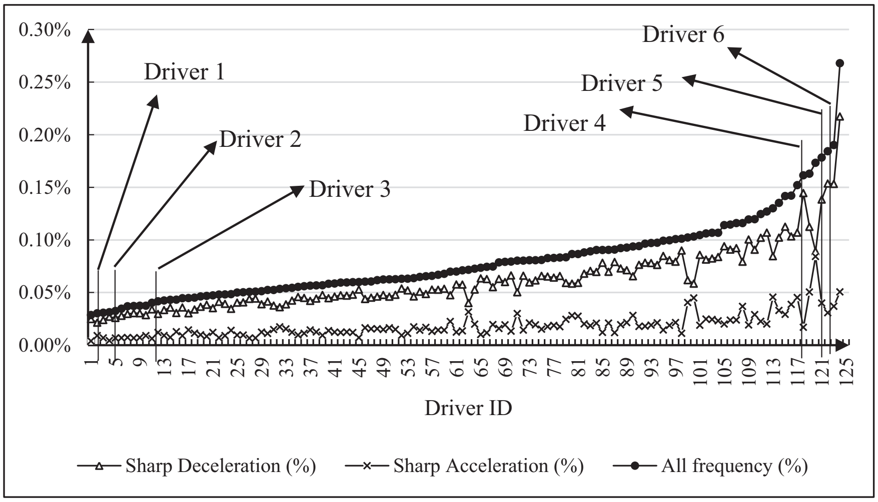


Fig. 3. The evaluation results of drivers' driving safety using fixed thresholds.

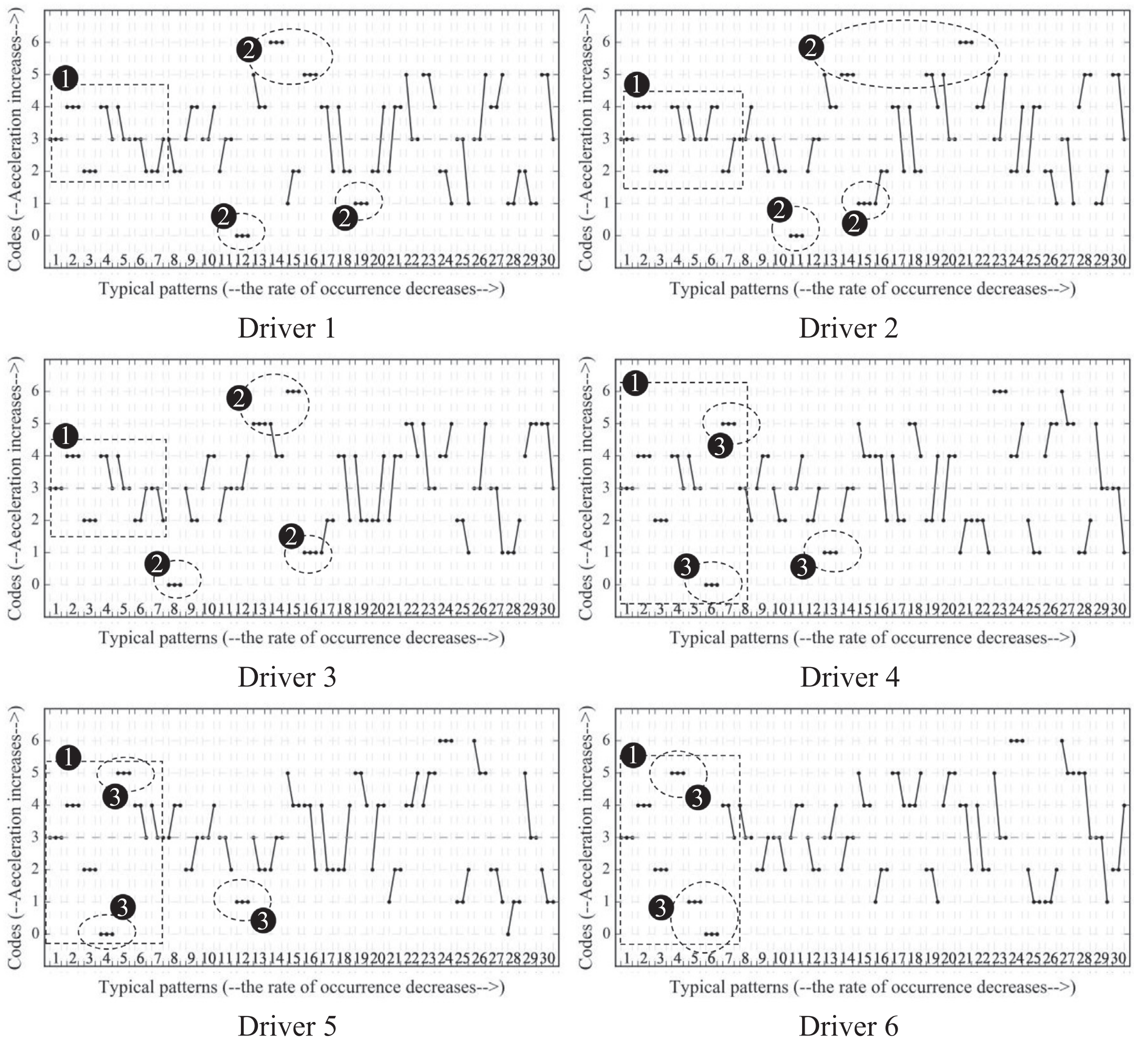


Fig. 4. Graphs of all driving behaviors.

For all driving behaviors, the first 30 driving patterns (typical patterns) were extracted and are shown in Fig. 4. Moreover, considering that the acceleration and deceleration behaviors are two important and independent manipulations, the typical patterns of both the acceleration and deceleration behaviors were extracted and are shown in Figs. 5 and 6. It should be noted that Figs. 5 and 6 only show the first 10 patterns because these patterns were enough to illustrate the driving behavior characteristics of the drivers and to tell the difference between drivers.

4.4. Results

(1) *Graph of all driving behaviors*

In Fig. 4, the three most frequent driving patterns for all drivers were cruising (code '333'), slight acceleration (code '444') and slight deceleration ('222'), regardless of whether they were safe drivers or risky drivers. The difference in the driving behavior characteristics between the three safe drivers and three risky drivers can be clearly observed through the first several typical patterns, enclosed by the dashed boxes labeled ①. The three safe drivers tended to choose a lower acceleration when accelerating and decelerating, while the three risky drivers tended to choose a sharper acceleration or deceleration.

In the comparison among the three safe drivers (drivers 1, 2, and 3), the driving patterns enclosed by the dashed circles labeled ②, which represent higher acceleration, show the different habits of the drivers, especially the rankings of patterns '000' and '111' (sharp and moderate deceleration) in the safe drivers' graphs. A driver with a higher driving safety level (driver 1) has lower rankings for these patterns. For the patterns '666' and '555', driver 1 had higher rankings (14 and 16, respectively) than the others, which indicates that driver 1 is more risky than drivers 2 and 3 if the only concern is the acceleration behavior. This phenomenon also indicates further differences in the acceleration and deceleration behaviors of the drivers.

In the comparison among the three risky drivers, the rankings of patterns '000', '111' and '555', enclosed by the dashed circles labeled ③, can clearly show the driving behavior characteristics: driver 6 tends to exhibit sharper deceleration behavior than the other two drivers. Another interesting finding is that the pattern '666' ranks in a lower position in the three risky drivers' behavior graphs than in the three safe drivers' graphs, which indicates that the risky drivers perform fewer sharp acceleration maneuvers than the safe drivers.

(2) *Graphs of acceleration behaviors*

Fig. 5 focuses on the characteristics of the drivers' acceleration behaviors. The three safe drivers have the same graph structure for the first five typical driving patterns. The main difference between the safe and risky drivers is in the ranking of pattern '555', enclosed by the dashed circles. The three risky drivers have higher rankings of this pattern than the three safe drivers. However, pattern '666' might lead to some questions. This pattern appears in the first ten patterns on the three safe drivers' graphs but not in the three risky drivers' graphs, which can also be observed in Fig. 4. This difference between the graph results and the safety label in Fig. 3 might also be related to the frequencies of the patterns, not only the rankings.

In the comparison among the three safe drivers, the rankings of pattern '555' increases with the worsening of the safety level (driver 1 to driver 3). There is also some question regarding pattern '666'. Except for the possible reason of its actual frequency, the interaction among patterns '555' and '666' and the other patterns might lead to the considered drivers' driving

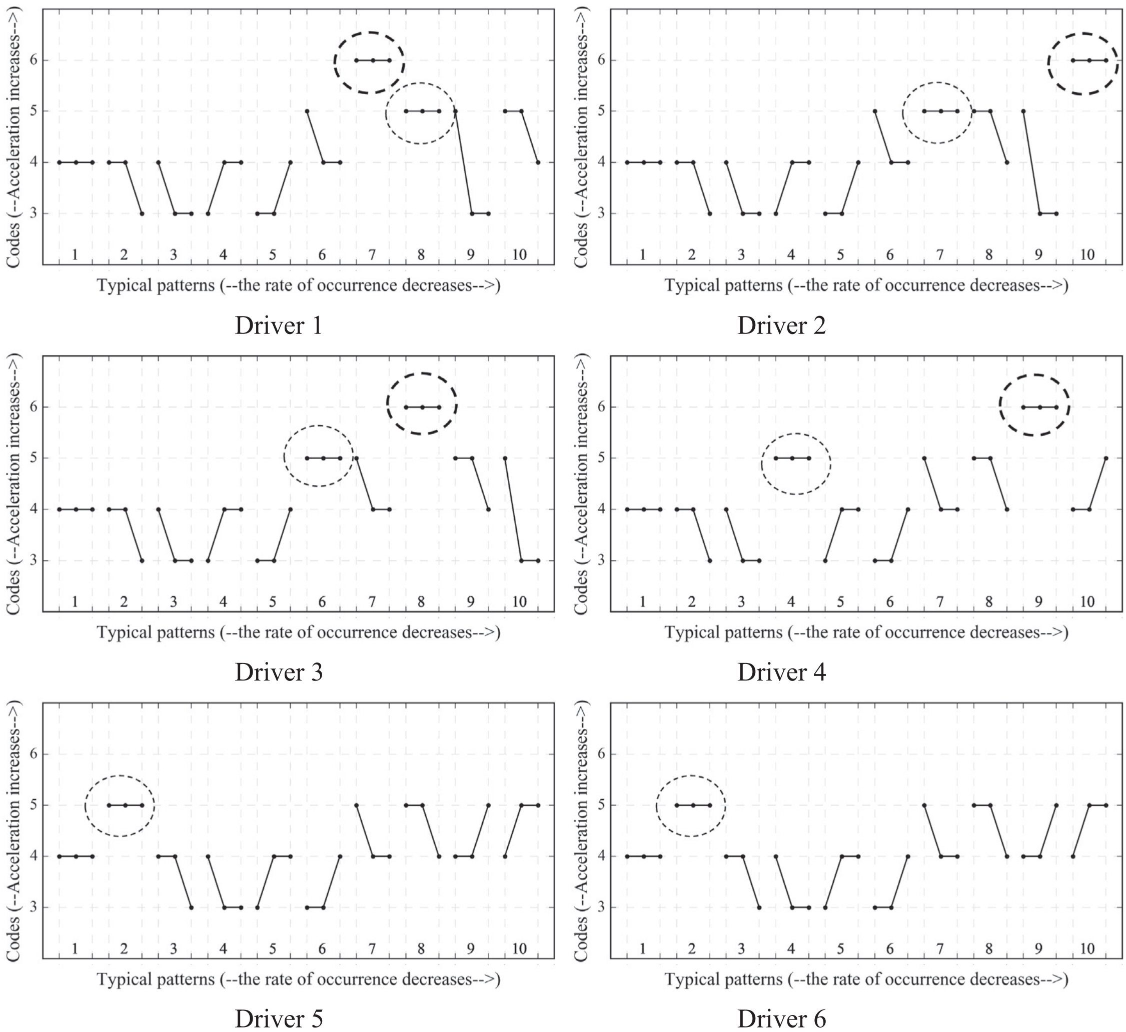


Fig. 5. Graphs of acceleration behaviors.

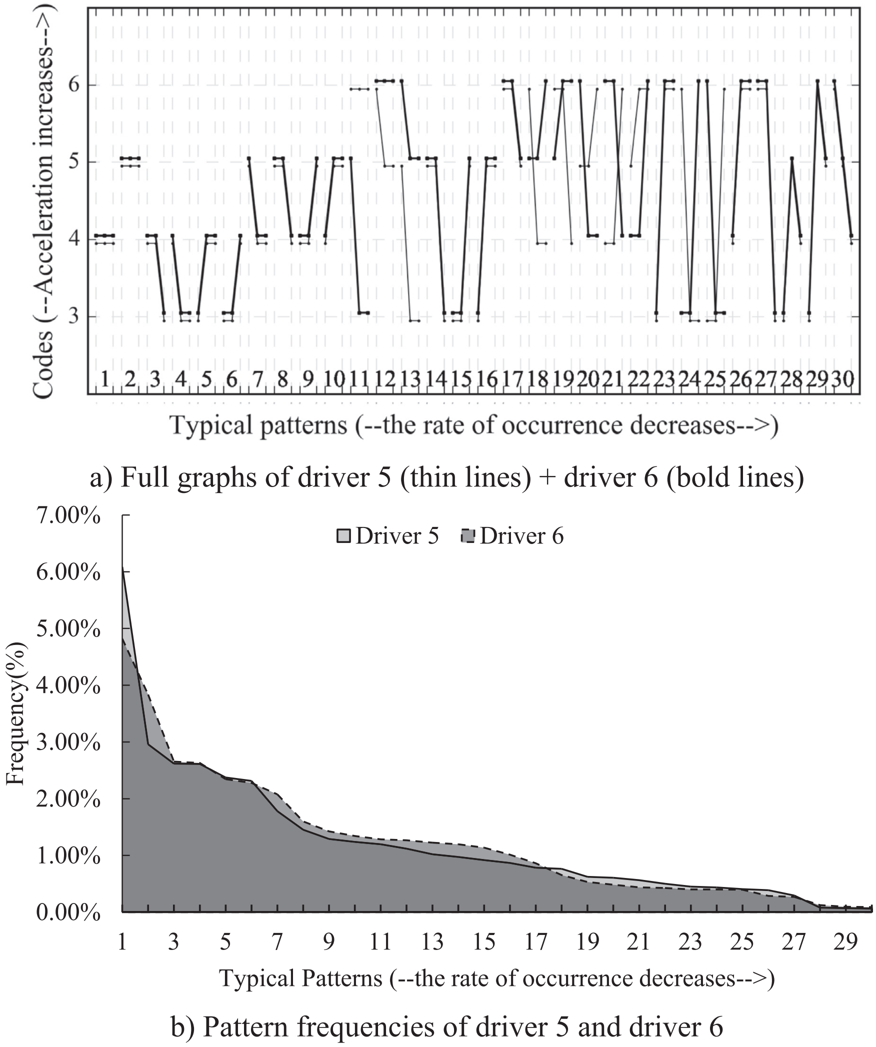


Fig. 6. Full graphs and pattern frequencies of acceleration behaviors of driver 5 (blue lines) + driver 6 (red lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

safety levels. In addition, the safety level is determined by the performance of both the acceleration and deceleration behaviors instead of only the acceleration.

In the comparison among the three risky drivers, driver 4 is obviously relatively safer than the others based on the ranking of pattern '222'. Driver 5 and driver 6 have the same structure in the first ten patterns; thus, the full 30 typical patterns and their frequencies are plotted in Fig. 6. If focusing only on the pattern graph, it seems that driver 6 is relatively safer than driver 5 due to the ranking of pattern '666'. However, driver 5 has higher frequencies for the first several patterns and lower frequencies for the 6th–18th patterns than driver 6, which indicates that driver 6's behaviors are more unpredictable, i.e., more dangerous. Specifically, the pattern '666' of driver 5 with a higher ranking (11) has a lower frequency than the pattern '666' of driver 6 (ranking 12). This phenomenon suggests that frequencies could be used as a supplement to accurately distinguish two or more drivers who have similar performances in the behavior graph.

(3) *Graphs of deceleration behaviors*

The graphs of the features of the deceleration behavior clearly differ, as shown in Fig. 7. The rankings of patterns '000' and '111' can clearly illustrate the differences among the drivers. With a decrease in the driving safety level, the rankings of these two patterns increase. The differences among the three safe drivers and the three risky drivers can also be observed based on these patterns' rankings.

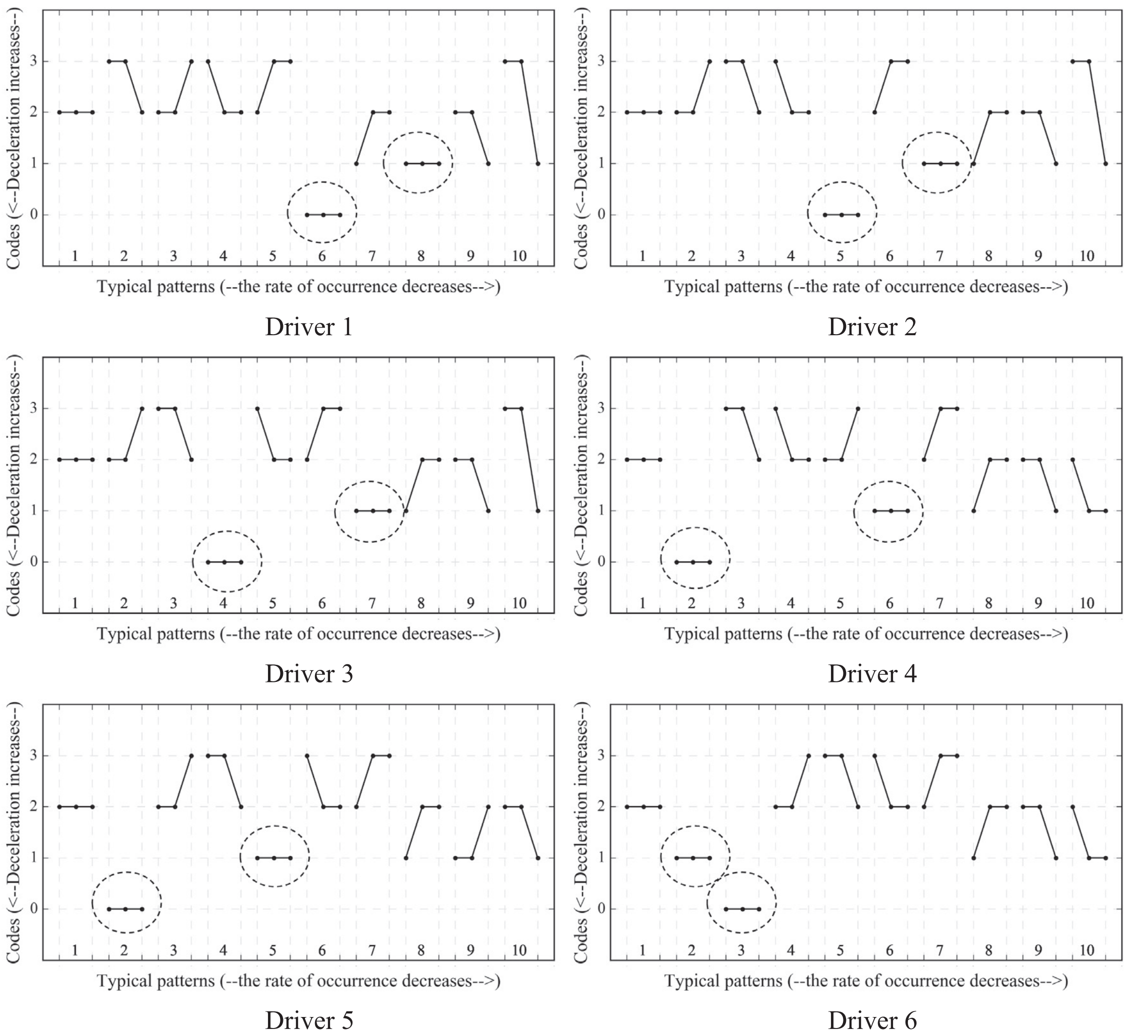


Fig. 7. Graphs of deceleration behaviors.

(4) *Quantitative analysis of driving safety*

Using the quantitative analysis algorithm described in Section 3, the driving behavior safety grades of the six drivers were calculated. Similar to the behavior graphs, three types of scores were taken into consideration: the scores of all driving behaviors, the scores of the acceleration behaviors, and the scores of the deceleration behaviors, as shown in Fig. 8.

Fig. 8 shows that the scores of all behaviors can effectively distinguish between safe and risky drivers, and the tendency of these types of scores is generally in accordance with the scores using the fixed-threshold method in previous work. Driver 5's score for all behaviors is lower than those of drivers 4 and 6. A careful examination of the cause of this result revealed that the frequencies of the typical patterns of driver 4 are higher than those of driver 5, which results in a higher score for driver 4 even though the graphs in Fig. 4 show that driver 4 is safer than driver 5. Similarly, the inconsistency between the scores based on the acceleration and deceleration behaviors of driver 2 is due to the higher frequencies of that driver's last few typical patterns. Furthermore, there is a difference between the scores for all behaviors and those for only the acceleration or deceleration behaviors. This phenomenon is acceptable due to the differences in the graph structures and the frequencies of the patterns.

The scores for the acceleration and deceleration behaviors exhibit similar trends. The scores for the deceleration behaviors are slightly higher than those for the acceleration behaviors.

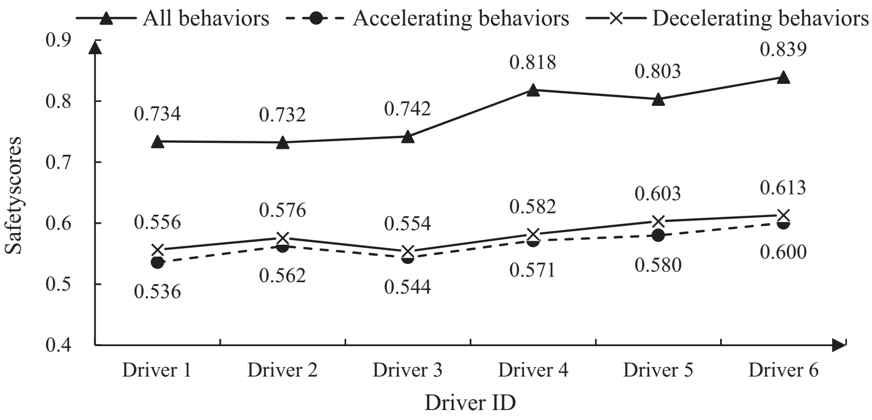


Fig. 8. Safety driving scores of drivers.

5. Discussion

The proposed method aims to model individual driving behaviors. The case study has proven the effectiveness of the proposed method. However, there are still some issues to be addressed.

The definition of a driving pattern and typical patterns. When defining the driving pattern, the behaviors during a three-second period are determined to be one pattern. The selection of three seconds is based on the consideration that it is a proper time that is not too short to adjust the vehicle and not too long to remember the motivation of why they are adjusting the vehicle. We also tested the performances using four and five seconds to develop the method. It was shown that the use of four or five seconds will result in huge numbers of driving pattern types, and the graphs are not as clear as those using three seconds. Thus, three seconds is used in this paper. When drawing the behavior graphs, the thirty most common patterns are regarded as the typical patterns for drivers. This selection is based on the consideration that thirty patterns are enough to reflect drivers' behavioral features. The results (the behavior graphs in Figs. 4–7) perform well, and even the first ten patterns is sufficient to tell the differences between drivers. In the future, the selection of the number of patterns will be more closely considered using percent thresholds (like the 99.9% cumulative most common patterns) to obtain better results.

The influence of the data amount. The proposed method is based on the extraction of drivers' typical patterns that appear most frequently during driving. Thus, the amount of raw data used in the modeling will directly determine the structure of the driving behavior graph. We conducted a test by modeling the selected six drivers' driving behaviors using one day's driving data (daily driving on Beijing city roads for approximately ten hours, including peak and off-peak driving). The results show different graph structures (as shown in Figs. 9–11) than the graphs in Figs. 4–7. However, even based on data with a smaller sample size, the features of the different drivers can still be well distinguished, reflecting the driving performance during the time of the data collection. The driving safety rankings of the six drivers can also be observed. Additionally, the driving safety scores based on these graphs are calculated, as shown in Fig. 12. It seems that driver 3 is the safest in terms of the one day's driving. However, one day, or ten hours, cannot be thought of as a lower limit sample size requirement of this method; this lower limit still needs further study. Although the accurate modeling of the individual driving behavior requires a large amount of data, comparisons among drivers can work well if the data amounts are roughly equal among drivers and sufficient to cover similar traffic conditions and road types. Of course, one day's driving (ten hours) is long enough for the feature extraction because these drivers are professional drivers and they typically drive in a consistent manner. For normal (nonprofessional) drivers, the driving data require more examination because these subjects generally drive along fixed paths, which may not cover enough driving conditions.

The influence of the driver's driving age. Novice drivers may not have formed fixed driving habits, and this variability will influence the modeling of the individual driving behaviors. However, the typical patterns detected using their driving data can still reflect their driving behavior features. Ignoring the comparison with other drivers, the modeled behavior graph can still be used to determine if a driver is safe or frequently engages in dangerous driving behaviors. This information is useful for driving skill improvement by comparing the current behavior graph with his or her previous graphs.

The influence of the normalization of the raw data. In Section 3, the raw data are normalized using Z-standardization before coding. Thus, the mean and standard deviation of the raw data will influence the behavior graph. The disadvantage of these data normalization processing is that if one driver's average acceleration is abnormally high, the graph will be biased. For example, the pattern '666' may indicate more sharp acceleration behaviors than expected, while code '000' may not actually indicate deceleration behaviors. We checked the mean standard deviation of the six drivers' acceleration data, as shown in Fig. 13a. It seems that the average acceleration values of all drivers are nearly equal to 0 m/s^2, which suggests that the bias of the graph can be ignored if the data are abundant enough (i.e., big data obeys a normal distribution). The standard deviations are slightly different in that the safe drivers have lower standard deviations than the risky drivers, which is easy to

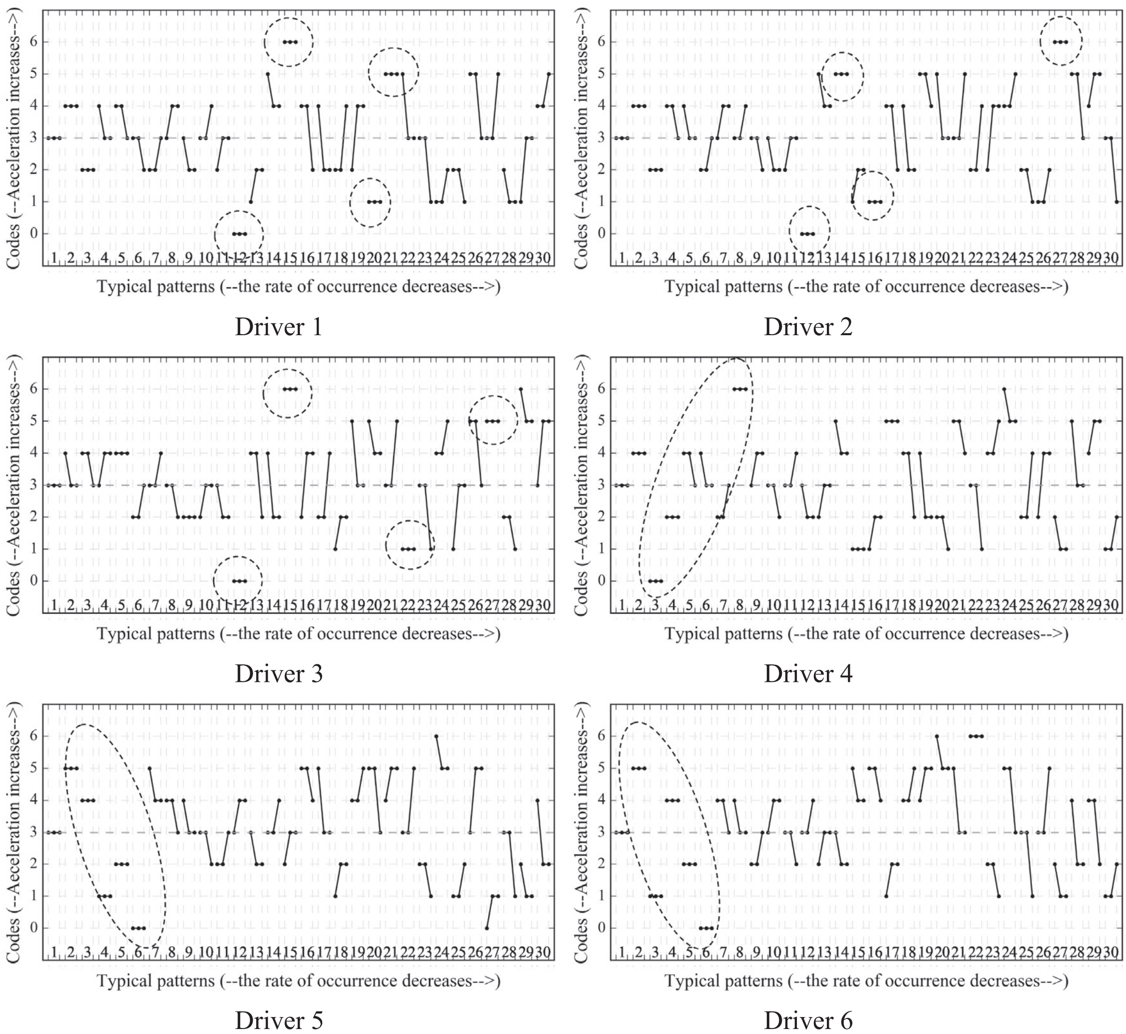


Fig. 9. Graphs of all driving behaviors using one day's driving data.

understand and indicates that the risky drivers are driving more dangerously than what the behavior graphs show. The higher standard deviation surely influences the graph explanation: grades '0' and '6' represent sharper acceleration or deceleration behaviors. However, the influence is positive, and the results of both the behavior graph-based qualitative and quantitative safety analyses are acceptable. Here, we took the standard deviation into the scoring method as a multiplier. The results change substantially, as shown in Fig. 13b. The introduction of the standard deviation has a huge influence on the results. However, the graphs shown in Figs. 4–7 can still distinguish between drivers very well. Thus, if focusing only on the visualization of the behavior features (the behavior graph), the graphs in the current version are enough to convey information. However, if a mathematical calculation is needed in future work, the standard deviation must also be taken into consideration. Despite its disadvantage, though, the advantage of the data normalization is that thresholds are not required for the detection of dangerous driving events.

The dividing thresholds for data grading. In this paper, the normalized data are divided into seven grades using the parameters in the SAX method. The dividing thresholds are symmetric, as shown in Fig. 1. Nevertheless, the effects of positive and negative accelerations may be different, which may necessitate the use of different sets of thresholds when dividing the grades. However, because of the difficulty in determining the thresholds, the proposed method in this version can still be used to describe the driving behavior by analyzing the positive and negative accelerations separately.

Capability of the method. In Section 3, the capability of the method was described. The possible driving patterns and possible behavior graphs are very significant in theory. However, a phenomenon was observed in the case study: most of the first 30 typical driving patterns were repeated, and the differences between the graphs were caused by their rankings. This phenomenon seems to reduce the capability of the method. Although we only consider 30 types of driving patterns, the

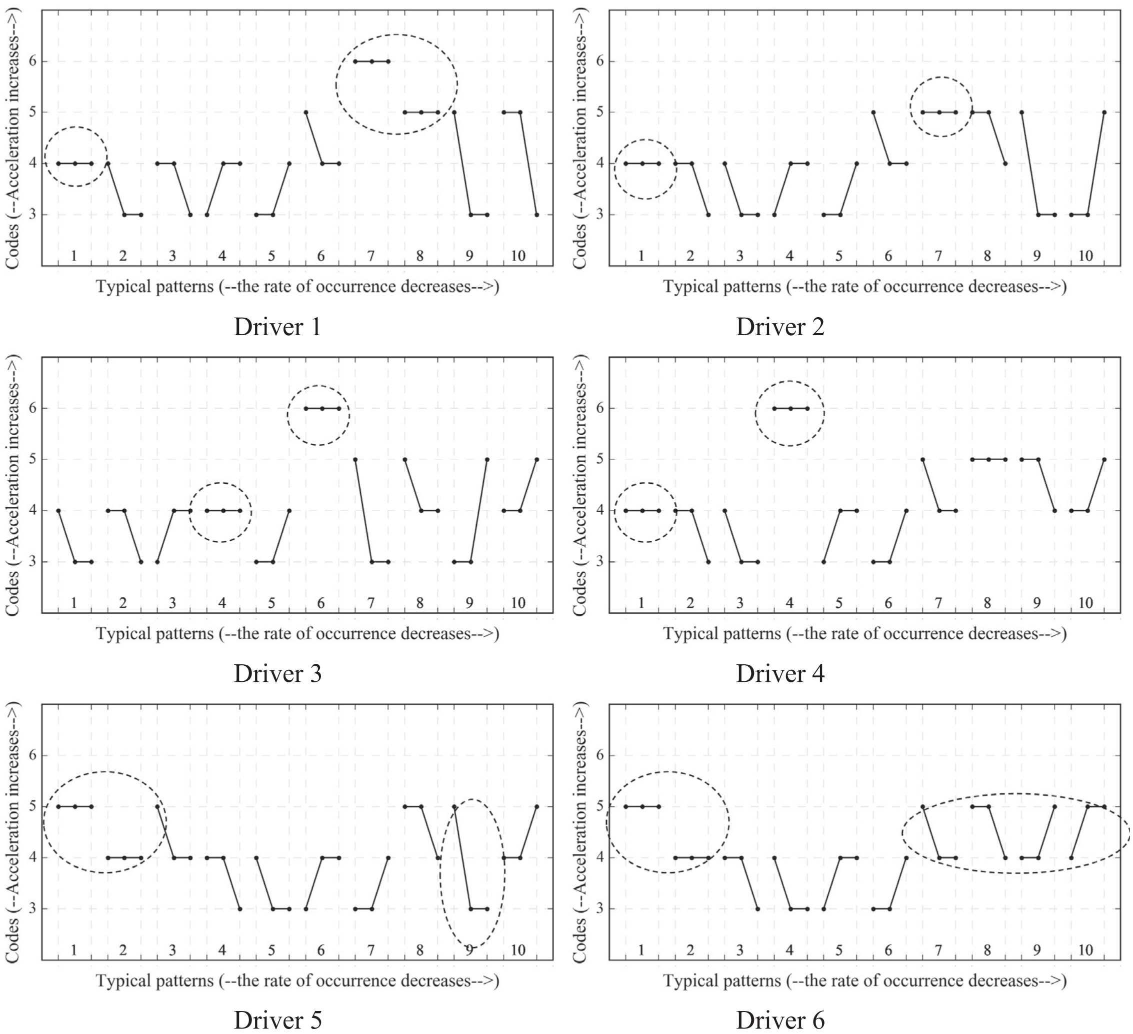


Fig. 10. Graphs of acceleration behaviors using one day's driving data.

number of possible types of graphs is. Obviously, this number is impractically large for the description of huge numbers of drivers.

The difference between the graph-based scores and fixed threshold-based scores. Based on a comparison of Fig. 3 and Fig. 8, the results of the proposed graphical modeling method and the results of the fixed threshold-based driving events method are slightly different. The scoring method proposed in Section 3 may cause inconsistency. However, we argue that the safety analysis of the driving behavior is still a difficult question due to its focus: the 'potential risk' lacks a clear definition. The proposed method can describe the features of drivers' behaviors, and the results of the quantitative method are in accordance with the results of the methods in previous studies. Thus, the proposed graphical modeling method is determined to be reasonable.

The application of the method. The graphs in this paper provide a concise presentation of drivers' typical behavior patterns, and they are proven to be plausible. However, in a future application, a quantitative analysis will be the focus using a large data set, and the graphs are merely a visualization method to provide an intuitive impression. The future application of the proposed method will involve three aspects: (1) Help for the improvement of driving behavior. In terms of the case study based on the longitudinal acceleration data, the detected typical driving patterns of one driver can be used to improve the driver's skill by providing pertinent advice like 'you are braking too harshly'. (2) An analysis of the changes in driver behavior when a drive is influenced by different external environments, like different signs, road alignments, or if drunk or not. Although the graphs in the case study are based on adequate data, the scores of patterns can be used in the evaluation because their scores are proven to be consistent with the safety level. It would especially be ideal if the data of different drivers are collected in similar situations. For instance, this method can help optimize the design of signs or road alignments. (3) Prediction of the patterns of the next second and sending warning messages. The proposed method is used to describe the

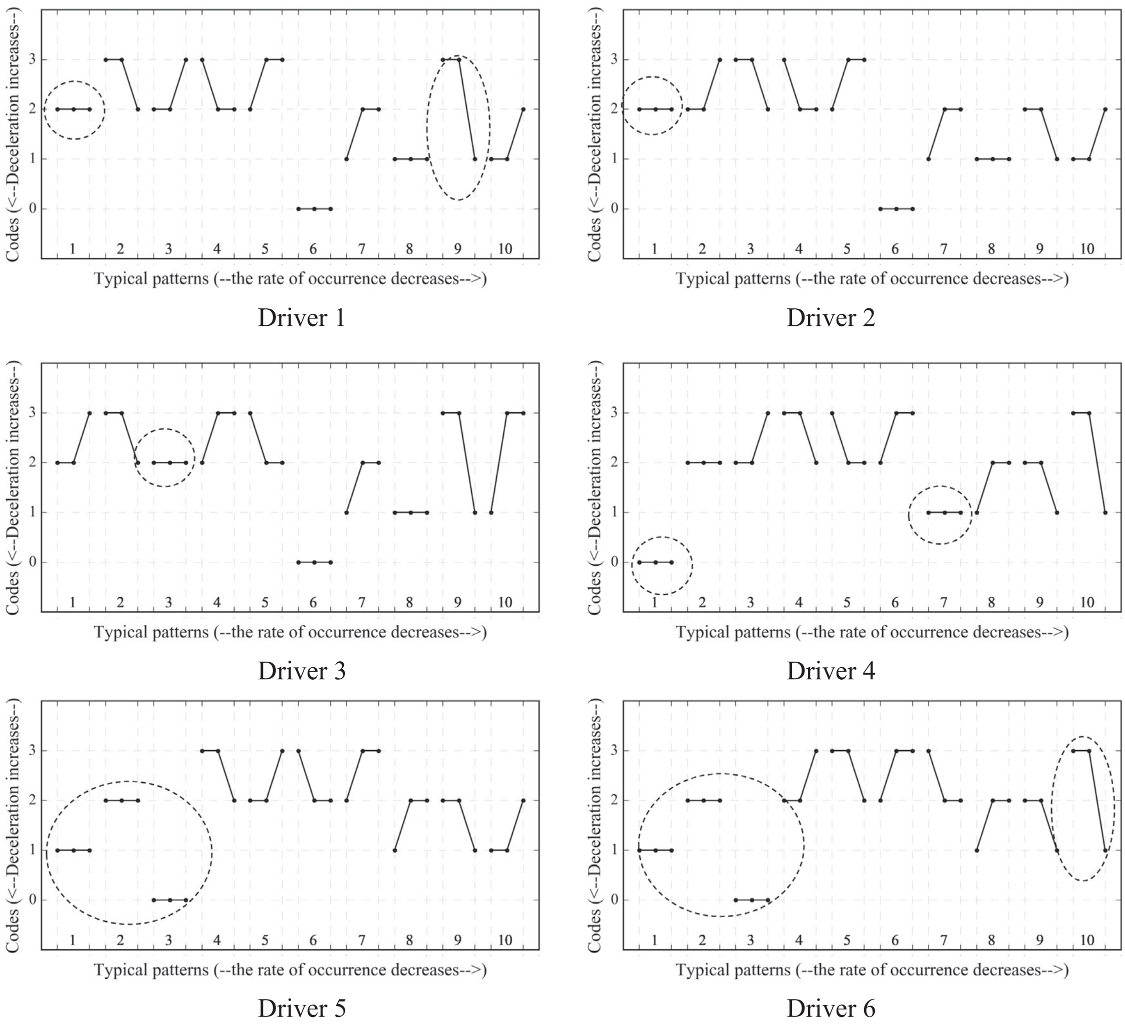


Fig. 11. Graphs of deceleration behaviors using one day's driving data.

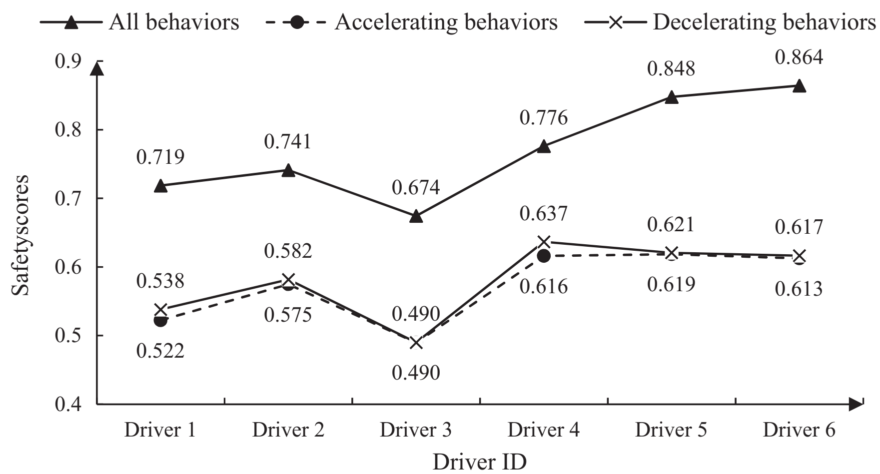
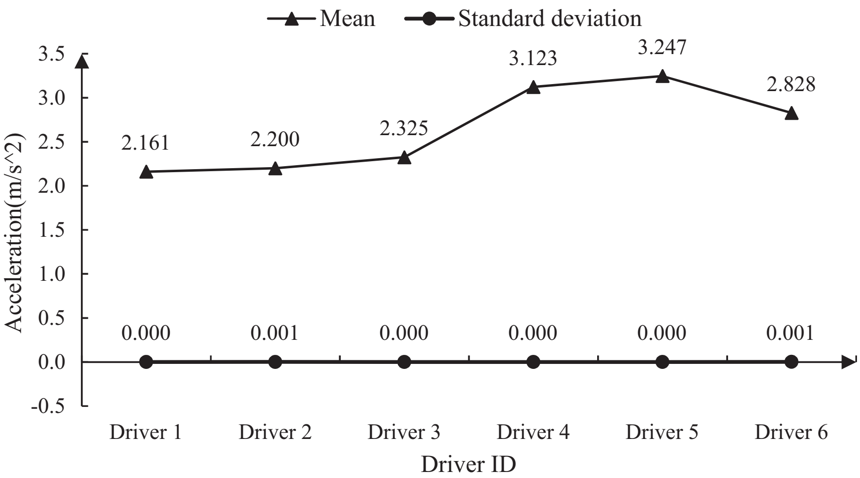
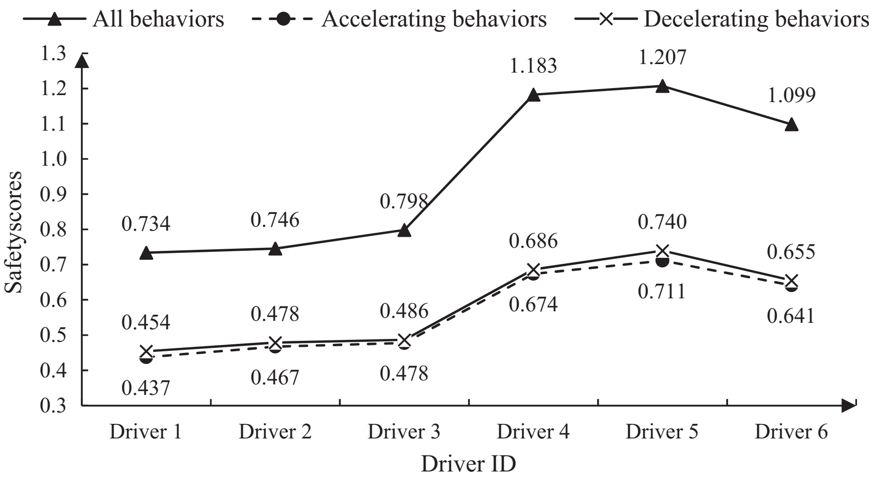


Fig. 12. Safety scores of the quantitative analysis using one day's driving data.



a) The mean and standard deviation of the raw data



b) The safety score considering the raw data's standard deviation

Fig. 13. The influence of the distribution of the raw data.

typical driving patterns of drivers, and driving behaviors can be seen as the combinations of these patterns. There would be some relationship between contexts. In this case, predicting the pattern of the next second will be feasible. If necessary, warning messages can be sent to drivers, which can be used in a driving assistance system. Besides the direct use of this method, this method should also be applied to other parameters, such as speed and steering wheel turning angle, to conduct a deeper analysis of drivers' driving operations to help explain the influence of the external environment. In the future, more verification experiments will be conducted to validate the applicability of this method to other parameters. Moreover, in addition to the driving safety analysis, this method can also be used to analyze the relationship between driving behaviors and fuel consumption or other aspects.

6. Conclusion

In this paper, a graphical modeling method that aims to model an individual's driving behavior is proposed. The proposed method focuses on drivers' fundamental driving behaviors by extracting and ranking their typical driving patterns. As a graphical modeling method, the behavior graphs can directly illustrate a driver's driving habits. Moreover, a quantitative analysis method based on the graph is also provided to help in the comparison among drivers. The results of a case study that focuses on a driving safety analysis show that the proposed method can describe the driving behavior features and distinguish between drivers. The quantitative analysis method is also verified to be useful.

The contribution of this paper is the proposal of a method that can describe drivers' fundamental driving patterns, which can be regarded as the basic units of driving behaviors. In addition to the analysis of driving safety, this method can also be applied to other research fields, such as the analysis of the relationship between behaviors and fuel consumption or the influence of the external environment, by examining changes in the graphs. This graphical modeling method provides another perspective on the analysis of driving behaviors.

Acknowledgments

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References

Bagdadi, Omar (2013). Assessing safety critical braking events in naturalistic driving studies. *Transportation Research Part F: Traffic Psychology and Behavior, 16*, 117–126.
Baldwin, K. C., Duncan, D. D., & West, S. K. (2004). The driver monitor system: A means of assessing driver performance. *Johns Hopkins APL Technical Digest, 25*(3), 269–277.
Bergasa, L. M., Almería, D., Almazán, J., Yebes, J. J., Arroyo & Drivesafe, R. (2014). An app for alerting inattentive drivers and scoring driving behaviors. In *Intelligent Vehicles Symposium Proceedings, 2014 IEEE* (pp. 240–245).
Chen, S. W., Fang, C. Y., & Tien, C. T. (2013). Driving behaviour modelling system based on graph construction. *Transportation Research Part C: Emerging Technologies, 26*, 314–330.
Chen, S. W., Fang, C. Y., Tien, C. T., & Wu, B. Y. (2014). *Dangerous Driving Event Prediction on Roadways*.
Constantinescu, Z., Marinoiu, C., & Vladoiu, M. (2010). Driving style analysis using data mining techniques. *International Journal of Computers Communications and Control, 5*(5), 654–663.
Dörr, D., Grabengiesser, D., & Gauterin, F. (2014). Online driving style recognition using fuzzy logic. In *2014 IEEE 17th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 1021–1026).
Eboli, L., Guido, G., Mazzulla, G., Pungillo, G., & Pungillo, R. (2017). Investigating car users' driving behaviour through speed analysis. *Promet-Trafficand Transportation, 29*(2), 193–202.
Eboli, L., Mazzulla, G., & Pungillo, G. (2016). Combining speed and acceleration to define car users' safe or unsafe driving behaviour. *Transportation Research Part C: Emerging Technologies, 68*, 113–125.
Ellison, A. B., Greaves, S. P., & Bliemer, M. C. (2015). Driver behaviour profiles for road safety analysis. *Accident Analysis and Prevention, 76*, 118–132.
Eren, H., Makinist, S., Akin, E., & Yilmaz, A. (2012). Estimating driving behavior by a smartphone. In *Intelligent Vehicles Symposium (IV)* (pp. 234–239). IEEE.
Fazeen, M., Gozick, B., Dantu, R., Bhukhiya, M., & González, M. C. (2012). Safe driving using mobile phones. *IEEE Transactions on Intelligent Transportation Systems, 13*(3), 1462–1468.
Hong, J. H., Margines, B., & Dey, A. K. (2014). A smartphone-based sensing platform to model aggressive driving behaviors. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems* (pp. 4047–4056).
Johnson, D. A., & Trivedi, M. M. (2011). Driving style recognition using a smartphone as a sensor platform. In *Intelligent Transportation Systems (ITSC), 14th International IEEE Conference on IEEE* (pp. 1609–1615).
Joubert, J. W., de Beer, D., & de Koker, N. (2016). Combining accelerometer data and contextual variables to evaluate the risk of driver behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour, 41*, 80–96.
Li, G., Li, S. E., Cheng, B., & Green, P. (2017). Estimation of driving style in naturalistic highway traffic using maneuver transition probabilities. *Transportation Research Part C: Emerging Technologies, 74*, 113–125.
Lin, J., Keogh, E., Lonardi, S., & Chiu, B. (2003). A symbolic representation of time series, with implications for streaming algorithms. In *Proceedings of the 8th ACM SIGMOD workshop on Research issues in data mining and knowledge discovery* (pp. 2–11).
Lu, J., Jiang, Z., & Wang, D. (2013). Driving behavior recognition based on sensors in mobile phone. In *ICTIS, 2013: Improving Multimodal Transportation Systems-Information Safety, and Integration* (pp. 119–124).
Musicant, O., Bar-Gera, H., & Schechtman, E. (2010). Electronic records of undesirable driving events. *Transportation Research Part F: Traffic Psychology and Behaviour, 3*(2), 71–79.
Paefgen, J., Kehr, F., Zhai, Y., & Michahelles, F. (2012). Driving behavior analysis with smartphones: Insights from a controlled field study. In *Proceedings of the 11th International Conference on mobile and ubiquitous multimedia* (pp. 36).
Saiprasert, C., Pholprasit, T., & Pattara-Atikom, W. (2013). *Detecting driving events using smartphone*. World Congress.
Symbolic Aggregate approXimation, https://jmotif.github.io/sax-vsm_site/morea/algorithm/SAX.html, Accessed July. 27, 2018.
Vaiana, R., Iuele, T., Astarita, V., Caruso, M. V., Tassitani, A., Zaffino, C., & Giofrè, V. P. (2014). Driving behavior and traffic safety: An acceleration-based safety evaluation procedure for smartphones. *Modern Applied Science, 8*(1), 88.
Van Ly, M., Martin, S., & Trivedi, M. M. (2013). Driver classification and driving style recognition using inertial sensors. In *Intelligent Vehicles Symposium (IV)* (pp. 1040–1045). IEEE.