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Driving style recognition and comparisons among driving tasks based on driver behavior in the online car-hailing industry

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ABSTRACT

As a product of the shared economy, online car-hailing platforms can be used effectively to help maximize resources and alleviate traffic congestion. The driver's behavior is characterized by his or her driving style and plays an important role in traffic safety. This paper proposes a novel framework to classify driving styles (defined as aggressive, normal, and cautious) based on online car-hailing data to investigate the distinct characteristics of drivers when performing various driving tasks (defined as cruising, ride requests, and drop-off) and undergoing certain maneuvers (defined as turning, acceleration, and deceleration). The proposed model is constructed based on the detection and classification of driving maneuvers using a threshold-based endpoint detection approach, principal component analysis, and *k*-means clustering. The driving styles that the driver exhibits for the different driving tasks are compared and analyzed based on the classified maneuvers. The empirical results for Nanjing, China demonstrate that the proposed framework can detect driving maneuvers and classify driving styles accurately. Moreover, according to this framework, driving tasks lead to variations in driving style, and the variations in driving style during the different driving tasks differ significantly for turning, acceleration, and deceleration maneuvers.

1. Introduction

With the introduction of the 'mobility as a service' (MaaS) concept, internet companies have seized the opportunity to develop online car-hailing applications that provide quick travel options for the public. Characterized by environmentally-friendly and energy-saving features, online car-hailing already functions as an efficient tool to improve the utilization rate of private cars, create jobs, and alleviate traffic congestion in urban areas. However, the drivers of online-hailed cars (referred to simply as 'drivers' hereafter) have low bars for entry into online car-hailing jobs (Zhou et al., 2019). Also, road anger is common among these drivers (Feng et al., 2016). The car-hailing platform itself, which directs drivers who are waiting for ride requests, picking up passengers, and taking passengers to their destination, also influences the drivers' driving styles, or driving habits, to some extent. To encourage these drivers to provide a safe and comfortable environment for passengers, the government and online car-hailing companies have invested significant resources into driver certification and online supervision for which recognition and analysis of the driver's driving style are important judgment factors.

The driving style of the driver is the main influential factor that determines a successful trip. Driving style plays an important role in vehicle energy management and driving safety, which in turn characterize safe (or unsafe) travel and the driving experience of passengers. Studies have shown that detecting driving style and providing drivers with feedback can help avoid unsafe driving behavior, reduce the frequency of traffic accidents, and improve traffic in general (Astarita et al., 2016; Hauber, 1980; Hickman and Geller, 2003; Taubman-Ben-Ari and Yehiel, 2012). In addition to affecting safety, driving style can significantly affect the fuel consumption of the vehicle (Meseguer et al., 2017). Moreover, because driving style affects vehicle maintenance costs, insurance costs, safety, etc., more and more research is focused on links between driving style and insurance premiums (Ellison et al., 2015; Kanarachos et al., 2018; Troncoso et al., 2011). In addition, driving style is the key to the development of driver assistance systems to improve the level of vehicle automation (Bellem et al., 2016; Karginova et al., 2012; Marina Martinez et al., 2018; Meiring and Myburgh, 2015; Sagberg et al., 2015). The safety and comfort of passengers depend on the

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driver's driving style (Eboli et al., 2017). These core findings related to driving style have guided many scholars to research driving style recognition and classification.

The literature on driving style can be viewed from three aspects: definition, classification, and research methods. First, driving style can be defined in multiple ways. For example, Ishibashi et al. (2007) considered driving style to be the driver's attitude towards thinking about driving tasks. Elander et al. (1993) believed that driving style is each driver's thinking about ways to drive. Dörr et al. (2014) proposed a practical description that defines driving style as the way to complete a driving task. Johnson and Trivedi (2011) believed that acceleration, deceleration, turning, and lane changing can be used to identify driving styles.

Previous studies also have classified driving styles in different ways. For simulated scenarios, Bär et al. (2011) classified driving styles into five categories: aggressive, anxious, economical, keen, and sedate. Aljaafreh et al. (2012) used fuzzy logic models to classify driving styles into four categories based on acceleration data: below normal, normal, aggressive, and very aggressive. Johnson and Trivedi (2011) used smartphones as sensors to classify driving characteristics into two categories: non-aggressive and aggressive. However, most studies classify driving styles into three categories: aggressive, normal, and cautious (Dörr et al., 2014; Higgs and Abbas, 2013; Xu et al., 2015). We selected these three categories to classify driving styles in this study.

In recent years, scholars worldwide have made substantial efforts to study driving styles in various ways. For example, Ishibashi et al. (2007) proposed a driving style questionnaire to extract key factors from self-reports and describe different styles. Other researchers have used the Multidimensional Driving Style Inventory to assess four broad domains of driving style (Taubman-Ben-Ari et al., 2004; Taubman-Ben-Ari and Skvirsky, 2016). However, responses to this questionnaire often reflected the subjective judgment of the participants which may deviate from their actual performance on the road. Some researchers have analyzed driving style by conducting simulation experiments (Bär et al., 2011; Chen et al., 2013; Doshi and Trivedi, 2010). Such simulations have shown that drivers can be led to exhibit different driving styles by manually controlling the driving environment. However, the problem with this simulation method is that no clear distinctions are evident among various driving styles.

Other researchers have collected realistic driving data from equipment installed on vehicles for analysis purposes (Boyce and Geller, 2002; Kleisen, 2013; Ma et al., 2020, 2019). For example, Constantinescu (2010) used hierarchical cluster analysis and principal component analysis (PCA) to analyze GPS tracking data, such as vehicle speed and acceleration, to classify driving styles into five categories. Van Ly et al. (2013a) used a clustering algorithm and support vector machine model to develop a driving style classification system based on the data collected during multiple trips of two drivers using a vehicle with an inertial sensor. Qi et al. (2019) proposed two topic models (mLDA and mHLDA) to obtain distinguishable driving style information with hidden structures from real-world driving scenarios. Van Ly et al. (2013a) used data collected by a smartphone and its inertial detector to study whether a driver's driving maneuvers could uniquely identify the driver.

Research into driving styles of drivers of online-hailed cars that is based on driving tasks is limited. Most previous studies have tended to assume that the driver's driving style is fixed within each trip, which ignores the fact that driving style may change during a single trip. For example, Feng et al. (2018) used support vector clustering based on detected maneuvers to classify driving style and found that the driving style of a single driver is not consistent and may vary within a single trip. The traffic environment and external conditions also can affect the driver's behavior; that is, even drivers who typically exhibit a normal and safe driving style may change to an aggressive driving style when they are required to complete a task within a limited time or encounter congested traffic or interference from other drivers. Therefore, dividing a journey into several driving tasks based on changes in the driver's physiological state may be a more reasonable way to investigate driving style.

This paper puts forward a new framework to analyze changes in driving style that take place during different driving tasks for online car-hailing platforms, which can identify driving maneuvers and classify driving styles. This paper is structured as follows. In Section 2, the data sources and tests are discussed in detail. In Section 3, the four-part framework for driving style classifications based on online car hailing data is proposed. The results for each part are presented and discussed in Section 4. Next, the variability in driving style during different driving tasks is analyzed based on the classified maneuvers. Finally, the main findings are summarized and future work is discussed in Section 5.

2. Data description

2.1. Participants

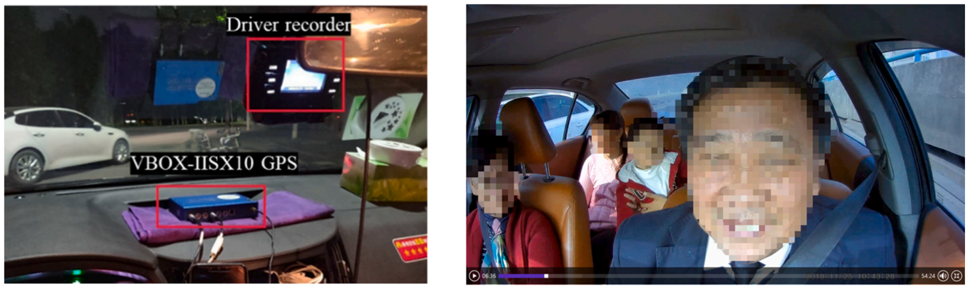
We recruited 10 full-time drivers (9 males, 1 female) who work for online car-hailing companies by posting information about the study online and screening the responses. These professional drivers (age range: 27–52 years, average age = 36, standard deviation (SD) = 7.7; driving experience: 4–22 years, average = 10 years, SD = 3.7) were paid for their participation in this study. We carried out naturalistic driving experiments using the same equipment to avoid systematic errors. We collected real driving data for more than 15 ride requests per driver in a single day of trips. All ten drivers were required to drive the vehicle in similar weather and pavement conditions during the same period in a single day (from 7 a.m. to 10 p.m.) to minimize potential disturbance caused by external factors. These tests were conducted with the consent of all participants. In addition to ensuring the safety of the drivers, we also guaranteed that participants' information was protected and kept confidential.

2.2. Experimental design

The real driving data used in this study were collected from ten different types of instrumented cars that are used in the online car-hailing industry. These vehicles were equipped with a high-definition driving recorder and a Racelogic VBOX-IISX10 GPS device for collecting the experimental data, as shown in Fig. 1 **(a)**. The GPS is a high-performance satellite receiver manufactured by Racelogic Ltd. and provides accurate vehicle kinematic measurement data. In these tests, the same equipment was installed in the vehicles at 10 p.m. the previous day and removed at 9 p.m. after the drivers had finished work. In order to avoid the effects of weather and for other reasons, we selected November 25, 2018 to April 23, 2019 (10 days) to carry out these tests. The time that the driver receiving a ride request and passengers getting into and out of the car, which are important events when differentiating the driving tasks, were captured from back-end ride request data for online car-hailing and recorded in the driving recorder (as presented in Fig. 1 (b)) respectively.

2.3. Data pre-processing

The data recorded by Racelogic's VBOX3i include satellite number, time, latitude, longitude, velocity, directional bearing, height, vertical velocity, longitudinal acceleration, and lateral acceleration, which are recorded at a sampling rate of 10 Hz. Because raw data are relatively volatile, we used a time window algorithm to smooth the data to 1 Hz; that is, the average value of all the data within one second was taken as the value of this second, as presented in Fig. 2. The window size fluctuates within 0–10 samples and depends on the amount of data contained per second. In addition, data that did not meet the specified number of satellites and time were removed, and some abnormal data were excluded using the Pauta criterion (Sheng et al., 2016). In the end, 250,626 records were reserved for analysis (see Table 1), and the



(a) Testing device (b) Order information from driving recorder

Fig. 1. Data collection equipment.

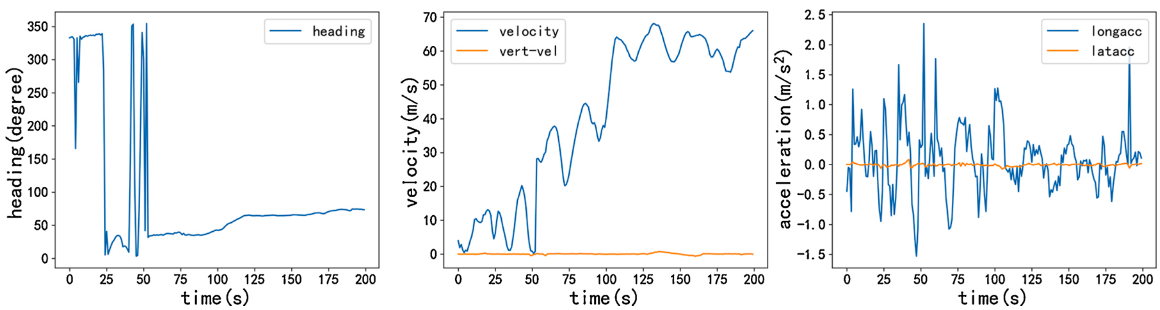


Fig. 2. Experimental data collected by VBOX.

Table 1
Descriptive Statistics for Pre-Processing Data.

Data type	Unit	Refreshing frequency (Hz)	Count	Min	Max	Mean	Standard deviation
Satellite	number	10	250,626	4	202	47.38	106392.73
Time	second	10	250,626	1000	240,000	67713.49	61.21
Latitude	minute	10	250,626	1903.93	1930.04	1918.41	53861.43
Longitude	minute	10	250,626	−7143.85	−7119.54	−7129.59	5.00
Heading	degree	10	250,626	0	158.50	30.35	3.98
Velocity	km/h	10	250,626	0	359.96	174.94	22.34
Height	meter	10	250,626	−659.99	1048.09	18.62	103.26
Vertical velocity	km/h	10	250,626	−87.16	81.54	0.00	17.37
Longitudinal acceleration	g	10	250,626	−4.09	16.43	0.01	0.85
Lateral acceleration	g	10	250,626	−9.54	5.44	−0.01	0.09

duration (percentage) for each driving task was determined as 31.1 % for cruising, 16.7 % for ride requests, and 52.1 % for drop-off.

3. Method

In order to investigate the variability in the driving style of the driver during a daily driving trip, we divided the driving tasks into the following three categories according to the tasks of professional drivers of online-hailed vehicles, as illustrated in Fig. 3:

- Cruising: The driver drives freely on city roads without receiving ride requests.
- Ride request: The time when the driver receives the request from the mobile phone client to the time the driver arrives at the passenger's designated pick-up location.
- Drop-off: The time between when the passenger gets into the car and the driver reaches the designated destination.

Fig. 4 presents a proposed new framework for driving style classifications that is based on online car hailing data. The framework is divided into four parts: maneuver detection, feature extraction, driving maneuver clustering, and driving style analysis. First, the framework uses a threshold-based endpoint detection approach to extract driving maneuvers from the trip. Second, to improve clustering efficiency, we performed PCA to reduce the dimensions of the features. Then, we extracted prominent factors by applying PCA to the statistical features.

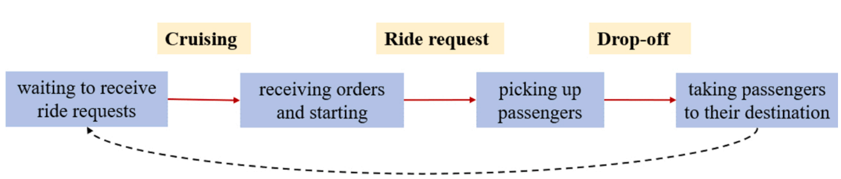


Fig. 3. Driving tasks.

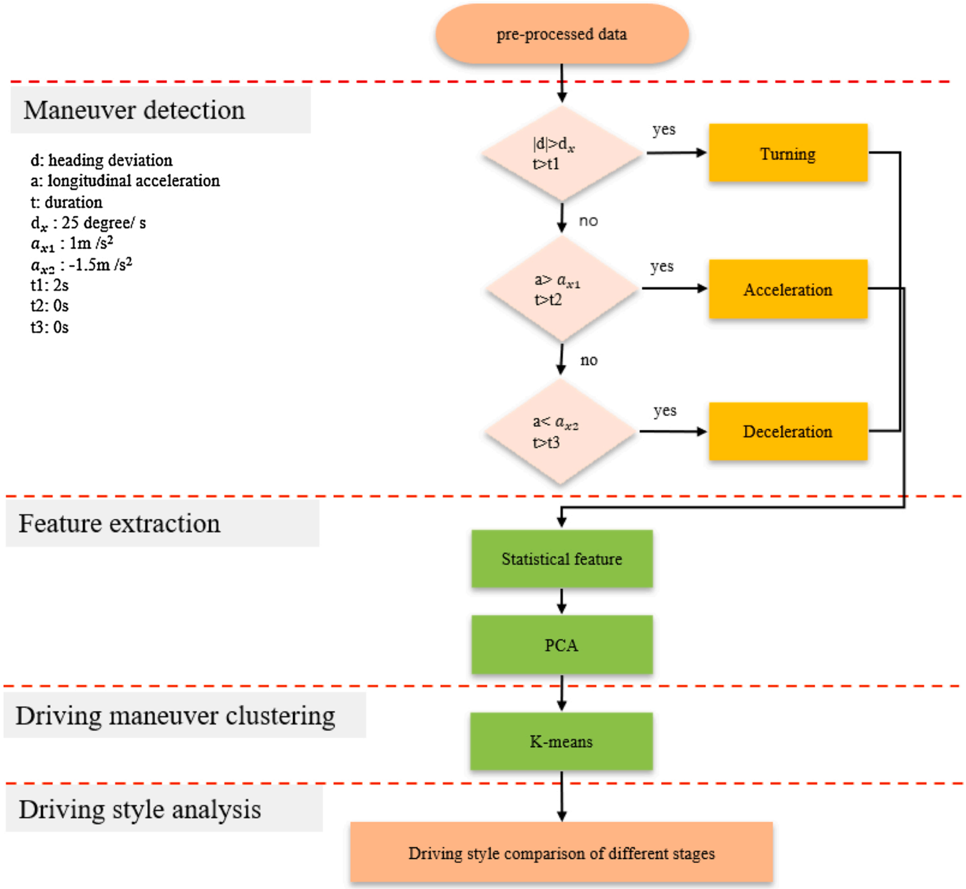


Fig. 4. Analysis framework of driving styles.

Third, we employed *k*-means clustering to classify the driving style of each detected maneuver. Lastly, we analyzed the changes in driving style during the different driving tasks based on the classified maneuvers.

3.1. Maneuver detection

Previous research has shown that acceleration, deceleration, and turning, which can be detected by inertial sensors, are representative of driver's actions and can be used to distinguish individual drivers (Van Ly et al., 2013b). Other complex driving maneuvers of the vehicle can be constructed using these three basic driving maneuvers. Therefore, in this study we used acceleration, deceleration, and turning maneuvers extracted from driving data for driving style analysis. Each type of maneuver may occur multiple times in each trip. These three driving maneuvers are determined based on thresholds.

After pre-preprocessing all the trip data, we calculated the deviation of the directional bearing between adjacent times as follows. If the directional bearing deviation is greater than threshold d_x, then the starting time of the turning maneuver is detected at this moment. If the directional bearing deviation is less than threshold d_x after a few seconds, then the end time of the turning maneuver is detected at this moment. Because we considered data only in cases of smooth traffic flow where the vehicle can turn easily, the vehicle directional bearing deviation for each second exceeds the threshold. Hallac et al. (2016) defined the threshold for a turning maneuver as satisfying the condition that the total bearing deviation during a time period exceeds 70 degrees and the duration is less than 10 s. Given that the Hallac et al. (2016) study was conducted in Ingolstadt, Germany, we compared their results with automobile turning maneuvers on urban roads in China and determined that the threshold for smooth turning maneuvers should be 25 degrees. Furthermore, if the maneuver duration is less than 3 s or more than 10 s, then the maneuver is not considered turning.

In this study, we used longitudinal acceleration to identify acceleration and deceleration maneuvers and we also used a threshold-based algorithm to detect these maneuvers. Fig. 5 presents examples of detected deceleration and acceleration. If the longitudinal acceleration of the vehicle exceeds a_{x1}, then this point is marked as the starting point of the acceleration until the moment when the longitudinal acceleration of the vehicle is less than the threshold, which is marked as the end of the acceleration maneuver. The deceleration action threshold corresponds to ax_2. In addition, maneuvers whose duration is less than 1 s were removed in order to reduce the error rate of maneuver recognition.

Based on previous work regarding maneuver detection (Brombacher et al., 2017; Feng et al., 2018; Johnson and Trivedi, 2011; Van Ly et al., 2013a) and considering local driving habits and several algorithm operation results, we determined numerical values for the three thresholds used in this paper:

- Acceleration: $a > 1.0$ m/s^2
- Deceleration: $a < -1.5$ m/s^2
- Turning: $|d| > 25$ degree/s

We validated this maneuver detection algorithm using data collected simultaneously from a driving recorder and VBOX. The video data were processed through a data collector web application by which driving maneuvers can be tagged manually to identify all driving maneuvers. Then, we compared the driving maneuvers identified by the driving recorder to those detected by the proposed algorithm. The validation results show that the proposed algorithm can identify most maneuvers correctly.

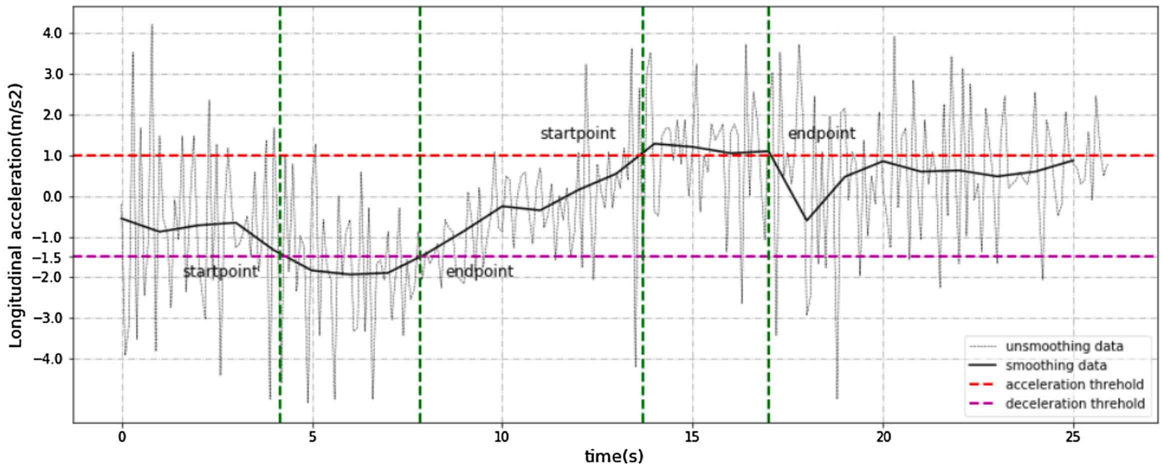


Fig. 5. Maneuver detection using threshold-based algorithm.

3.2. Feature extraction

When the driver makes a turn, not only does the directional bearing deviation per second represent the driving style of the driver, but it also indicates that changes in features such as velocity and acceleration can represent the driving style of the driver. Similarly, when the driver accelerates or decelerates, if the directional bearing deviation is great and the velocity is large, then the driver is observed to drive unsteadily and the driving style tends to become aggressive. That is to say, the bearing deviation, velocity, and acceleration are all affected by the driver's behavior, which can clearly represent changes in driving style.

Therefore, we selected directional bearing deviation, velocity, vertical velocity, longitudinal acceleration, and lateral acceleration as the feature parameters for the turning, acceleration, and deceleration maneuvers that we employed to analyze driving style. As all three maneuvers are time-continuous groups that are extracted from preprocessed driving data, statistical feature parameters need to be extracted from the time series data to represent these maneuvers. The mean, standard deviation, maximum value, and minimum value are used in this paper to represent each detected maneuver, which correspond to 20 statistical parameters, as presented in Table 2. Hence, each detected maneuver is characterized by 20 statistical parameters that serve as the input parameters for maneuver clustering. In order to reduce the number of statistical parameters and derive more representative parameters, we conducted PCA to reduce the complexity of computation. PCA is a commonly used dimensionality reduction method in statistics. It uses the principle of orthogonal transformation to convert a large number of interrelated variables into linear uncorrelated variables while retaining as much information as possible from the original data (Itkonen and Lehtonen, 2020). The explained variance ratio, which is the variance contribution percentage of the original feature parameters represented by the principal component, is the proportion of the original information content represented by each principal component in the total original information content represented by all the principal components. In this paper, the PCA algorithm is applied to each of the three maneuvers respectively, and the principal component after dimension reduction must represent at least 95 % variance of the original parameters.

Table 2
Statistical Parameters.

Term	Parameter	Unit
Dma	directional bearing deviation maximum	degree/s
Dme	directional bearing deviation mean	degree/s
Dmi	directional bearing deviation minimum	degree/s
Ds	directional bearing deviation standard deviation	degree/s
Lama	lateral acceleration maximum	m/s^2
Lame	lateral acceleration mean	m/s^2
Lami	lateral acceleration minimum	m/s^2
Las	lateral acceleration standard deviation	m/s^2
Longma	longitudinal acceleration maximum	m/s^2
Longme	longitudinal acceleration mean	m/s^2
Longmi	longitudinal acceleration minimum	m/s^2
Longs	longitudinal acceleration standard deviation	m/s^2
Vema	vertical velocity maximum	km/h
Veme	vertical velocity mean	km/h
Vemi	vertical velocity minimum	km/h
Ves	vertical velocity standard deviation	km/h
Vma	velocity maximum	km/h
Vme	velocity mean	km/h
Vmi	velocity minimum	km/h
Vs	velocity standard deviation	km/h

3.3. Maneuver clustering

Cluster analysis is an unsupervised machine learning method used for data mining. Its main goal is to amplify the similarity of similar data and the differences of different types of data for comparison and differentiation purposes. Previous work has shown that *k*-means clustering is superior to hierarchical clustering in terms of cluster performance if the recorded data have multiple attributes (Yang et al., 2018). The main idea of this algorithm is to iteratively assign all sample data to the nearest cluster using a predetermined *k*-cluster center point. When the cluster centers converge, the sum of the Euclidean distances of all the sample data to the center point of the corresponding cluster is the shortest distance.

After feature extraction is completed, the principal component of each detected maneuver is used as the input vector for clustering. Here, the feature values of each driving maneuver have significant differences. For example, the directional bearing deviation value of the turning maneuver is high, the longitudinal acceleration value of the acceleration maneuver is high, and the longitudinal acceleration value of the deceleration maneuver is significantly less than those of the features that correspond to the turning maneuver and acceleration maneuver. In this study, such differences remained among the principal components of the three maneuvers after we implemented PCA to reduce the number of features. Therefore, the data for the three driving maneuvers of turning, acceleration, and deceleration were clustered separately to improve the clustering efficiency and enhance the representativeness of the maneuvers. In this work, we applied the *k*-means algorithm to cluster the respective maneuvers into different classes. Fig. 6 provides a flowchart of the driving style classification determination process.

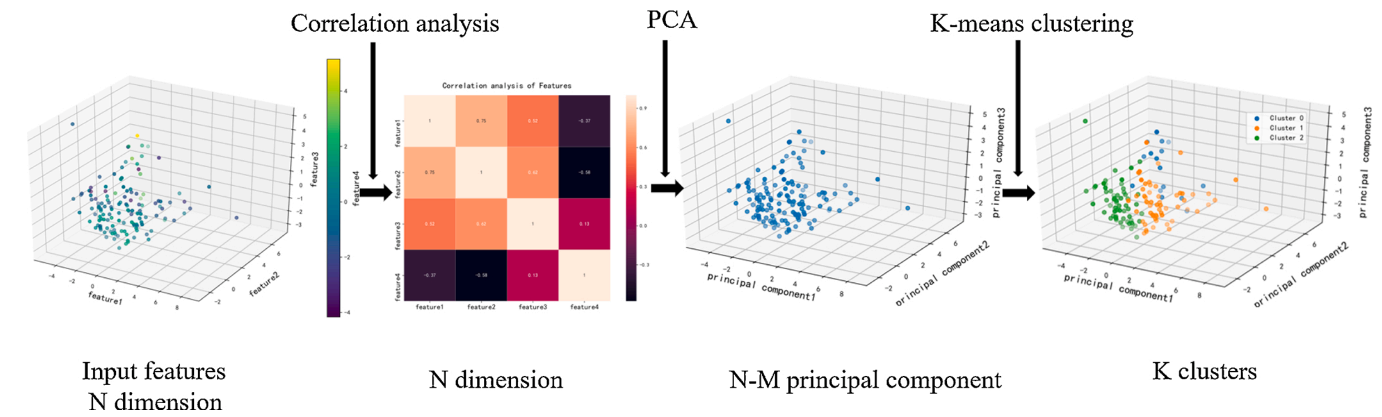


Fig. 6. Flowchart of driving style classification process.

3.4. Driving style classifications

After clustering the driving maneuvers respectively, each maneuver corresponded to a unique category label. Then, the algorithm classified the driving style of the different driving tasks based on the cluster of the detected maneuvers. The proportion of driving maneuvers that corresponded to the different cluster labels in each driving task was calculated, as shown in Eq. (1).

$$p_i = \frac{N_i}{\sum_i N_i} \tag{1}$$

Where i is the cluster category that corresponds to the driving style ($i = 1, 2, 3$), N_i is the number of each driving maneuver that is labeled i in the cluster category, and p_i is the proportion of driving styles numbered i for each driving maneuver during each driving task.

Then, we calculated the mean of p_i for each of the three different driving maneuvers to represent the overall proportion of driving styles for all driving maneuvers during each driving task.

4. Results and discussion

Based on the proposed framework, the four sections in this paper separately present the results of each step. The first section discusses all three maneuvers that were detected using the determined threshold-based method. The second section introduces the parameters that were selected for each detection maneuver and the number of principal components determined via PCA. The third section presents the cluster results for each of the three maneuvers separately. Here in the fourth section, we analyze and discuss the differences in the driving styles of the drivers in terms of the three driving tasks based on the cluster labels of the detected maneuvers.

4.1. Driving maneuver detection

After preprocessing ten days of driving data collected by VBOX3i for ten different drivers during various trips, the threshold-based algorithm detected 1808 turning maneuvers, 8050 acceleration maneuvers, and 2703 deceleration maneuvers. Table 3 presents the number of maneuvers for each of the ten drivers.

4.2. Feature extraction

In order to study the correlations among the selected parameters, we conducted correlation analysis of the 20 extracted statistical features. The correlation coefficient between two indicators reflects the dependency between them; the greater the correlation coefficient, the stronger the degree of correlation between the two indicators. By calculating the correlation coefficient between any two features, the redundancy of these data can be shown, which avoids information duplication that can be caused by analyzing data directly. Fig. 7 presents the correlation analysis results for the three maneuvers. The red squares indicate a strong negative correlation between the corresponding two features and the blue squares indicate a strong positive correlation between the corresponding two features. The absolute value of many elements near the diagonal of the correlation coefficient matrix is greater than 0.5, which indicates redundancy in the statistical characteristic values extracted for driving maneuvers.

We carried out PCA to reduce the dimensions of the data. After implementing the PCA algorithm to reduce the dimensions of the statistical features for the three maneuvers to preserve at least 95 % variance of the original data, we obtained 11 principal components for the turning maneuver, 12 for the acceleration maneuver, and 11 for the deceleration maneuver. Table 4 presents the explained variance ratio for each principal component relative to the different maneuvers.

4.3. Driving maneuver clustering

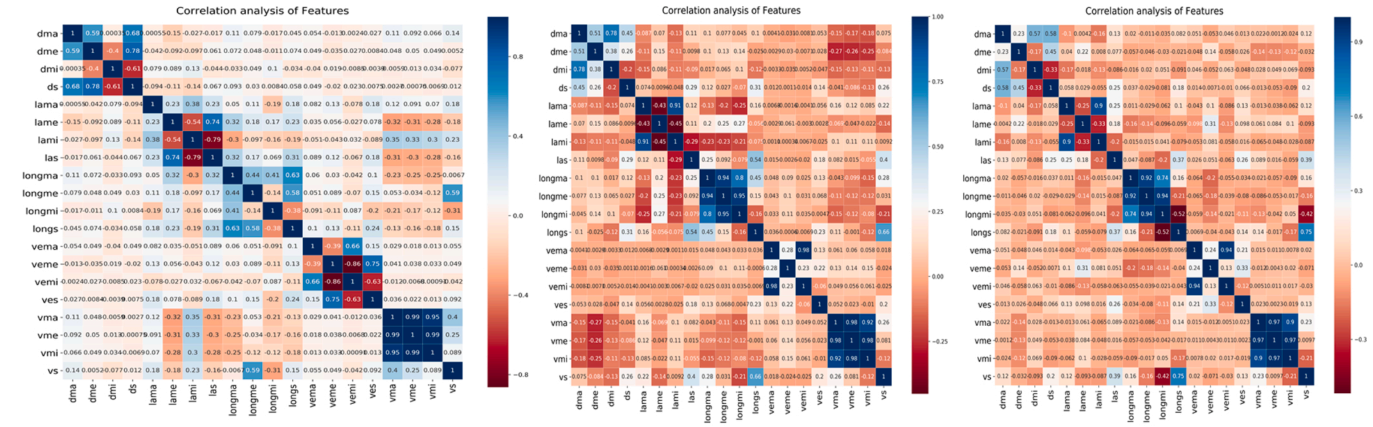
After extracting the principal components using the PCA algorithm, we used the *k*-means algorithm to cluster the three driving maneuvers of turning, acceleration, and deceleration, respectively. These three maneuvers are discussed in the following paragraphs and Fig. 8 presents the results.

4.3.1. Turning maneuver

The 11 principal components of the 1808 turning maneuvers were clustered; Fig. 8 **(a)** shows the three categories after clustering. The characteristic statistical parameters for directional bearing deviation, velocity, vertical velocity, longitudinal acceleration, and lateral acceleration of the turning maneuvers included in each category were

Table 3
Number of Detected Maneuvers for Each of Ten Drivers.

Maneuver type	Driver number										
	1	2	3	4	5	6	7	8	9	10	Sum
Turning	299	129	222	225	267	149	80	150	151	136	1808
Acceleration	687	386	680	1164	1291	779	465	934	905	759	8050
Deceleration	192	93	253	366	452	222	202	424	243	256	2703



(a) turning (b) acceleration (c) deceleration

Fig. 7. Feature correlation analysis for different maneuver types.

Table 4
Explained Variance Ratio of Each Principal Component versus Maneuver.

Maneuver	Principal Components										
	1	2	3	4	5	6	7	8	9	10	11	12
Turning	0.206	0.151	0.137	0.110	0.084	0.068	0.057	0.050	0.045	0.040	0.018	
Acceleration	0.192	0.147	0.131	0.103	0.098	0.084	0.055	0.048	0.036	0.034	0.029	0.026
Deceleration	0.161	0.148	0.116	0.110	0.099	0.086	0.077	0.064	0.039	0.037	0.027	

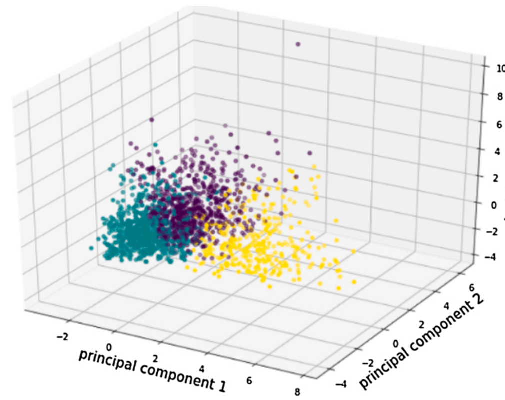
averaged respectively (Table 5), and the average values were used to represent the cluster center point of each category, as shown in Fig. 8 **(b)**. Then, the driving style of each category could be identified according to the feature values of the clustering center. The clustering effects of five features (directional bearing deviation mean, directional bearing deviation standard deviation, directional bearing deviation maximum, directional bearing deviation minimum, and longitudinal acceleration mean) are relatively obvious, but not so obvious for the other 15 features. Therefore, these five parameters were selected for cluster analysis to identify the driving styles for each category. The overall trend is that the values of the five features are the highest in Category 1, followed by Category 3, and lowest in Category 2. When the driver makes a sharp turn, the directional bearing deviation is great and the longitudinal acceleration is also great, which indicates that the driving style of the driver is aggressive. When the driver makes a smooth turn, the directional bearing deviation and longitudinal acceleration are relatively small, which indicates that the driving style is cautious. The analysis results show that the driving style of Category 1 is aggressive, the driving style of Category 2 is cautious, and the driving style of Category 3 is normal.

4.3.2. Acceleration maneuver

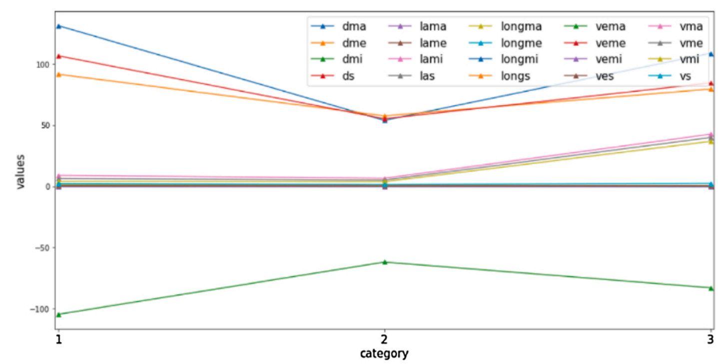
The 12 principal components of 8050 acceleration maneuvers were clustered, Fig. 8 **(c)** shows the three categories after clustering. The average values of the characteristic statistical parameters for directional bearing deviation, velocity, vertical velocity, longitudinal acceleration, and lateral acceleration of the acceleration maneuvers were calculated to identify the driving style of each category (Table 5), as shown in Fig. 8 **(d)**. Because the effect of bearing deviation on the identification of driving style for acceleration maneuvers is not as significant as that of speed and acceleration, the derivative features of velocity and acceleration were selected as the basis for distinguishing the driving style for the three clusters. The clustering effects of five parameters (vertical velocity mean, vertical velocity maximum, longitudinal acceleration maximum, longitudinal acceleration mean, and longitudinal acceleration minimum) are relatively obvious, but not so obvious for the other 15 parameters. The overall trend is that the values for the five features are the highest in Category 3, followed by Category 2, and lowest in Category 1. When the driver accelerates sharply, the longitudinal acceleration is great and the velocity is also great, which indicates that the driving style is aggressive. When the driver accelerates steadily, the longitudinal acceleration and velocity are relatively small, which indicates that the driving style is cautious. Therefore, these five parameters were selected for cluster analysis to identify the driving styles for each category. The analysis results show that the driving style of Category 1 is cautious, the driving style of Category 2 is normal, and the driving style of Category 3 is aggressive.

4.3.3. Deceleration maneuver

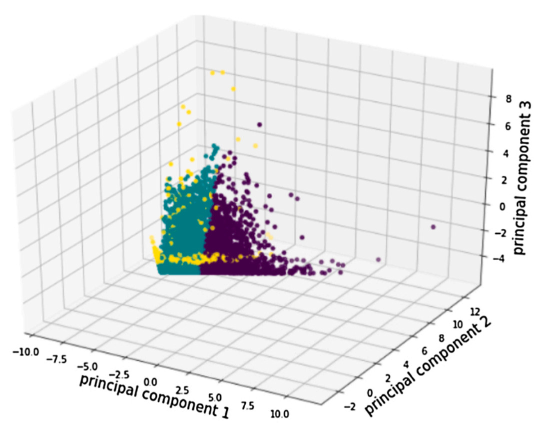
Similar to the turning and acceleration maneuvers, the 11 principal components of the 2703 deceleration maneuvers were clustered; Fig. 8 **(e)** shows the three categories after clustering. The average values of the characteristic statistical parameters for directional bearing deviation, velocity, vertical velocity, longitudinal acceleration, and lateral acceleration of the acceleration maneuvers were calculated to identify the driving style of each category (Table 5), as shown in Fig. 8 **(f)**. Because the effect of the directional bearing deviation on the identification of driving style for the acceleration maneuvers is not as significant as that of speed and acceleration, the derivative features of velocity and acceleration were selected as the basis for distinguishing the driving style for the three clusters. The derivative values of velocity and longitudinal acceleration exhibit apparent clustering effects, but their trends differ. As the driving style analysis of the deceleration maneuvers is based mainly on longitudinal acceleration, four parameters (longitudinal acceleration mean, standard deviation, maximum, and minimum) were selected for cluster analysis to classify the driving styles. The overall trend is that the values for the four features are the highest in Category 2, followed by Category 3, and lowest in Category 1. When the driver brakes sharply, the longitudinal acceleration is great, which indicates that the driving style of the driver is aggressive. When the driver



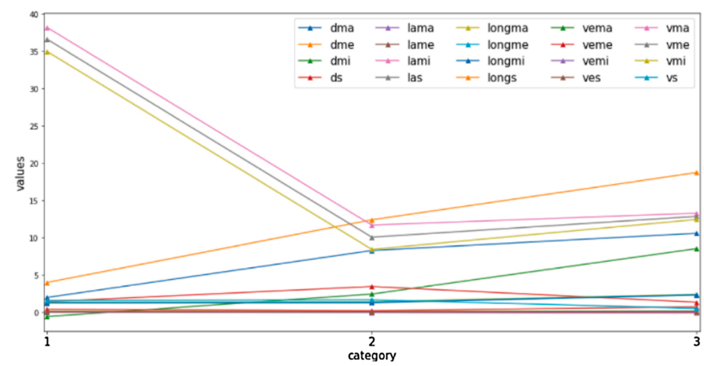
(a) cluster results for turning



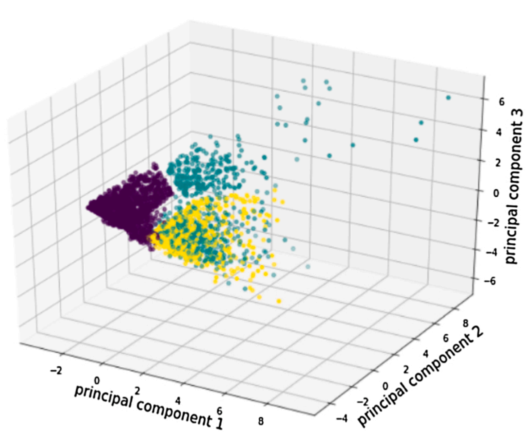
(b) cluster centers for turning



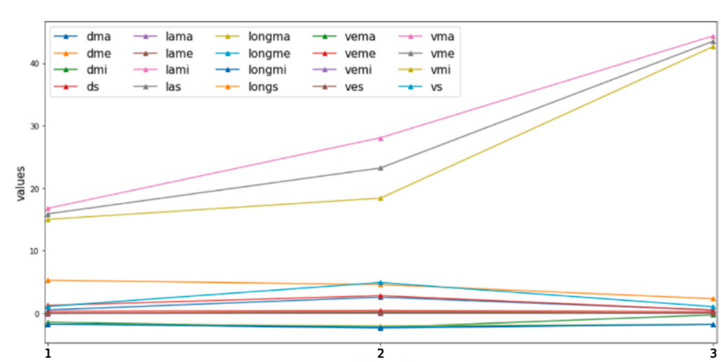
(c) cluster results for acceleration



(d) cluster centers for acceleration



(e) cluster results for deceleration



(f) cluster centers for deceleration

Fig. 8. Cluster results for different driving maneuvers.
Note: The principal components of each detected maneuver were used as input vectors for clustering; we used three principal components to show the cluster analysis results. The averaged values of the characteristic statistical parameters were used to represent the cluster center point of each category.

Table 5
Feature Values of Three Cluster Centers for Three Maneuvers: Turning, Acceleration, and Deceleration.

Feature	Turning			Acceleration			Deceleration		
	1	2	3	1	2	3	1	2	3
Dma, degree/s	131.01	53.74	108.47	1.95	8.26	10.56	0.52	2.57	0.50
Dme, degree/s	91.34	57.39	79.29	3.97	12.38	18.71	5.28	4.59	2.33
Dmi, degree/s	−104.5	−61.90	−82.85	−0.60	2.41	8.52	−1.43	−2.25	−0.26
Ds, degree/s	106.37	55.07	84.21	1.39	3.43	1.31	1.25	2.82	0.50
Lama, m/s^2	0.03	0.02	0.02	−0.01	−0.03	−0.11	0.00	0.01	−0.01
Lame, m/s^2	0.06	0.06	0.02	0.06	0.06	0.14	0.03	0.03	0.03
Lami, m/s^2	−0.10	−0.07	−0.02	−0.04	−0.05	−0.13	0.00	−0.01	−0.01
Las, m/s^2	0.06	0.05	0.02	0.01	0.01	0.01	0.00	0.01	0.00
Longma, m/s^2	1.07	0.62	0.34	1.33	1.39	2.37	−1.70	−2.01	−1.76
Longme, m/s^2	0.64	0.44	0.46	1.27	1.31	2.32	−1.72	−2.18	−1.78
Longmi, m/s^2	−0.30	−0.22	−0.46	1.22	1.24	2.28	−1.74	−2.36	−1.80
Longs, m/s^2	0.60	0.40	0.34	0.06	0.08	0.06	0.02	0.20	0.03
Vema, km/h	0.22	0.08	0.16	0.07	0.03	0.12	−0.04	0.15	0.01
Veme, km/h	0.19	0.14	0.14	0.38	0.19	0.71	0.30	0.42	0.26
Vemi, km/h	−0.17	−0.13	−0.08	0.02	−0.02	0.05	−0.05	0.00	−0.01
Ves, km/h	0.17	0.10	0.10	0.03	0.03	0.05	0.01	0.10	0.01
Vma, km/h	8.81	6.45	42.43	38.19	11.67	13.27	16.78	28.06	44.35
Vme, km/h	6.19	4.95	39.77	36.60	10.04	12.84	15.89	23.23	43.49
Vmi, km/h	3.87	3.65	36.61	34.97	8.41	12.42	15.02	18.40	42.64
Vs, km/h	2.08	1.28	2.38	1.56	1.63	0.50	1.08	4.91	1.05

decelerates smoothly, the longitudinal acceleration is small, which indicates that the driving style is cautious. The analysis results show that the driving style of Category 1 is cautious, the driving style of Category 2 is aggressive, and the driving style of Category 3 is normal.

4.4. Driving style analysis

After separately clustering the data sets for the turning, acceleration, and deceleration maneuvers, the numbers of the three maneuvers based on different driving styles were counted to compare the changes in driving style for the different driving tasks. In order to analyze the changes in driving styles in terms of the different driving tasks, we calculated the proportion of different driving styles in terms of the three driving tasks for each driver. The results indicate that the driving style of a single driver is not always consistent and may vary within a single trip. Fig. 9 presents plots that show the variation in driving style (aggressive, normal, and cautious) among the different driving tasks (cruising, ride request, and drop-off). In addition, we calculated the average values of 20 statistical parameters of the three driving styles during different driving stages to analyze the differences in driving behaviors among the three driving tasks (see Table 6).

Because different trips have different traffic conditions and require different driving tasks, we calculated the mean value of the proportion of the different driving styles in each trip to analyze the differences in driving style among the three driving maneuvers of turning, acceleration, and deceleration. Table 7 presents the results.

Fig. 10 presents the cluster results in terms of comparisons of driving styles (aggressive, normal, and cautious) for the three driving tasks (cruising, ride request, and drop-off). Fig. 10 **(a)** indicates that the driving styles of the drivers for the three driving tasks are inconsistent across maneuvers (turning, acceleration, and deceleration). The overall trend is that the percentage of aggressive driving is the highest during the ride request task, followed by the drop-off task, and is lowest in the cruising task. For cruising, the proportion of aggressive driving for all maneuvers is 0.249, and the proportion increases significantly during both the ride request task and drop-off task, with 0.288 for the ride request task and 0.254 for the drop-off task. The proportion of normal driving shows no obvious change for the three driving tasks, whereas the proportion of cautious driving shows a decreasing trend for the ride request task and drop-off task compared to the cruising task. The proportion of aggressive driving during the ride request task is relatively greater than for the other two driving tasks for all maneuvers, indicating that drivers may engage in dangerous driving behaviors, such as frequent overtaking and continuous sharp braking, on urban roads during the ride request task to avoid the possibility that potential passengers who are waiting may cancel ride requests. For all maneuvers, the proportion of aggressive driving for the drop-off task is greater than the cruising task, which indicates that drivers often drive at a relatively high and unstable speed to improve their efficiency when carrying the passenger to the destination, which often results in creating chaotic traffic situations and providing a poor travel experience for passengers. By analyzing the three maneuvers separately, as presented in Fig. 10 **(b) through (d)**, the driving styles while turning, accelerating, and decelerating are shown to vary dramatically among the three driving tasks.

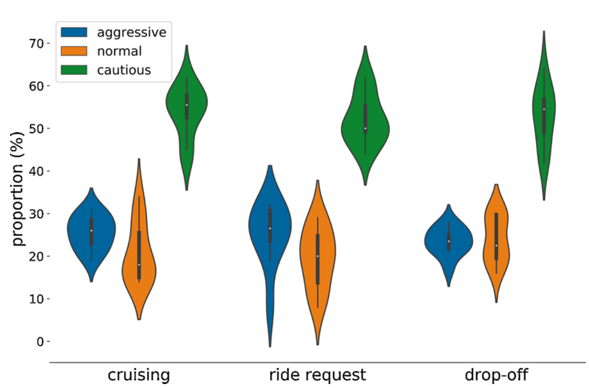


Fig. 9. Driving style comparisons for three driving tasks for each driver.

4.4.1. Turning maneuver

The cautious driving style accounts for the highest proportion of turning maneuvers for the cruising task, and the aggressive driving style accounts for the highest proportion of turning maneuvers for the ride request task and drop-off task. At the same time, the proportion of cautious driving for the ride request task and drop-off task decreases. These findings demonstrate that, after receiving a ride request, the driver is eager to arrive quickly at the passenger's location. To avoid delays at road intersections, the driver makes a sharp turn. After picking up the passenger, the driver tends to drive aggressively when turning in order to carry the passenger to the destination as soon as possible.

4.4.2. Acceleration maneuver

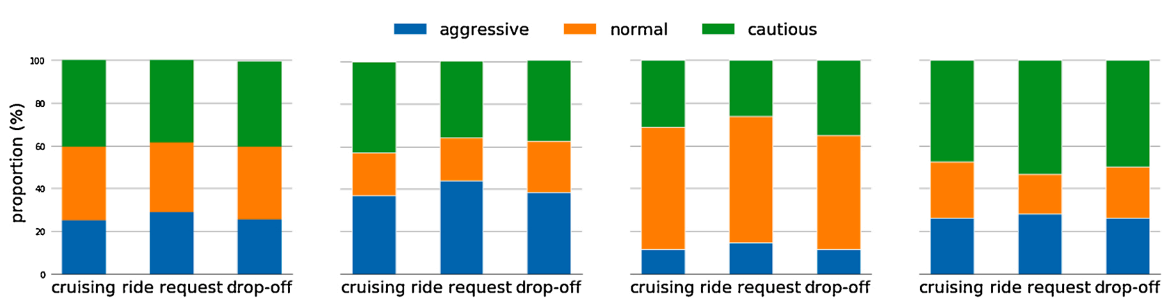
Normal is the dominant driving style during acceleration for all three driving tasks. However, the aggressive driving style accounts for the

Table 6
Statistical Parameters of Different Driving Styles for Each Task.

Feature	Cruising			Ride request			Drop-off		
	Aggressive	Normal	Cautious	Aggressive	Normal	Cautious	Aggressive	Normal	Cautious
Dma, degree/s	26.23	29.58	13.49	27.30	31.08	13.35	22.65	25.30	8.77
Dme, degree/s	28.97	20.60	15.73	31.69	21.87	15.54	24.33	18.61	11.38
Dmi, degree/s	−9.32	−17.63	−12.01	−0.78	−22.94	−11.50	−8.12	−16.62	−8.44
Ds, degree/s	16.57	22.17	12.06	13.27	24.40	12.01	14.29	19.82	8.20
Lama, m/s2	−0.05	0.01	−0.01	−0.07	0.02	0.00	−0.06	0.01	−0.01
Lame, m/s2	0.09	0.04	0.05	0.10	0.04	0.06	0.09	0.04	0.05
Lami, m/s2	−0.07	−0.05	−0.04	−0.08	−0.05	−0.03	−0.07	−0.05	−0.03
Las, m/s2	0.01	0.03	0.02	0.01	0.03	0.01	0.01	0.03	0.01
Longma, m/s2	0.29	0.59	0.91	0.39	0.87	0.90	0.12	0.67	0.92
Longme, m/s2	0.25	0.42	0.81	0.35	0.68	0.81	0.09	0.49	0.85
Longmi, m/s2	0.06	0.10	0.70	0.20	0.27	0.69	−0.08	0.16	0.75
Longs, m/s2	0.11	0.25	0.11	0.09	0.30	0.11	0.10	0.26	0.08
Vema, km/h	10.31	33.23	19.81	11.33	29.30	17.94	14.15	31.84	22.31
Veme, km/h	9.53	29.04	18.70	10.73	24.82	16.90	13.36	27.48	21.21
Vemi, km/h	8.80	24.71	17.62	10.17	20.24	15.90	12.61	23.00	20.14
Ves, km/h	0.78	3.92	1.18	0.61	4.23	1.12	0.81	4.13	1.17
Vma, km/h	0.02	0.12	0.02	0.24	0.10	0.02	0.10	0.19	−0.01
Vme, km/h	0.28	0.19	0.19	0.56	0.20	0.34	0.40	0.31	0.27
Vmi, km/h	−0.03	−0.02	−0.04	0.18	−0.12	−0.07	0.06	−0.01	−0.07
Vs, km/h	0.02	0.07	0.03	0.03	0.11	0.05	0.02	0.11	0.03

Table 7
Number of Maneuvers and Percentage of Driving Style for Three Driving Tasks for All Drivers.

Task	Driving Style	Turning		Acceleration		Deceleration		All Maneuvers	
		No.	%	No.	%	No.	%	No.	%
	aggressive	248	36.8	284	11.6	218	26.4	750	24.9
Cruising	normal	138	20.5	1406	57.3	216	26.2	1760	34.7
	cautious	287	42.6	764	31.1	391	47.4	1442	40.4
	aggressive	138	43.7	193	14.7	113	28.0	444	28.8
Ride Request	normal	65	20.6	773	59.1	75	18.6	913	32.8
	cautious	113	35.8	343	26.2	216	53.5	672	38.5
	aggressive	315	38.5	500	11.7	384	26.1	1199	25.4
Drop-off	normal	198	24.2	2279	53.2	357	24.2	2834	33.9
	cautious	306	34.7	1508	35.2	733	49.7	2547	39.9



(a) All maneuvers (b) Turning (c) Acceleration (d) Deceleration

Fig. 10. Driving style comparisons for three driving tasks.

highest percentage for the ride request task compared to the other two tasks. This finding indicates that the driver frequently accelerates, overtakes, and tries to reach waiting passengers quickly by driving at a high speed to pick up passengers as soon as possible after receiving the ride request, which can severely affect traffic safety. The proportion of aggressive driving for the acceleration maneuver during the drop-off task is greater than during the cruising task. This finding indicates that the driver employs high acceleration and velocity (i.e., speed) when driving passengers to their destination, which reflects that the driver wants to complete the ride request quickly while striving to receive more requests within the same time, so as to improve revenue. However, this driving behavior leads to a bad travel experience for passengers.

4.4.3. Deceleration maneuver

Cautious is the dominant driving style during the deceleration maneuver for all three driving tasks. This outcome demonstrates that drivers tend to be conservative and calm when slowing down. The proportion of aggressive driving for the deceleration maneuver during the ride request task is greater than during the drop-off task and cruising task. This finding shows that the driver employs high speed during the ride request task and suddenly decelerates when encountering a red light or traffic congestion at intersections.

5. Conclusions

This paper proposes a new driving style classification framework to analyze the driving styles of online car-hailing drivers while completing successive driving tasks. The framework is constructed based on maneuver detection, feature extraction, driving maneuver clustering, and driving style analysis. The analysis and comparison results indicate that the driver's driving style for the three driving tasks is inconsistent, which suggests that driving tasks lead to variations in driving style. The overall trend is that the proportion of aggressive driving for all maneuvers (turning, acceleration, and deceleration) is greatest for the ride request task (0.288), followed by the drop-off task (0.254), and is lowest for the cruising task (0.249). We also found that the variations in driving style during the three driving tasks differ significantly for turning, acceleration, and deceleration maneuvers. For the turning maneuver, the cautious driving style accounts for the greatest proportion for the cruising task (0.426) whereas the aggressive driving style accounts for the greatest proportion for the ride request task (0.437) and drop-off task (0.385). For the acceleration maneuver, normal is the dominant driving style during the three tasks (0.573 for cruising, 0.591 for ride request, and 0.532 for drop-off), and the aggressive driving style accounts for the greatest proportion for the ride request task (0.147) compared to the other tasks (0.117 for drop-off and 0.116 for cruising). For the deceleration maneuver, cautious is the dominant driving style for the three tasks (0.474 for cruising task, 0.535 for ride request task, and 0.497 for drop-off task), and the proportion of aggressive driving for the ride request task (0.28) is higher than for the cruising task (0.264) and drop-off task (0.261). Furthermore, the proposed framework can correctly identify most turning, acceleration, and deceleration maneuvers from inertial sensor data and is able to classify driving maneuvers well.

The findings of this study indicate some problems associated with online car-hailing platforms. Due to the particularity of online car-hailing services, the driver's psychology will differ subtly for each driving task, which may lead to different driving behaviors or driving styles. This information will be useful for the safety management of the online car-hailing industry. The findings of this study should encourage online car-hailing platforms to offer specialized training for drivers through which driving safety knowledge could be strengthened and appropriate driving behaviors would be standardized.

Although the proposed framework is able to identify maneuvers and classify driving styles for online car-hailing drivers, due to the large number of samples, we did not analyze each driver's changes in driving style during the different driving tasks. Future work will focus on individual drivers in detail to analyze the correlations between the overall driving style of each driver and the changes in driving style across the three driving tasks. We will also consider combining the three maneuvers to identify the driving style. In this study, we collected data for only 10 online car-hailing drivers due to limitations of the test conditions, which meant that the data are not representative in terms of age, gender, and experience. We plan to recruit more participants in future studies.

CRediT authorship contribution statement

Yongfeng Ma: Conceptualization, Methodology, Validation, Formal analysis, Resources, Supervision, Project administration, Writing - review & editing. **Wenlu Li:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Kun Tang:** Conceptualization, Methodology, Writing - review & editing. **Ziyu Zhang:** Conceptualization, Investigation, Writing - review & editing. **Shuyan Chen:** Conceptualization, Methodology, Writing - review & editing.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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