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Identifying Potentially Risky Intersections for Heavy-Duty Truck Drivers Based on Individual Driving Styles

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Abstract: In developing countries, heavy-duty trucks play an important role in transportation for infrastructure construction. However, frequent truck accidents cause great losses. Previous studies have mainly focused on passenger drivers; to date, little has been done to assess the driving behavior of heavy truck drivers. The overall objective of this study is to classify driving styles at intersections, analyze the impacts of differing types of traffic control at intersections on driving styles, and identify potentially risky intersections. We selected 11 heavy-duty truck drivers and collected kinematic driving parameters (including driving speed and both lateral and longitudinal acceleration) from field experiments in Nanjing for our study. Our study on driving styles followed the following steps. First, we reduced data size and extracted data features on the basis of time windows in Python. Second, driving styles were classified into three driving styles: cautious, normal, and aggressive, based on the K-means clustering method, and the corresponding thresholds for each category were obtained. Kinematic driving parameters were used as driving style measurements. Third, according to classifications of driving style, the impacts of four different intersection traffic control types: two-phase signalized, multiphase signalized, stop, and yield intersections, on driving styles have been analyzed using the multinomial logit model. Moreover, based on the above analysis, potentially risky intersections were identified. The results suggest that different types of traffic control at intersections lead to variations in driving styles and have different influences on driving styles. In terms of accuracy, our method, which uses driving speed, both lateral and longitudinal acceleration, and jerk as features, performs better than traditional methods which only use speed and acceleration. The results of the study allow us to analyze the driving data of heavy-duty trucks and identify drivers who drive more aggressively during a trip. In addition, the results show that aggressive driving styles mostly occur at stop intersections and in the dilemma zones of signalized intersections. Therefore, early-warning interventions can be provided during a driver's trip by analyzing the different types of traffic control at intersections on the route in advance. Finally, the cumulative analysis of driving styles at intersections over multiple trips can be used to identify potentially high-risk intersections. It is possible to eliminate potential risks in these areas through measures such as early warnings and by improving traffic management control methods.

Keywords: driving style; driving behavior; K-means clustering; traffic control types of intersections; heavy-duty trucks

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1. Introduction

With the development of urban transportation and the yearly increase in the number of vehicles, a large number of drivers are entering the urban transportation environment. At the same time, the number of traffic accidents has increased significantly. In order to reduce the frequency and severity of traffic accidents, researchers have conducted numerous studies on vehicles and drivers. Human factors (driving behavior and driving style) are important factors in determining the success of transportation trips. Research has shown that detecting and identifying driving behavior and driving style and providing feedback to drivers can help avoid unsafe driving behavior, reduce the frequency of crashes, and improve overall driving safety [1].

The literature on human factors affecting driving can be classified according to two perspectives: driving-behavior detection and identification, and driving-style definition and classification. First, new techniques have been proposed to detect and identify driving behavior in response to the large data volume, high accuracy, and time-series nature of driving data. A novel system that uses dynamic time warping (DTW) and smartphone-based sensor-fusion were proposed to detect and record driving actions without external processing [2]. Smartphone-sensor data streams were applied to analyze driving behavior. An inclusive, stepwise framework was used to describe the path from driving data collection to crowd-sensed data for feature extraction [3]. The DTW based on the detection technique was researched in motion-sensor-based, time-series data. It is able to automatically adjust based on time deformations and different speeds associated with time-dependent data and improve classification accuracy to detect sudden braking and aggressive driving behaviors using sensory data collected from the smartphone [4]. Nonetheless, speech has been found to be a suitable input source in understanding and analyzing drivers' behavioral states due to the underlying emotional information that is communicated when the driver speaks, and such changes can be measured. The Mel frequency cepstral coefficient (MFCC) feature-extraction method, coupled with the multilayer perceptron (MLP) classifier, was employed to obtain drivers' behavioral-state recognition performance [5]. Methods of LSTM and convolutional neural networks were used to identify abnormal driving behaviors, such as rapid acceleration, rapid braking, and rapid lane changing [6]. Deep learning was also applied to identify abnormal driving behaviors in normalized driving-behavior data, and an autoencoder was used as a building block to represent the driving function of abnormal driving detection for the first time [7]. A novel method called dynamic basic activity sequence matching (DAS) was proposed. DAS is a combination of machine learning methods and flexible threshold-based methods to distinguish between normal and abnormal driving patterns [8].

Most current research on driving behaviors is based on the analysis of vehicle kinematic parameters. Some scholars have analyzed vehicle kinematic parameters under dangerous driving conditions, such as the distribution characteristics of speed and acceleration over time and space, and they have tried to characterize various dangerous driving behaviors and formulate corresponding grade-evaluation standards [9,10]. Most studies are based on simple weighting and threshold-determinations of indicators such as speed and acceleration changes. Some only consider one component of acceleration (the relationship between longitudinal acceleration and velocity or lateral acceleration and velocity). Few studies involve comprehensive analysis and determination of multiple characteristic indicators. The movement of the vehicle has been described by analyzing the vehicle speed and acceleration recorded by an actual test, and a method was proposed to define whether the driver's behavior was safe [11]. In Lee and Jang's study, a deep learning network model was developed based on vehicle-motion state data which was collected by installing sensors in 43 taxis to identify potential aggressive driving behaviors [12].

Based on the identification of driving behaviors, the researchers developed the concept of driving style. 'Driving style' is defined as the way in which a driving task is accomplished. Acceleration, smartphone data, and fuel consumption can all be used for the identification of driving style. It has been suggested that acceleration, deceleration, cornering, and lane changing can be used to identify driving style. In addition, based on data collected by smartphone sensors, the study concluded that driving styles can be characteristically divided into two categories: typical (nonaggressive) and aggressive [2]. Processing acceleration data through fuzzy logic models, one study proposed four categories of driving style: below normal, normal, aggressive, and very aggressive [13]. However, in most studies, driving styles are divided into three categories: aggressive, normal, and cautious. These three dominant categories have also been applied in this study to classify driving styles. A novel technique to robustly classify driving style is the support vector clustering approach, which attempts to differentiate the variations in an individual's driving pattern and provide an objective driver classification. Driving styles were classified as aggressive, normal, or defensive [14].

It is worth noting that most of the previous research has focused on studies related to passenger cars and their drivers. However, with the continuous development of logistics traffic, the number of professional logistics transport vehicles is increasing. At the same time, the number of traffic accidents related to logistics transport vehicles is increasing each year. Among them, heavy-duty trucks have become the main contributor to fatal vehicle collisions. According to the incomplete statistics available for China, heavy-duty trucks accounted for 32.04% of all types of vehicles involved in criminal traffic accidents between 2016 and 2019. Among all types of vehicles, heavy-duty trucks accounted for more vehicles in the problem categories of speeding, overloading, and unsafe vehicle conditions, accounting for nearly 30% of the total. The Federal Motor Carrier Safety Administration found that, for a traffic accident, on average, the death of a heavy-duty truck driver will lead to the death of six other people (other vehicle drivers, passengers, pedestrians, etc.).

At the same time, potentially high-risk areas for traffic accidents cannot be ignored. Some areas are prone to traffic accidents because of their traffic and environmental characteristics. Collisions occurred more frequently at intersections than on other areas of the roadway [15]. When considering turning-off accidents, 42.6% of urban accidents occur at intersections, which means it is necessary to focus on the control of intersections to improve safety and avoid accidents. At signalized intersections, the signal phase also needs to be considered as it creates a dilemma zone for drivers. Right-angle crashes and rear-end crashes caused by the dilemma zone are important factors affecting traffic safety and the efficiency of intersections. At unsignalized intersections, the passing state of vehicles is determined by traffic flow and the driver's own behavioral characteristics [16]. Due to slow heavy-duty-truck acceleration and poor braking performance, the drivers of such vehicles are often unwilling to slow down or even stop when they pass through intersections and other areas so as to maintain a constant speed, creating potential safety hazards. Meanwhile, the abilities of truck drivers could become impaired during extensive periods of driving. Especially in China, truck drivers tend to overestimate their driving ability in emergency situations and may be subject to a greater accident risk due to overconfidence [17]. Based on the above points and the great severity of truck accidents, intersection areas become high-risk areas for heavy-duty trucks [18–45].

Obtaining a better understanding of the driving style of truck drivers at intersections that contribute to a greater crash risk is critical for the development of efficient safety measures and policies. Therefore, this paper focuses on the driving performance and crash-risk prediction of heavy construction-vehicle drivers in intersection areas. This article uses time-series data collected by sensors to analyze heavy-duty truck drivers' driving behaviors and styles at intersections. In addition, it introduces the concepts of acceleration and jerk so as to study the driving behavior and driving style of large-scale, engineering vehicles when passing through intersections. It analyzes the influences of different types of intersections on the driving styles of heavy-duty truck drivers.

This paper aims to propose a new framework for classifying the type of driving styles of heavy-duty truck drivers at intersections and explore the influence of different types of intersections on heavy-duty truck drivers' driving styles. This paper is structured as follows. In Section 2, the data sources and research methods are discussed in detail. In Section 3, the results of driving-style classification at intersections, which are based on time-series data, are proposed. The thresholds of driving-style recognition are also presented. The results of each of the three style classification components are discussed. Then, based on the multinomial logit model, the results of the probability analysis of driving styles at different types of intersections are presented. The analysis of the impacts of intersection types on driving styles is proposed at the end. Finally, the main findings are summarized, and future work is discussed.

2. Methods

A mixed-methods approach was employed to identify and analyze driving styles of heavy-duty truck drivers at intersections. First, preprocessing of the data by data reduction and data extraction was performed in Python. Then, based on the definitions of style and intersection, the research utilized the K-means cluster method to classify driving styles and define the appropriate thresholds. Finally, an MNL model was employed to analyze the impacts of different types of intersections on driving styles. Based on these comparisons, potentially high-risk intersections could be marked on a map. Flow Chart of this research is shown in Figure 1.

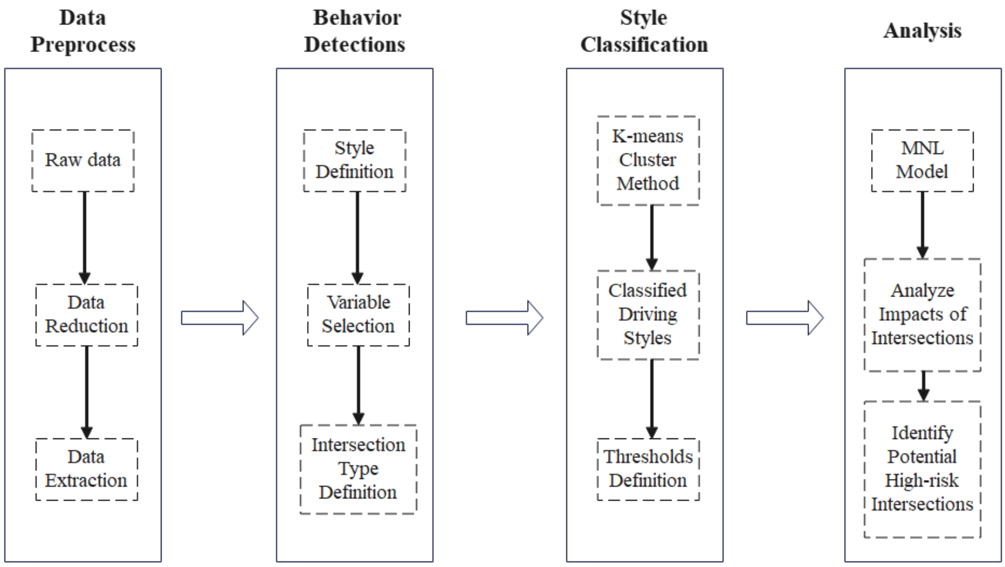

Figure 1. Flow Chart of Driving-Style Analysis of Heavy-Duty Truck Drivers at Intersections.

2.1. Driving-Behaviour Detection

The first step in driving-style classification is driving-behavior detection. Driving style can be classified as the typical behavior of all dynamic behavior that drivers take on roads. From an objective perspective, velocity, acceleration, and jerk were used as measurements to detect and recognize driving behaviors. Then, driving style was classified based on these data.

Velocity is the most direct factor in driving-behavior detection. In the study, velocity data was collected at a frequency of 10 hz per second. As a result, large amounts of instantaneous velocity data generated on a long trip can make analysis difficult. According to previous studies, velocity can only show some abrupt state change. This means that, if velocity is chosen as the only driving-style measurement, a few minor state changes will be ignored.

Acceleration and jerk were applied as measurements in this paper to analyze driving style. These two features were represented by $\bar{a}$ and $\bar{J}$. $\bar{a}$ is the acceleration vector, which consists of a_{lat} (lateral acceleration in the direction transverse to the direction of motion) and a_{long} (longitudinal acceleration in the same direction of motion).

The $|\bar{a}|$ modulus is expressed as

$$|\bar{a}| = \sqrt{{a_{long}}^2 + {a_{lat}}^2}. \tag{1}$$

Jerk is expressed as

$$\overline{J}_{n+1} = a_{n+1} - a_n. \tag{2}$$

where, $\overline{J}_{n+1}$ is the jerk at n + 1th data segment of driving performance, and a_n and a_{n+1} are accelerations at nth and n + 1th data segment of driving performance respectively.

At the same time, changes in acceleration and jerk can also indicate changes in speed, thus reflecting subtle changes in driving behavior. We use variance to check the dispersion of acceleration and jerk. If drivers conduct frequent aggressive or conservative driving behaviors, their acceleration and jerk will change frequently, and the degree of dispersion will increase accordingly.

Finally, the following four derivative parameters were applied to represent the variance of driving-style performance, which were calculated from acceleration and jerk: mean acceleration ($|\overline{a}|_{mean}$), standard deviation of acceleration ($|\overline{a}|_{std}$), mean jerk ($|\overline{J}|_{mean}$), and standard deviation of jerk ($|J|_{std}$).

$$|\overline{a}|_{mean\_i} = \frac{\sum_{j=1}^{N_i} X_{ij}}{N_i}\ , \tag{3}$$

$$|\overline{a}|_{std\_i} = \sqrt{\frac{\sum_{j=1}^{N_i} \left(X_{ij} - |\overline{a}|_{mean\_i}\right)^2}{n}}, \tag{4}$$

$$|\overline{J}|_{mean\_i} = \frac{\sum_{j=1}^{N_i} Y_{ij}}{N_i}\ , \tag{5}$$

$$|J|_{std\_i} = \sqrt{\frac{\sum_{j=1}^{N_i} \left(Y_{ij} - |\overline{a}|_{mean\_i}\right)^2}{n}}, \tag{6}$$

where X_{ij} and Y_{ij} are the jth spot acceleration and spot jerk in the ith data segment of driving performance, respectively. N_i is the sample size of the acceleration or jerk in the ith data segment of driving performance.

According to previous research, driving styles in this paper are classified into three categories: Cautious, Normal, and Aggressive.

2.2. Cluster Method

In this paper, the K-means clustering method was used for research on index thresholds and the classification of indicators. Clustering factors should select indicators that have a significant impact on the classification of a hierarchical structure. At the same time, they need to be easy to operate, collect, and quantify. Based on the above analysis, this paper selected average acceleration, standard deviation of acceleration, average jerk, and standard deviation of jerk as clustering factors of driving style. The whole algorithm was implemented in Python. The detailed algorithm steps are shown below:

Step 1 Selection of K-value

Select the number k of classes to be clustered and choose k centroids. K represents the number of classes of data classification. In this paper, three classes of driving style are defined based on previous studies, so the value of k is 3.

Step 2 Distance calculation

For each sample point, find the nearest centroid, and the closest point to the same centroid is a class, thus completing a clustering. The K-means algorithm uses Euclidean distance to represent the distance between the same kind of sample points. The closer the distance is, the higher the similarity of the sample points is.

The principle of the K-means algorithm is as follows:

For N sets of data, $G = \{x_1, x_2, \ldots, x_N\}$, $x_1, x_2, \ldots, x_n$ are the parameters that affect the classification of driving styles in each segment. x_i = {average acceleration, standard deviation of acceleration, average jerk, standard deviation of jerk} . Let K = 3.

Set up K clustering centers and calculate the Euclidean distance between data and clustering centers. The data belong to the nearest clustering centers.

Define cluster centers $\{R_m\}$, where 1 < m < K. Define f_{nk} as a category determination variable. If x_n belongs to class m, then f_{nk} = 1, and if x_n does not belong to class m, then f_{nk} = 0.

Objective function is expressed as:

$$\mathrm{D} = \sum_{n=1}^{N} \sum_{m=1}^{K} f_{nk} \, ||x_n - R_m||^2 \tag{7}$$

Step 3 Determine whether the class situation of the sample points before and after clustering is the same; if it is, the algorithm terminates, otherwise it enters Step 4.

When the objective function is the smallest, the clustering results are obtained. The clustering center is

$$R_m = \frac{\sum_n f_{nk} x_n}{\sum_n f_{nk}} \tag{8}$$

Step 4 For the sample points in each class, calculate the centroids of these sample points as the new centroids of the class, and continue to Step 2.

2.3. Multinomial Logit Model

The outcome of driving style is expressed in nomial factors, resulting in the applicability of the multinomial logit model (MNL model) to analyze impacts of different intersection types on driver's driving-style choices. The condition for the establishment of the MNL model is that V_{in} and ε_{in} are independent of each other, and $\varepsilon_{in} \ \sim \ Gumbel(0,1) \ Distribution$.

The MNL model function is shown as follows:

$$P_{in} = \frac{\exp(V_{in})}{\sum_{j \epsilon A_n} \exp(V_{jn})}, \ i \ \in \ A_n \tag{9}$$

In the function, P_{in} represents the probability of i driving style at n intersection. V_{in} represents the fixed item section of i driving style at nth intersection, A_n represents the set of driving styles of n intersections, and j is the element in set A_n.

The MNL model uses the maximum likelihood estimation method to calibrate the parameters. Based on the overall probability density function, it is followed by a likelihood function containing unknown parameters. When the likelihood function value is the largest, the corresponding variable parameter estimates are solved. All model parameter calibrations in this article were performed with the help of the logistic panel in STATA.

3. Field Experiment Design

3.1. Participants

In China, truck drivers are predominantly (95.8%) male. Therefore, this study only focuses on male heavy-duty truck drivers. Professional heavy-duty truck drivers of Lanye Construction Group in Pukou district, Nanjing, China were recruited for the study. All participants met the occupational standards and held a valid driver's license. A total of 11 truck drivers participated in the study, ranging in age from 31 to 53 years (mean $\pm$ SD: 40.8 $\pm$ 6.6 years). On average, their driver's licenses were 12.8 years old, with a standard deviation of 5.1 years. Their education levels ranged from elementary school to an undergraduate degree, and 73% of participants' highest level of education was junior or senior high school. No serious traffic accidents had occurred in the previous 3 years for any participant. Before the field experiment, medical examinations were performed to ensure all of the drivers were in good physical condition and without mental illness or cognitive impairment. Each subject signed an informed consent agreement prior to participation and received compensation when he finished the study. This study followed China's laws on scientific research on healthy human volunteers.

3.2. Apparatus

The experimental field driving system consisted of a VBOX-IISX10 GPS Acquisition System, drivers, and a heavy-duty truck. The trial truck was a HOWO concrete mixer truck. The total mass of the truck was 25,000 kg. The external dimensions of the truck were 9100 × 2500 × 3900 (mm). The trail system was implemented, configured, and developed.

For the purpose of collecting spatial and time data for the concrete-mixer-truck driver's daily work, the conditions of the heavy-duty truck consisted of loaded and load-free.

The sampling frequency of kinematic driving parameters was 10 Hz, and all measurements of the kinematic driving parameters was collected. The recorded trial data from the VBOX was processed in D-lab and VBOX Tools software.

3.3. Field Experimental Procedure

Before the beginning of the trial, the heavy-duty truck was equipped with a VBOX, and the conditions of all drivers and trucks were examined. The 11 heavy-duty truck drivers who volunteered to participate recorded their daily work data for one day in compliance with the Chinese Road Traffic Safety Law Implementation Regulations that driving time cannot exceed 8 h in a 24 h period. As a result, they performed their round-trip once a day.

The VBOX system was installed in the test truck to collect speed, longitudinal acceleration, and lateral acceleration data. All field tests were carried out in good weather conditions. There was no crash or near-crash that occurred during the tests. The field tests were conducted from 8 May 2019 to 29 May 2019.

All driving routes are shown in the Figure 2, indicated by orange lines. The location was in District Luhe, Nanjing. The sample intersection types are marked in different colors in Figure 2. All routes were round-trip.

Figure 2. Field experiment routes and sample intersection types.

The trips in the field experiment were random and based on the business plan of the company. Due to individual independence, although a few intersections can be repeated on several trips, these intersections can be considered independently in this research. It is also important to take into consideration the different environments of the intersections, such as weather, traffic volume, and driver characteristics. In the experiments, the traffic-control types of intersection are divided into four types: Two-phase signalized intersection, Multiphase signalized intersection, Stop intersection, and Yield intersection. The experiment collected data from 740 intersections in one month. Of these, 162 were two-phase signalized intersections, 177 were multiphase intersections, 208 were stop intersections, and the other 193 were yield intersections. In summary, this study includes 339 signalized intersections and 401 unsignalized intersections. There were 2 invalid intersections at stop intersections and 4 invalid intersections at yield intersections, making the total number of researched intersections 734. The intersection composition is shown in Table 1.

Table 1. Intersection composition.

Intersection Type	Counts	Existing Area
Yield	189	Rural
Stop	206	Urban
Two-phase signalized	162	Urban and Rural
Multiphase signalized	177	Urban

As shown above, the largest difference in the number of intersections can be found between stop intersections and two-phase signalized intersections, with a difference of 46. The whole proportion of signalized intersections was 45.81%, and the proportion of unsignalized intersections was 54.19%. The trip environment was composed of urban roads and rural roads; the composition conforms to the actual situation. Among signalized intersections, the proportion of two-phase signalized intersections was 21.89% and multiphase signalized intersections was 23.92%. Similarly, for unsignalized intersections, the proportion of Stop intersections was 28.11% and Yield intersections was 26.08%. The proportions of the four intersection types were close to equal, for the purpose of this experiment. This means the analysis of the influence of intersection type on a driver's driving style was not biased due to the difference in sample size.

4. Data Description and Processing

4.1. Data Description

Descriptive statistics were generated for all variables (velocity, longitudinal acceleration, latitudinal acceleration, acceleration, and jerk) as shown in Table 2. The total number in the experimental sample is 479,552. Velocity varies from 0 to 95.78 km/h. Acceleration has a wide range, and it can be seen as the acceleration and deceleration process of the truck. The means of the longitudinal acceleration and latitudinal acceleration are 0 since, during driving time, the truck maintained a constant speed most of the time. The SD of velocity remains at a high value because the velocity varies frequently in the route. The other SDs are small, reflecting the truck travelled smoothly overall.

Table 2. Descriptive statistics of kinematic variables.

	Min	Max	Mean	SD
Velocity (km/h)	0	95.78	28.03	15.71
Longacc (m/s^2)	−3.63	7.40	0	0.17
Latacc (m/s^2)	−8.32	1.82	0	0.07
Acc (m/s$^{2)}$	0	10.81	0.13	0.13
Jerk	−5.61	10.42	0	0.13

Figure 3 shows a boxplot of the above-described factors in this study. It can be seen that velocity is concentrated in the range of 15–40 km/h. This indicates that drivers tended to drive slowly in most cases. However, there remains a part of the time when the truck was travelling at high speed, even up to 95 km/h. This poses certain safety risks. The average value of lateral acceleration is 0, and most of the variation is concentrated within 0.5 m/s^2, indicating that the truck drivers mostly maintained presence in a single lane while driving. However, there are still some abnormal latitudinal acceleration values, indicating that the drivers turned at large angles while driving. Reasons for this may include cornering, lane changing, and avoiding emergencies. The values for longitudinal acceleration are mostly concentrated in the range of -1 to 1.5 m/s^2, indicating that the driver was basically driving normally. However, there are some higher values of acceleration variation, which indicate there was some aggressive behavior during driving sessions. As a result, the boxplot of acceleration illustrates that these heavy-duty truck drivers exhibited some aggressive behavior during their driving sessions.

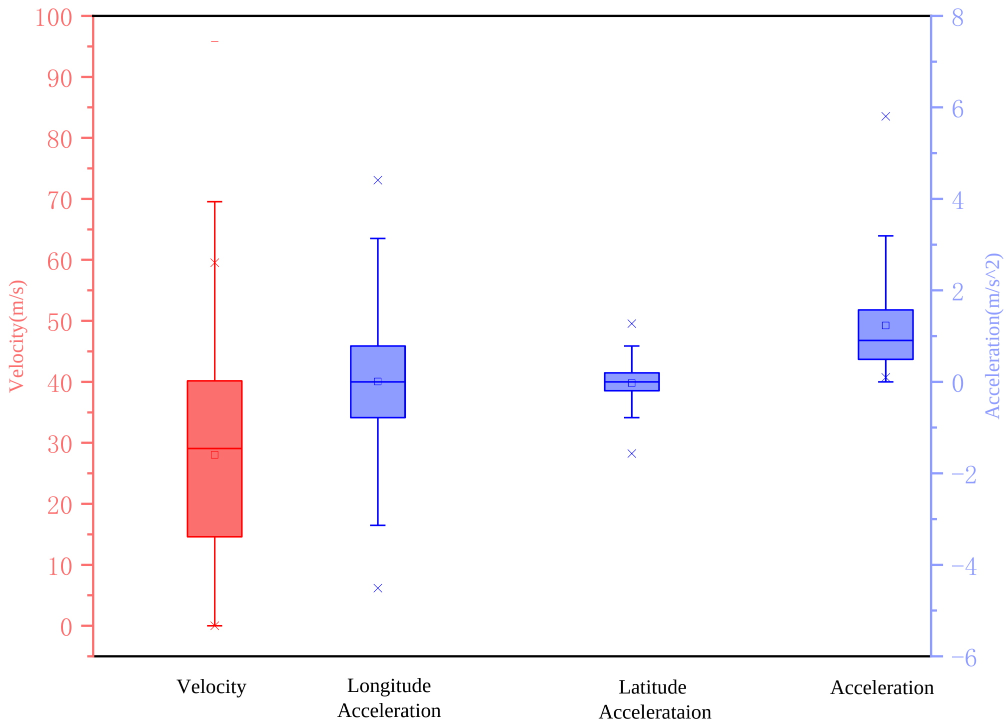

Figure 3. Boxplots of Kinematic Variables.

4.2. Data Reduction and Extraction

The purpose of data reduction was to reduce the amount of data collected by the VBOX. The time frequency of the data recording was 10 Hz, and for a day-trip's records, a huge amount of data was generated. In this paper, the time window method was applied to achieve data reduction.

Let ω be window size and Δt be time step. Therefore, at any given time t_c, the time window can be expressed as a range from $t_c - \omega$ to t_c. The next window starts at time $t_c + \Delta t$. In a previous study, window size was 6 s or 9 s [18]. In this paper, since the location of the study was at an intersection, the window size must be small enough to show all phenomena. If the time window is too large, the minor state change may be ignored. At the same time, the time window cannot be too small, so that data cannot be redundant, and data noise will be retained. As a result, the window size applied in this paper was 6 s, and the step was 2 s. The step is used to make sure all the state changes will be retained, and the trend of state changes will be smoother. In other words, it helps keep the state consistent in one progress of passing through the intersection. The size of 6 s and step of 2 s of the time window in this study is able to capture the transient behavior accurately and avoid the capture of multiple events in one interval. For instance, given a time of 6 s, the time window range will be $[0, 6]$, and the step of 2 s, the next window is $[2, 8]$. The illustration of time window and window step is shown in Figure 4.

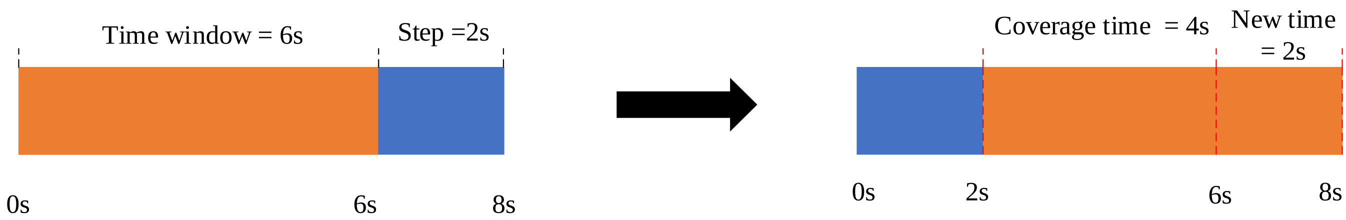

Figure 4. Time Window and Window Step.

All selected raw data were allocated to different segments by unit time window (6 s). Using data of 2500 s as a sample time period in one trip shows the effectiveness of using time windows for data reduction. The raw data of acceleration and jerk is shown in Figure 5a,b, and the data processed by the time window is presented in Figure 5c,d.

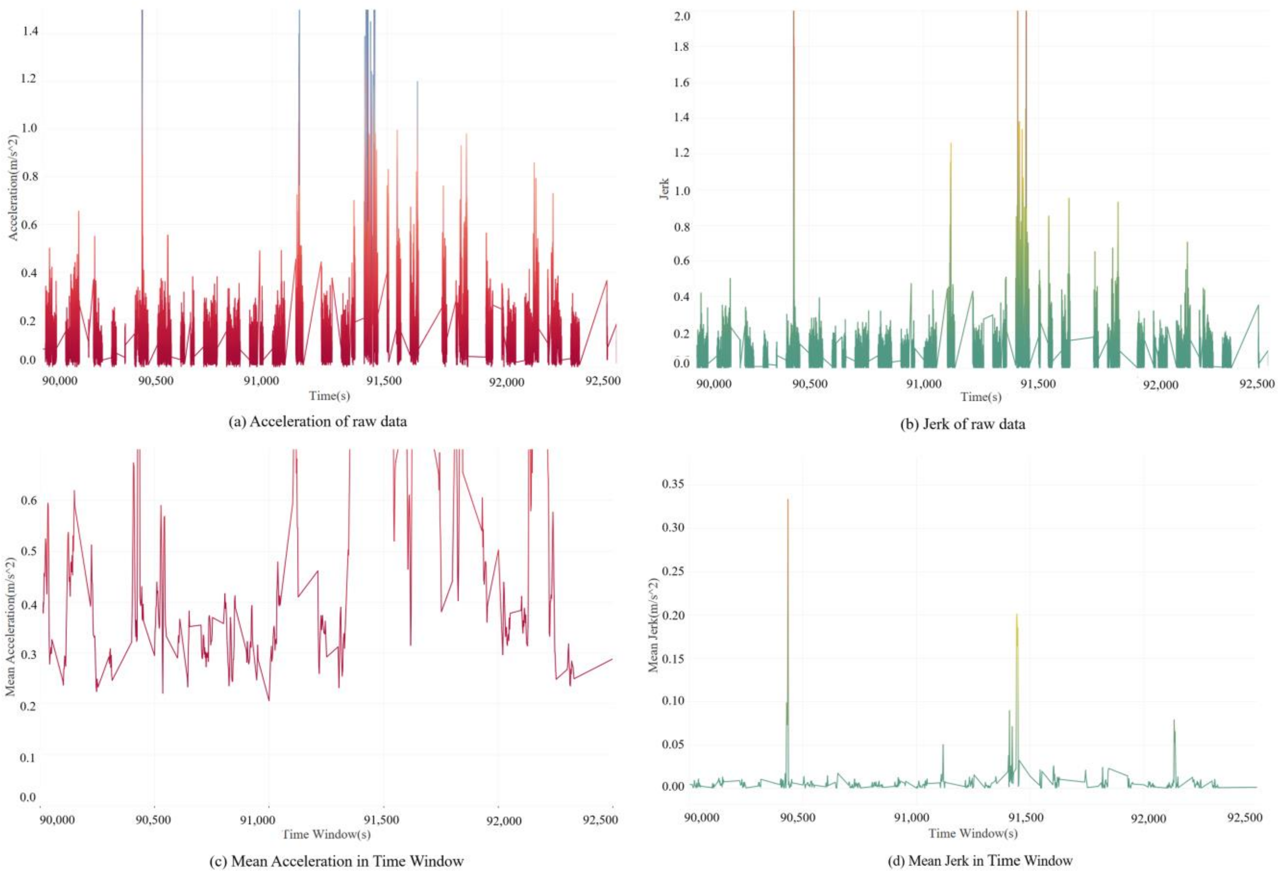

Figure 5. Data reduction of acceleration and jerk by time window.

The time period includes several intersections, and as seen in the above figure, there are several separate groups. This reflects that it was a good decision to use the method with acceleration, jerk, and their derivative parameters. The group clearly shows the state changes of the truck when it passes through intersections.

After extracting the specific data, according to Equations (1)–(6), the four derivative features were calculated. Figure 5a,b illustrates the acceleration and jerk in the raw data. As shown in Figure 5a,b, the acceleration in the raw data has a large number of peaks and valleys, and the amplitudes are similar for a certain period of time. These short-term continuous and intensive changes make it difficult to detect accurate driving behaviors and classify driving styles. These state changes cannot be ignored for the accuracy of detection and classification.

By using time windows to process the original VBOX data, as seen in Figure 5c,d, the noise in the data was removed, and the number of data reduced. This helps to reduce the difficulty of data feature extraction and data cluster. In Figure 5c,d, the changes in mean acceleration and jerk are clear and visible. As shown in the figure, the most obvious state changes are retained. At the same time, the integration and elimination of redundancy in the minor state changes have been carried out, reducing a large amount of subtle or repeated data while retaining most of the characteristics of the data. As a result, data processed by time window is better for classifying driving styles based on these features. It can also help prevent classifying multistyle states in the same driving time period.

Figure 5c,d also shows the relationship between acceleration and jerk in the period during which a truck passes through an intersection. It can be noted that, when acceleration varies greatly in unit time, the absolute value of jerk increases, which means that $|\overline{J}|_{mean}$ is negatively correlated with $|\overline{a}|_{mean}$. Therefore, jerk can represent the change in acceleration and can be applied to identify the driving state as a supplement. Mean acceleration is represented as $|\overline{a}|_{mean}$, standard deviation of acceleration as $|\overline{a}|_{std}$, mean jerk as $|\overline{J}|_{mean}$, and standard deviation of jerk as $|J|_{std}$.

The second step is to extract the data from all of the intersections for the entire selection. The data collected in the long trip only requires all the accurately recorded data of the driver, from entering the intersection until exiting the intersection. Therefore, all other data from the road sections should be ignored.

Using VBOX Tools and Google Earth, all of the 2-dimensional coordinates of the intersections on the test routes were located. A dilemma zone is located in signalized intersections where drivers driving at the legal speed limit can neither stop nor clear the intersection successfully, which may cause an impact on traffic safety. Therefore, in this paper, the range of the intersection influence area included the 200 m before a truck would pass through the intersection. The standard for extracting the data was all of the vehicle's kinematic parameters within an area 200 m away from the intersection, which is shown in Figure 6.

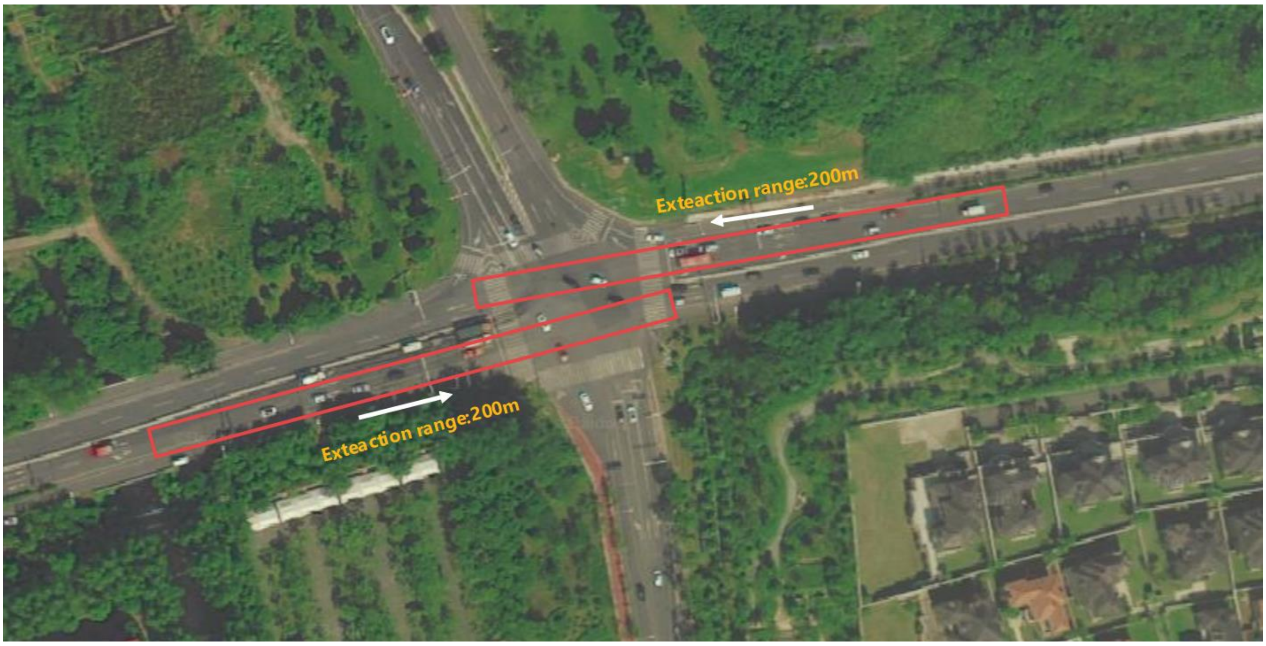

Figure 6. Extraction range of intersection data.

Relying on the distance formula and the latitudinal and longitudinal data, all data within the range of 200 m from intersections were extracted using Python.

Figure 7 shows the process of a test truck driver passing through the intersections encountered in one trip. Driving data for all intersections are shown in the figure, with each colored line segment indicating an intersection. The mean acceleration and jerk data were processed by time window.

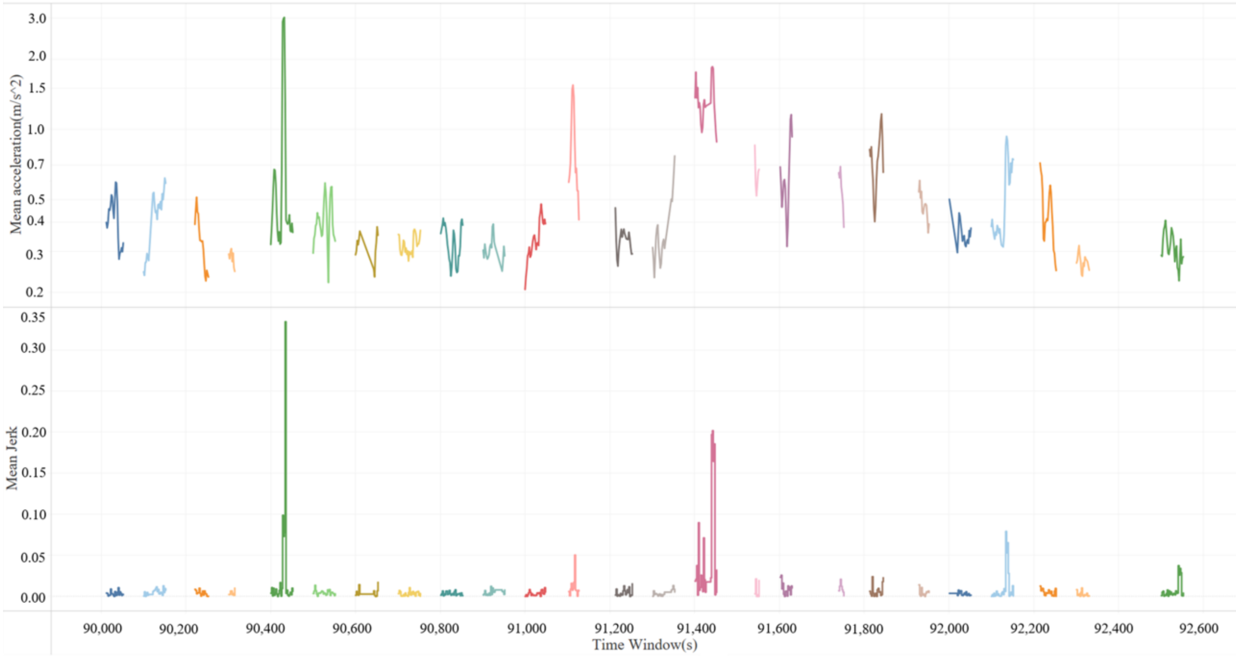

Figure 7. Acceleration and jerk at intersections in time windows.

As seen in Figure 7, at intersection 5 (which is represented by a green line), the acceleration fluctuates and the change in jerk is also very steep, indicating that the speed change of the truck was very dramatic when it passed through intersection 5. However, at intersection 6 (light green line), although the acceleration fluctuated, the jerk basically remained stable in a small range, 0–0.05. What does that illustrate? The process of the driver passing through the intersection was basically a process of slowly and constantly accelerating.

Since the heavy truck described in this article was a concrete mixer, its weight could reach 40–50 tons during the transportation process. According to the speed limit, the maximum speed of the heavy-duty truck could not exceed 80 km/h. According to power performance and braking performance, the acceleration could not exceed 0.4 g (3.92 m/s^2). The final data sample excluded the abnormal data and abnormal interference to the test truck. Sample data are shown in Table 3.

Table 3. Sample data processed by time window.

Time	$\lvert\overline{a}\rvert_{mean}$ (m/s^2)	$\lvert\overline{a}\rvert_{std}$ (m/s^2)	$\lvert\overline{J}\rvert_{mean}$	$\lvert J\rvert_{std}$	No. of Crossing
101,700	0.9973	0.5398	0.0358	0.2652	1
101,702	0.9485	0.3153	0.0336	0.1678	1
101,704	0.9448	0.2817	0.0028	0.1044	1
101,706	1.0852	0.3414	0.0011	0.1003	1
101,708	0.8823	0.4861	0.0229	0.1104	1
101,710	0.7189	0.2573	0.0005	0.0203	1
101,712	0.7794	0.2207	0.0101	0.0625	1
…	…	…	…	…	…
102,110	1.6754	0.7505	0.0205	0.1783	5
102,112	2.2657	0.5997	0.0286	0.1719	5

After data reduction and extraction, the four derivative parameters of acceleration and jerk were calculated as measurements of classifying and analyzing driving styles of heavy-duty truck drivers. After this step, a cluster method was conducted to classify the driving styles of the heavy truck drivers at intersections, which is discussed in the next section.

5. Results

5.1. Driving-Style Classification

Based on the four derivative driving features, this study used the K-means cluster method to classify the three driving types—aggressive, normal, and cautious—and define the thresholds among them.

The cluster steps are as follows:

Step 1 Select mean acceleration ($|\overline{a}|_{mean}$), standard deviation of acceleration ($|\overline{a}|_{std}$), mean jerk ($|\overline{J}|_{mean}$), and standard deviation of jerk ($|J|_{std}$) as the components of clustering factor data.

Step 2 Determine the number of clusters to be 3; that is, define k = 3. Each step of the clustering analysis redefines the center of the class.

Step 3 Run K-means clustering analysis function in STATA. Output clustering results.

STATA classified the data into three categories: cautious, normal, and aggressive. After sorting and processing the data, the parameter ranges of the three types of driving behavior are shown in Table 4.

Table 4. Results of *K*-means clustering.

Variable Name	Cautious	Normal	Aggressive
$|\overline{a}|_{mean}$ (m/s^2)	[0, 0.36)	[0.36, 0.99]	(0.99, 3.92)
$|\overline{a}|_{std}$ (m/s^2)	[0, 0.10)	[0.10, 0.41]	(0.41, ∞)
$|\overline{J}|_{mean}$	[0, 0.005)	[0.005, 0.019]	(0.019, ∞)
$|J|_{std}$	[0, 0.04)	[0.04, 0.14]	(0.14, ∞)

The data in each time window includes four variables, and the driving style of each time window is defined according to the clustering results. The output results show there were 15,544 time windows seen as being of a cautious driving style, 3666 time windows defined as being of a normal driving style, and 193 time windows defined as being of aggressive driving style. Due to the use of four variables, traditional two-dimensional images could not be used for the cluster display. Thus, the cluster method can be used to detect the thresholds between a normal driving state and the two abnormal driving states. As shown in Table 4, the result of *K*-means clustering defines the thresholds of mean acceleration and jerk of a driving style. The other two parameters are used to make certain that acceleration and jerk changes are in line with the characteristics of the driving style within the current time window.

By determining the threshold, it is possible to divide the acceleration and jerk when a heavy truck passed through the intersection and accurately identify the abnormal state. Figure 8 shows the data from 5 intersections as an example. The passing time of each intersection is from 16 s to 40 s, and the average passing time is 29.6 s. The average passing velocity is 24.32 km/h, which meets the operating conditions of heavy trucks in the actual environment.

As seen in Figure 8, driving styles at intersection 1–5 are “Normal”, “Normal”, “Normal”, “Cautious”, and “Normal”, respectively. Jerk in Figure 9 proves the accuracy of classification. Within the thresholds, the area is divided into three categories, and all driving types can be classified within the area.

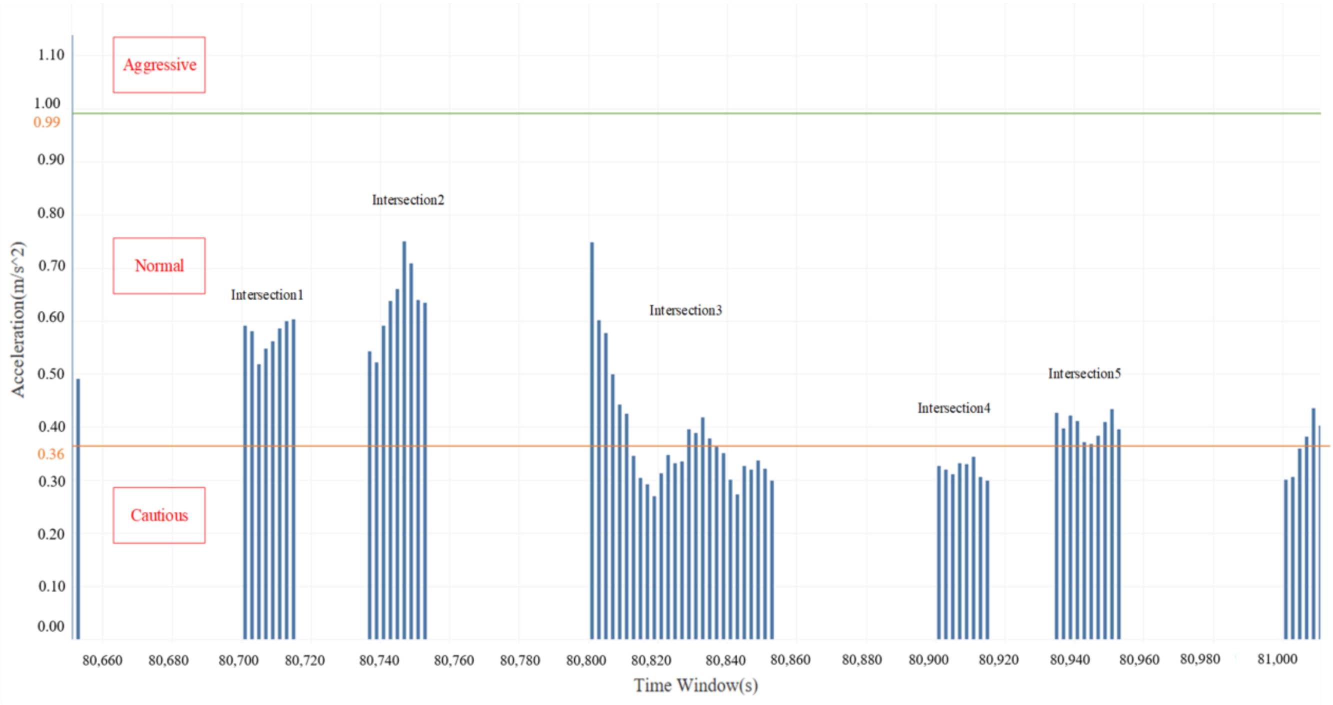

Figure 8. Thresholds of style classification by acceleration.

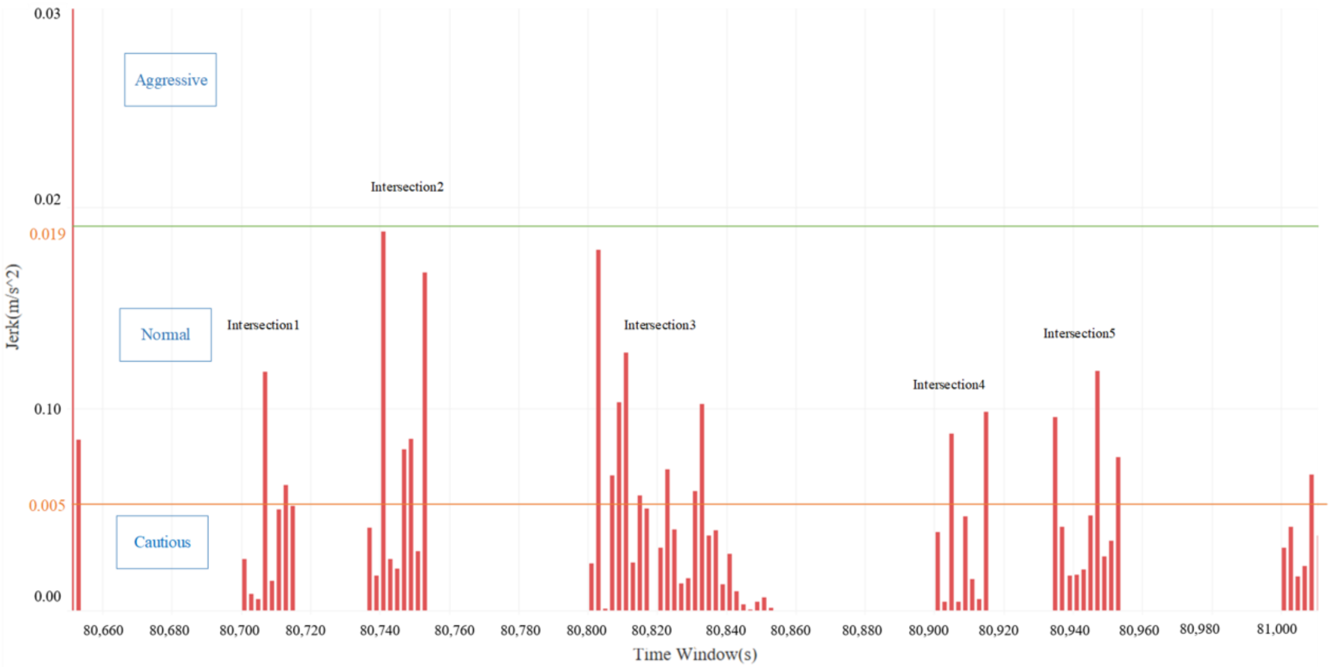

Figure 9. Thresholds of style classification by jerk.

After classification, the results show that cautious and normal driving states account for the majority of cases. For a specific intersection, there were multiple states in the continuous time series of vehicle trajectories. When passing through an intersection, if abnormal driving behavior happened continuously in the time window, the driving state can be defined as abnormal. Based on the results of K-means, each state of the time window has been determined. In this paper, if the driving styles in two consecutive time windows were determined as aggressive, the driving style of the driver on this intersection was viewed as aggressive. The results are shown in Table 5.

Table 5. Distributions of driving styles at experimental intersections.

Type	Cautious	Normal	Aggressive
Two-phase signalized	94	59	9
Multiphase signalized	117	49	11
Stop	89	90	27
Yield	105	75	9

5.2. Comparisons of Driving Styles at Different Intersections

The influence factors include two-phase signalized intersections, multiphase signalized intersections, stop intersections, and yield intersections. The driving style based on the results of the clustering can be classified as aggressive, normal, and cautious. After the multinomial logit model processing, the Chi2 value = 27.41, and the p value = 0.0001. The Confidence Interval is 95%, making the results significant. The model is used to predict the probability of driving style at different types of intersections, and the results are shown in Table 6.

Table 6. Probability of driving style at different types of intersection based on MNL model.

Type	Cautious	Normal	Aggressive
Two-phase signalized	0.5802	0.3642	0.0556
Multi-phase signalized	0.6610	0.2768	0.0621
Stop	0.4320	0.4369	0.1311
Yield	0.5556	0.3968	0.0476

6. Discussions

The relationships between driving styles and intersections in this experiment are shown in Table 5. Intersection passages are assigned a driving style based on the largest portion of drivers' styles. A total of 56 intersection passages were classified as aggressive, 273 as normal, and 405 as cautious. Overall, the number of cautious driving styles was the highest, and the number of aggressive driving styles was the lowest.

We noted that the driving styles of drivers at intersections were inconsistent. The proportion of aggressive driving behavior is 8%, normal driving style accounts for 37%, and cautious driving style accounts for 55%.

According to the results, it can be seen that most heavy-duty truck drivers tended to be cautious when passing through intersections. This phenomenon can result due to a general concern for safety. The brake performance of heavy trucks appears to be worse than that of cars, so if they move too fast, they cannot avoid danger when they encounter an emergency at the intersection. At the same time, the danger of heavy accidents is more serious. Unlike car accidents, in case of emergency, due to the inertia of its own weight and poor braking ability, accidents with heavy vehicles, such as concrete mixer trucks, can involve serious occurrences, including rollovers, overturning, and squeezing, accompanied by high fatality rates. As a result, most of the heavy-duty truck drivers appeared to be cautious to avoid potential dangers.

Another 37% of drivers appeared normal when driving. This phenomenon is mainly due to the driver's avoidance of peak driving times and bad road-traffic conditions. At the same time, due to the slow speed of heavy trucks, the speed in the dilemma area of the intersection may be lower than the minimum passing speed, so heavy truck drivers tend to travel normally and safely.

The last 8%, that being aggressive driving, show that in a few cases, heavy truck drivers engage in aggressive driving at intersections. This may be due to a driver's desire to cross through the intersection within the green light phase or some other factors, such as there being no other passing vehicles. For heavy trucks, stopping at an intersection and then re-accelerating is a tedious process. At the same time, relatively high fuel consumption and an uncomfortable driving experience will prompt some drivers to choose to pass quickly when navigating through the intersection. Another reason is that, since most heavy-duty trucks are controlled by manual gears, frequently raising and lowering the gears will cause uncomfortable driving and reduce the service life of the vehicle.

The probability of each driving style at the four types of intersection is shown in Figure 10.

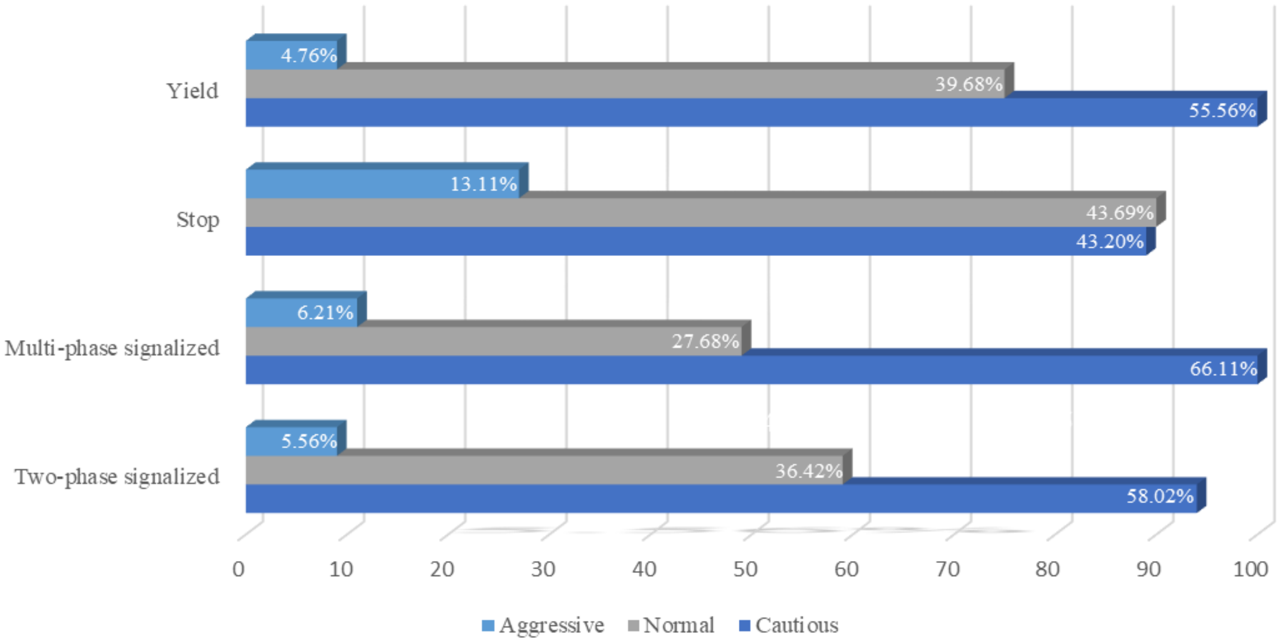

Figure 10. Probability of driving style at four types of intersection.

By analyzing the three driving styles, the probability of intersection types can be seen in Figure 10. The probabilities of four intersection types in the cautious style have relatively average performances. Heavy-duty truck drivers have a slightly higher probability of cautious driving at multiphase signalized intersections and two-phase intersections at 66.11% and 58.02%, respectively. Since these two types of intersections are both signalized intersections, it can be suggested that signalized intersections have more positive effects on drivers and traffic safety. This may be accounted for by signalized intersection phases, complex road conditions, and a complete and strict traffic supervision mechanism.

A normal driving style is more likely to occur at stop intersections and yield intersections, which scored at 43.69% and 39.68%, respectively. This makes sense considering these two types of intersections are unsignalized intersections. Unsignalized intersections are often set up on road sections with relatively little traffic, so drivers are able to drive relatively easily on these road sections, and their speeds will be higher than when driving on urban roads.

Figure 11 shows the probability of an aggressive style at the four types of intersections. Stop intersections account for the largest proportion at 13.11%. When drivers pass through stop intersections, they tend to travel at a normal speed. If there are some vehicles approaching the intersection at the same time, this will cause the drivers to take actions to avoid collision. This can cause rapid speed changes and be determined as characterized by the aggressive driving style. This may result in some potential accidents. The probability associated with multiphase intersections accounts for 6.21%, and the probability associated with two-phase signalized intersections accounts for 5.56%. These two are both higher than the probability of aggressive driving at yield intersections. Because these two are signalized intersections, the driver faces a dilemma. When drivers are in a dilemma, they tend to drive faster to pass through the intersection during the green interval. If the green interval is too short to cross, it will lead to an abrupt stop. These can be determined as characterized by aggressive driving styles and are risky.

(**a**) (**b**) (**c**)

Figure 11. Hotspot map of intersection driving-style distribution: (**a**) cautious, (**b**) normal, and (**c**) aggressive.

In this paper, intersections are identified as signalized and unsignalized, and driving styles are compared at each type, as shown in the following Table 7.

Table 7. Differences in driving styles between signalized and unsignalized intersections.

Intersection Type	Cautious	Normal	Aggressive
Signalized	211	108	20
Proportion of signalized	62.24%	31.86%	5.90%
Unsignalized	194	165	36
Proportion of unsignalized	49.11%	41.78%	9.11%

At signalized intersections, the proportion of aggressive driving styles for all events is 5.90%, and the proportion at unsignalized intersections is 9.11%. The proportion of normal driving styles at unsignalized intersections is larger than at signalized intersections, while the proportion of cautious driving styles has a decreasing trend at signalized intersections compared to unsignalized intersections. The proportion of aggressive driving events at unsignalized intersections is relatively high, indicating that drivers may engage in dangerous driving behaviors at unsignalized intersections, such as frequent acceleration and overtaking or continuous emergency braking, in order to avoid lateral cars and crossing pedestrians. At the signalized intersections, the drivers' aggressive driving event ratio is relatively high, indicating that drivers often drive at a relatively high and unstable speed to reduce the time spent passing through intersections and improve the efficiency of taking orders. This has an impact on intersection safety, as it can lead to chaos in traffic flow and a poor traffic experience for passengers. In all, drivers tend to drive more cautiously and safely at signalized intersections than at unsignalized intersections, resulting in reasonable laws and regulations, perfect infrastructures, and good management in China.

The proportion of unsignalized intersections is relatively large at 54%. Among them, the percentage of stop intersections is 52%, and the percentage of yield intersections is 48%. Unsignalized intersections usually have less traffic volume, so drivers can pass through at normal speeds. The high probability of aggressive driving styles at unsignalized intersections shows that a large number of drivers may choose to pass through the intersection without stopping or pre-decelerating. Poor brake performance and relatively low traffic volume can cause this phenomenon. In the few stop intersections on the test route, drivers frequently did not accelerate and decelerate since doing so at unmanned parking intersections causes relatively high fuel consumption and uncomfortable driving experiences.

According to the above identification results, the distribution of different types of driving styles at intersections is shown in Figure 11.

The distribution of cautious and normal driving styles are close to the same, but the aggressive driving style is concentrated at the intersections shown in the figure. As shown in Figure 11a,b, drivers tend to drive cautiously and normally at most intersections, especially at intersections in urban areas (points highlighted in red in the figure). In contrast, Figure 11c shows the intersection locations where aggressive driving by drivers occurs with high frequency. These intersections can be considered as potential crash areas and are therefore judged to be potentially dangerous. Through this method, potentially dangerous intersections can be identified, thus warning drivers in advance and allowing road managers to make changes so as to reasonably control and improve driving safety.

According to the discussion above, it can be concluded that:

(1) Aggressive driving styles mostly occur at stop intersections and in the dilemma area of signalized intersections. In response to this phenomenon, stop intersections on road sections where heavy-duty trucks travel frequently should be set up after careful inspection, and corresponding warning signs need to be added. At the same time, it is necessary to use on-board GPS and on-board smart devices to carry out active warnings, such as voice warnings, to prevent drivers who have frequent aggressive driving styles. Considering the dilemma area at signalized intersections, reasonable signal phase, suitable position arrangements, and suitable signal intersection structure design can help improve drivers' safety and their performances.
(2) Drivers tend to be more cautious at signalized intersections, so it is necessary to promote safe operation rules. It is also necessary to strengthen the maintenance of the corresponding infrastructure for heavy-duty trucks as they are more destructive to the road.
(3) Drivers drive cautiously at yield intersections. Yield intersections are usually set at intersections with lower branch-road grades. At this time, the probability of pedestrians crossing the street is relatively high. Using a cautious or normal driving style could help drivers to improve safety.

To sum up, all four types of intersections have influences on drivers' driving styles. The driving style of one driver is not always constant and can change due to different intersection types, road conditions, the driver's characteristics, etc. Stop intersections have a positive relationship with the aggressive driving style, which correlates to potentially risky intersections. When preparing the route plan, signalized intersections should primarily be considered to avoid potential dangers from an aggressive driving style. The phase plan and the structure of signalized intersections should also be well researched to prevent truck drivers from aggressive driving and avoiding a long waiting time.

This paper also has some limitations. The limitations of the research are as follow:

(1) The sample size of the study is relatively small.
(2) A single research method was used, and the comparison of different methods should be conducted.
(3) There is a lack of research on driver attributes.

These issues will be studied in future work.

7. Conclusions

This research investigated the driving styles of heavy-duty truck drivers when passing through different types of intersections. At the same time, based on the data, a method of classifying driving styles at intersections is proposed, and a probability model of drivers' driving-style selections at different types of intersections is obtained. First, a field driving experiment was conducted to obtain the kinematic data of heavy-duty truck drivers at intersections, including longitudinal acceleration, lateral acceleration, and speed data. In addition, GPS data was recorded. Then, all data were processed into four derivative features: mean acceleration ($|\overline{a}|_{mean}$), standard deviation of acceleration ($|\overline{a}|_{std}$), mean jerk ($|\overline{J}|_{mean}$), and standard deviation of jerk ($|J|_{std}$). The K-means cluster method was applied to classify the three driving styles at different intersections. Finally, an MNL model was used to analyze the probability of drivers' driving-style choices at different types of intersections.

Previous research has focused on passenger drivers and driving styles on roads. Most research on intersections has focused on accident data. In this paper, we propose a new framework to investigate the driving safety of heavy-duty truck drivers at intersections. The framework can identify drivers' driving styles at intersections and calculate the proportion of drivers' driving styles at intersections on a trip. The results of this study will provide safety guidance and warning advice for heavy-duty drivers before they pass through intersections, based on the statistics of driving styles. At the same time, based on thresholds of the different driving styles of truck drivers, the influences of different types of intersections on driving styles have been analyzed. The results help provide safety reminders for different types of drivers at specific intersections to improve driver safety and the overall safety of the intersection. The research makes a certain contribution to route planning and preparation, the development of advanced driver assistance systems, assessments of drivers' levels, and the avoidance of dangerous driving at intersections. Overall, the research results will contribute to active driving safety protection.

Future research should adopt a larger sample size and explore the effects of personal attributes and more types of intersections on groups of drivers, while taking into consideration the effects of the driver's age, gender, and education level on driving choices and behaviors. After analyzing the impacts of the four types of intersections on driving styles, further study could extend to the intersection types' comprehensive influence on drivers' driving styles. Future research will also consider the vehicle's load state, driver's fatigue level, sleep quality, and other factors affecting a driver's driving style at different types of intersections.

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