Accident Analysis and Prevention 104 (2017) 125–136

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Can vehicle longitudinal jerk be used to identify aggressive drivers? An examination using naturalistic driving data

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ARTICLE INFO

Keywords:
Driver behavior
Aggressive driving
Jerk
Naturalistic driving study

ABSTRACT

This paper investigated the characteristics of vehicle longitudinal jerk (change rate of acceleration with respect to time) by using vehicle sensor data from an existing naturalistic driving study. The main objective was to examine whether vehicle jerk contains useful information that could be potentially used to identify aggressive drivers. Initial investigation showed that there are unique characteristics of vehicle jerk in drivers' gas and brake pedal operations. Thus two jerk-based metrics were examined: (1) driver's frequency of using large positive jerk when pressing the gas pedal, and (2) driver's frequency of using large negative jerk when pressing the brake pedal. To validate the performance of the two metrics, drivers were firstly divided into an aggressive group and a normal group using three classification methods (1) traveling at excessive speed (speeding), (2) following too closely to a front vehicle (tailgating), and (3) their association with crashes or near-crashes in the dataset. The results show that those aggressive drivers defined using any of the three methods above were associated with significantly higher values of the two jerk-based metrics. Between the two metrics the frequency of using large negative jerk seems to have better performance in identifying aggressive drivers. A sensitivity analysis shows the findings were largely consistent with varying parameters in the analysis. The potential applications of this work include developing quantitative surrogate safety measures to identify aggressive drivers and aggressive driving, which could be potentially used to, for example, provide real-time or post-ride performance feedback to the drivers, or warn the surrounding drivers or vehicles using the connected vehicle technologies.

1. Introduction

Road accidents accounted for 35,092 fatalities and 2.44 million injuries in the United States in 2015 (National Center for Statistics and Analysis, 2016). A study by American Automobile Association (AAA) Foundation for Traffic Safety (AAA, 2009) found that potentially-aggressive driving actions such as speeding, failure to yield right of way, reckless driving, were associated with 106,727 or 55.7% of the fatal crashes from 2003 to 2007. National Highway Traffic Safety Administration (NHTSA, n.d.), after discussions with law enforcement and the judiciary, defines aggressive driving as occurring when "an individual commits a combination of moving traffic offenses so as to endanger other persons or property." NHTSA's Fatality Analysis Reporting System (FARS) takes a list of actions that may have involved aggressive driving that include speeding, failure to yield right of way, reckless driving, erratic driving, improper passing, improper following, racing, etc. (NHTSA, 2016)

To reduce the number of crashes, it is promising to investigate methods to quantitatively measure aggressive driving behaviors and identify aggressive drivers, and then develop in-vehicle systems and other countermeasures that could prevent or mitigate the unsafe situations that may arise from aggressive driving, for example, by providing real-time or post-ride performance feedback to the drivers, or warning the surrounding drivers or vehicles using the connected vehicle technologies.

Aggressive driving behaviors are often considered as contextual-based which depend on both drivers' individual characteristics and environmental factors (Dula and Geller, 2003; Neuman et al., 2003; Tasca, 2000). In the past decades, several methods have been proposed for detecting aggressive driving behaviors based on metrics from vehicle sensor data such as excessive speed, hard braking, heavy acceleration, and aggressive turns (Wahlberg, 2006; Johnson and Trivedi, 2011; Chen et al., 2015). Data fusion methods that combine signals from multiple sources have also been examined (Johnson and

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http://dx.doi.org/10.1016/j.aap.2017.04.012
Received 8 February 2016; Received in revised form 22 March 2017; Accepted 17 April 2017

Trivedi, 2011; Rodriguez Gonzalez et al., 2014). However, given the complexity of real-world driving environments, most of the methods have not been able to distinguish aggressive driving from normal driving with both a high detection rate (true positive) and a low false alarm rate (false positive). Considering that driver aggression is multi-dimensional and may be exhibited in various aspects of driving, it may be valuable to explore and examine new quantitative measures that may contain information about aggressive driving.

While most previous studies have used common vehicle kinematics such as speed, longitudinal and lateral acceleration to measure driving aggressiveness, less attention has been given to vehicle jerk, which is the change rate of vehicle acceleration with respect to time. Jerk has been used as a measure of the smoothness or abruptness of a movement in many domains such as the trajectory planning of the human arm (Viviani and Flash, 1995) and industrial robots (Macfarlane and Croft, 2003). Vehicle jerk has been shown to be related to a driver's physiological feelings of ride comfort (Huang and Wang, 2004). And it has been used as a quality measurement of vehicle suspension vibration (Hrovat, 1997) and transmission shift (Huang and Wang, 2004). The International Organization for Standardization (ISO) for adaptive cruise control systems also set a requirement that the negative jerk of the vehicle during automatic braking shall not exceed $-2.5\ \mathrm{m/s^3}$ (ISO 15622, 2010). Inspired by the minimal-jerk theory of human arm movement (Flash and Hogan, 1985), Hiraoka et al. (2005) proposed a car following model with the basic assumption that a driver follows a lead vehicle with a goal of minimizing the jerk. A driving simulator study (Othman et al., 2008) found that the larger the jerk was when the driver was starting to accelerate or decelerating to stop, the higher the self-reported drivers' stress levels. Vehicle jerk has also been used to detect safety critical events (Bagdadi and Várhelyi, 2013), traffic conflicts (Zaki et al., 2014), and change of instantaneous driving decisions (Liu et al., 2015). Most relevant to this paper includes a study which classified a driver's style of aggressiveness using his/her jerk profile (Murphey et al., 2009) and a study which identified accident-prone drivers (Bagdadi and Várhelyi, 2011; Bagdali, 2013). The former study developed an algorithm to classify a driver's style (from calm, normal, to aggressive) using the driver's jerk profile, roadway type, and traffic congestion level. The algorithm was evaluated using experiments conducted in a vehicle simulation program. The latter study developed a critical jerk method and showed that the expected number of accidents for a driver increases with the number of critical jerks caused by the driver. In both studies, the jerk was examined regardless of the drivers' pedal operations.

The main objective of this paper is to examine whether vehicle longitudinal jerk (termed simply as 'vehicle jerk' in the rest of the paper) could be potentially used to identify aggressive drivers. We hypothesized that the vehicle jerk indicates how smoothly a driver accelerates and decelerates the vehicle, and aggressive drivers may use large jerk more often by operating the gas and brake pedal compared to normal drivers. Vehicle sensory data from an existing naturalistic driving study were used for the analysis and validation. Naturalistic driving data have the advantages of providing more realistic and detailed driving behavior in real-world settings as compared to typical laboratory tests using driving simulators or a test track. Specifically, we firstly investigated the characteristics of the vehicle jerk associated with drivers' gas and brake pedal operations, and developed two jerk-based metrics: (1) driver's frequency of using large positive jerk when pressing the gas pedal, and (2) driver's frequency of using large negative jerk when pressing the brake pedal. To validate the performance of the two metrics, drivers in the dataset were firstly divided into two groups based on three classification methods: (1) their behavior of using excessive speed, (2) their behavior of following too closely to a front vehicle, and (3) their association with any crash or near-crash in the dataset. Statistical analysis were conducted to examine whether the metrics are significantly different between the aggressive and normal drivers. The age and gender effects on the metrics were also analyzed. The efficacy of using the metrics to identify aggressive drivers were further demonstrated using a Receiver Operating Characteristic (ROC) analysis. A sensitivity analysis was conducted to examine whether the findings were consistent with varying parameters in the analysis.

2. Methods

2.1. Data extraction

Data from an existing naturalistic driving study, the Integrated Vehicle-Based Safety System (IVBSS) program (Sayer et al., 2011) were used in this paper. The IVBSS program was designed to build and test an integrated in-vehicle crash warning system that includes forward crash warning, lane departure warning, curve speed warning, and lane change warning. Sixteen Honda Accords (2006 or 2007 model year) with automatic transmissions were used as test vehicles. A total of 108 randomly sampled drivers from three age groups (younger (20–30 years old), middle-aged (40–50 years old), and older (60–70 years old)) balanced for gender participated in the study. Participants used the test vehicles as a substitute for their personal vehicles in an unsupervised manner for over a 40-day period. The first 12 days for each driver was the baseline period, during which no warnings were presented to the drivers. For the purpose of this study, only the data from the 12-day baseline period were used. And the following five criteria were further applied to the data query and extraction:

(1) Vehicle was traveling on a freeway (not including entrance or exit ramps);
(2) Cruise control function was not activated;
(3) Vehicle was traveling at a speed of at least 25 mph (40 km/h);
(4) Each continuous driving segment lasted at least 30 s.
(5) After applying the criterion (1)–(4), each driver needed to have a total of at least 50 miles of driving data to be included in the following analyses.

The resulting dataset represents a total of 21,172 miles or 317 h of freeway driving data from 88 out of the 108 drivers in the IVBSS program. Twenty drivers were excluded because they did not have enough freeway driving data as required by criterion (5). The analysis in the rest of this paper were based on this resulting dataset.

2.2. Variables and data analysis

The vehicle sensor data channels used in this paper include vehicle speed, gas pedal travel, brake cylinder pressure. The vehicle speed was measured from the transmission output shift speed sensor, and obtained from the CAN (Controller Area Network) bus. The gas pedal travel indicates the gas pedal position in percentage from idle (0%) to floored (100%). The brake cylinder pressure indicates how hard the brake pedal was pressed. All the channels described above have a sampling rate of 10 Hz. Numerical differentiation was applied to get the vehicle acceleration and jerk as the first and second derivative of the vehicle speed. Numerical differentiation was also used to get the gas pedal velocity as the first derivative of the gas pedal travel. The two-point numerical derivatives with first order accuracy shown in Eq. (1) was used.

$$\dot{x}(t) = \frac{x(t) - x(t - \Delta t)}{\Delta t} \tag{1}$$

where $\dot{x}(t)$ is the derivative of x at time t. Δt is a small change of t (set to 0.3 s).

Following common practice in calculating vehicle jerk from previous studies (Bagdadi, 2013; Zaki et al., 2006), a second order Savitzky-Golay filter with a 1.0 s time window was applied to $x(t)$ to smooth the data before getting the derivatives using Eq. (1). Varying values of the time window width (0.2, 0.6, 1.4, and 1.8 s) were also tested in a sensitivity analysis.

The main objective of this paper was to examine whether vehicle jerk contains useful information that could be potentially used to identify aggressive drivers. Measures of drivers' use of large jerk were examined. A large jerk is defined as a driving event in which the jerk value exceeded a pre-defined threshold. The threshold was set based on the percentile of the jerk distributions from the empirical data (detailed descriptions provided in the following sections). The number of large jerk associated with each driver was then calculated. Given that the 88 drivers in the dataset had different exposures to freeway driving, the frequency of using large jerk for each driver was further calculated by dividing the number of large jerk by their driving mileage in the dataset. We further hypothesized that the vehicle jerk has different characteristics when the driver was pressing the gas pedal versus brake pedal. Thus two jerk-based metrics were proposed: (1) the frequency of using large positive jerk when the driver is pressing the gas pedal, and (2) the frequency of using large negative jerk when the drivers is pressing the brake pedal.

2.3. Driver classification methods

To validate the performance of the two metrics, we divided the 88 drivers into an aggressive group and a normal group from three different aspects of aggressive driving: (1) traveling at excessive speed (termed as "speeding" in the rest of the paper), (2) following too close to the vehicle in front (termed as "tailgating" in the rest of the paper), and (3) crash risks. The three methods would be applied independently.

In the first method, we aimed to separate the drivers by the aggressive behavior of speeding. According to AAA (2009), speeding was the most common potentially-aggressive action, which was associated with 30.7% of fetal crashes in their study. To quantify the speeding behavior of each driver, the percentage of time a driver was traveling faster than 85 mph (137 km/h) is calculated using Eq. (2).

$$\%\ of\ time\ speeding = \frac{time\ spent\ traveling\ faster\ than\ 85\ mph}{time\ spent\ traveling\ faster\ than\ 60\ mph} \times 100 \tag{2}$$

85 mph was used because a preliminary examination showed it was about 99th percentile of the vehicle speed distribution from all the drivers in the dataset (more details in Section 3.2.2). It is 15 mph higher than the 70 mph (112 km/h) posted speed limit on most freeways in the dataset. Varying values (75, 80, and 90 mph) were also tested in a sensitivity analysis. In the calculation only the time when the driver was traveling faster than 60 mph (97 km/h) was considered (the denominator in Equation 2). This was based on the presumption that if a vehicle was traveling slower than 60 mph (10 mph below the posted speed limit), it was likely due to factors such as traffic congestion or road construction rather than the less aggressiveness of the driver. After this calculation for each driver, all drivers were ranked by this percentage in a descending order. Then the top 25% (N = 22) drivers were put into a "speeding" group. The remaining drivers (N = 66) were put into a "non-speeding" group.

In the second method, we aimed to separate the drivers by the aggressive behavior of tailgating. Among all other aggressive behaviors according to NHTSA's definition (NHTSA, 2016), tailgating was used primarily due to its convenience to be quantitatively measured compared with other aggressive behaviors such as failure to yield or erratic driving. To quantify the tailgating behavior of each driver, the percentage of time the driver was following the vehicle in front with a headway of shorter than 0.4 s is calculated using Eq. (3).

$$\%\ of\ time\ tailgating = \frac{time\ spent\ with\ headway\ less\ than\ 0.4\ s}{time\ spent\ with\ headway\ less\ than\ 5\ s} \times 100 \tag{3}$$

0.4 s was used because a preliminary examination showed it was about 99th percentile of the time headway distribution (from large to small) for all the drivers in the dataset (more details in Section 3.2.3). Varying values (0.3, 0.5, and 0.6 s) would also be tested in a sensitivity analysis. In the calculation only the time when the time headway was less than 5 s was considered (the denominator in Eq. (3). This was based on the presumption that if the time headway is larger than 5 s, it was likely free-flow rather than following the vehicle in front. After this calculation for each driver, all drivers were ranked by this percentage in a descending order. Then the top 25% (N = 22) drivers were put into a "tailgating" group. The remaining drivers (N = 66) were put into a "non-tailgating" group.

In the third method, we aimed to separate the drivers by their crash risks. Due to the limited freeway, baseline driving data (described in Section 2.1 above), the entire IVBSS data that include driving on both freeway and other road types during the entire 40-day study period were used to identify crashes and near-crashes. Following the common practice of identifying safety-critical events in naturalistic driving studies (e.g., Dingus et al., 2006; Lin et al., 2008), vehicle longitudinal acceleration was used with a triggering threshold of $-0.6g$ to identify the potential crashes and near-crashes. Then a review of the events' forward-facing camera videos were conducted to verify the crash or near-crash, and to remove the events that did not have an imminent crash risk (e.g., tire strike, hard braking at red light, etc.) Lastly the drivers who were associated with crash or near-crash would be put into a "higher crash-risk" group, and the remaining drivers would be put into a "lower crash-risk" group.

The statistical differences of the jerk-based metric between the two groups of drivers using the three classification methods were tested. The performance of using the metrics as a classifier of aggressive drivers was examined using a Receiver Operating Characteristic (ROC) curve analysis, which is a useful technique to visualize the classifier performance especially in domains with unequal costs of false alarms (false positive) and misses (false negative) (Fawcett, 2006). The effects of age, gender were also examined. Lastly, a sensitivity analysis was conducted to examine whether the findings were consistent with varying filter parameters (time widow width) of the filter in the jerk calculation, as well as the threshold values for defining the speeding and tailgating group.

3. Results

3.1. Data description

3.1.1. Vehicle jerk associated with drivers' gas and brake pedal operations

The characteristics of vehicle jerk with associated gas and brake pedal operations from a 20-s driving segment are illustrated in Fig. 1. The top and middle figures are the vehicle acceleration and jerk calculated using the methods described in the previous section. The bottom figure shows the driver's gas pedal operation indicated by the gas pedal travel and the driver's brake pedal operation indicated by the brake cylinder pressure.

The driver first applied the gas pedal (from $t = 0$ to 4 s), then applied neither pedal (i.e., engine-braking, from $t = 4$ to 6 s), then applied the brake pedal (from $t = 6$ to 11 s), then applied the gas pedal twice (from $t = 13$ to 16.5 s, and from $t = 17$ to 20 s). At the beginning of the braking from $t = 6$ to 8 s (indicated by the increase of the brake cylinder pressure), the acceleration kept decreasing (to the negative side), and the jerk reached its negative peak. At the end of the braking from $t = 9$ to 11 s when the driver was releasing the brake pedal, the acceleration kept increasing (to the positive side), and the jerk reached its positive peak. Similarly when the driver was pressing the gas pedal from $t = 13$ to 16 s, at the beginning when the driver was pressing down the pedal (from $t = 13$ to 14 s), the acceleration kept increasing, and the jerk reached its positive peak. At the end when the driver was releasing the gas pedal (from $t = 15$ to 16.5 s), the acceleration kept decreasing, and the jerk reached its negative peak. To sum up, large positive jerk was produced with the driver was releasing the brake pedal or pressing down the gas pedal, and large negative jerk was produced with the driver was pressing down the brake pedal or releasing the gas pedal.

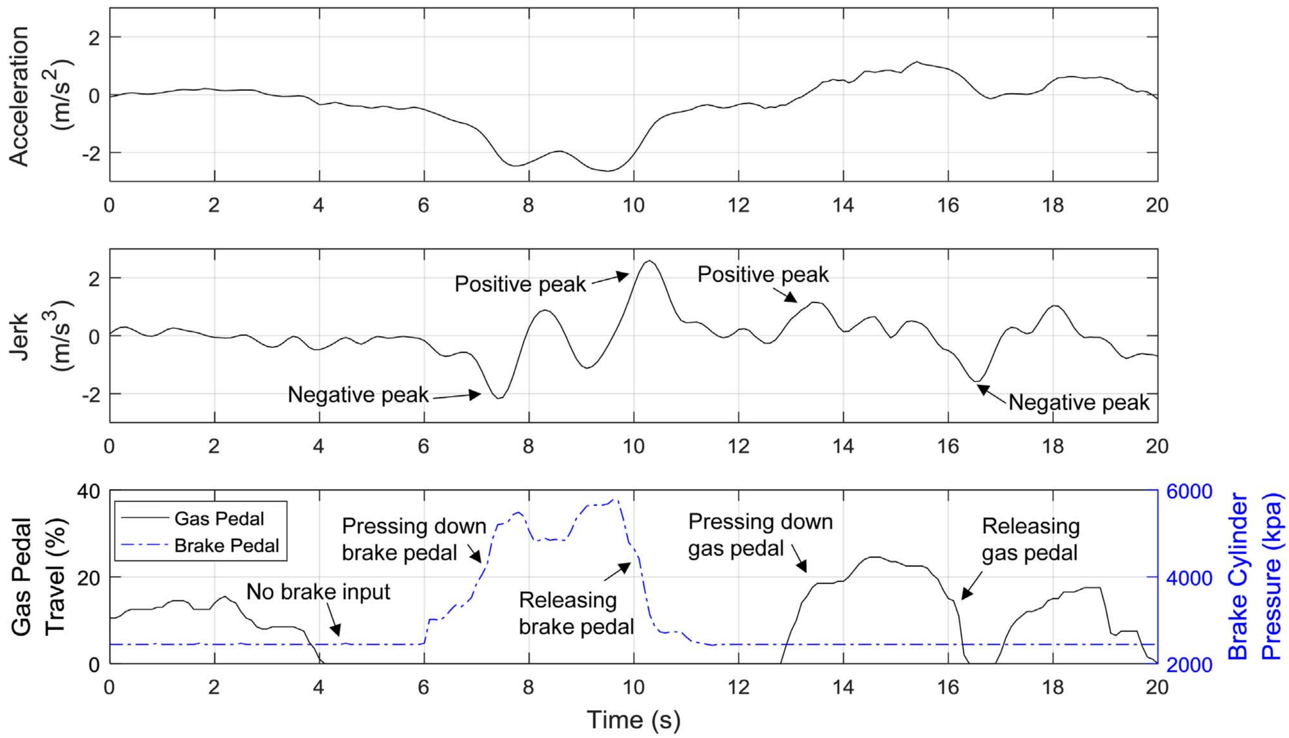


Fig. 1. Illustration of jerk produced by pressing and releasing the brake and gas pedal.

3.1.2. Vehicle jerk distributions

A decomposition of the time series data (N = 11,376,674, or 317 h of driving) by drivers' pedal operations shows 90.3% of the time the drivers were applying the gas pedal, 1.5% of the time applying the brake pedal, and 8.3% of the time applying neither pedal. The distributions (in percentage) of the acceleration and jerk under the three types of pedal operations are shown in Figs. 2 and 3. The statistics are summarized in Table 1. As expected, the acceleration distribution from the three types of pedal operations show clearly different profiles. Applying the gas pedal generated most of the positive acceleration. Applying the brake pedal generated most of the larger deceleration. Applying neither pedal (engine-braking) generated mostly gentle decelerations. In terms of jerk, all three distributions centered at around 0. However, the jerk produced by applying the brake pedal had a wider range on the positive side than the jerk produced by applying the gas pedal. This suggests that the large positive jerk was generally produced by releasing the brake pedal rather than pressing down the gas pedal. This can also be illustrated from Fig. 1 that the positive peak of jerk when releasing the brake pedal near t = 10.5 s is higher than the positive peak of jerk when pressing down the gas pedal near t = 13.5 s.

3.1.3. Correlation between vehicle jerk and gas pedal velocity

Considering for the majority of the time drivers were pressing the gas pedal, we were interested to examine whether the jerk associated with drivers' gas pedal operation contains useful information about aggressive driving. Fig. 4 illustrates the relationship between the vehicle acceleration and gas pedal travel (top figure), and between the vehicle jerk and gas pedal velocity (bottom figure). It seems to suggest that the acceleration is positively correlated to the gas pedal travel, and the jerk is positively correlated to the gas pedal velocity. Linear regression tests were conducted to the data associated with gas pedal depression (285 h of driving data). A delay of 0.2 s was applied to the acceleration and jerk data before the test. Results show that there is a positive correlation between acceleration and gas pedal travel (R^2 = 0.552), but no correlation between acceleration and gas pedal velocity (R^2 = 0.000). There is no correlation between jerk and the gas pedal travel (R^2 = 0.007), but a positive correlation between jerk and the gas pedal velocity (R^2 = 0.513). These results suggest that when the driver was pressing the gas pedal, the vehicle acceleration reflects how much the driver's foot was pressing the gas pedal, and the vehicle jerk reflects how fast the driver's foot was pressing the gas pedal.

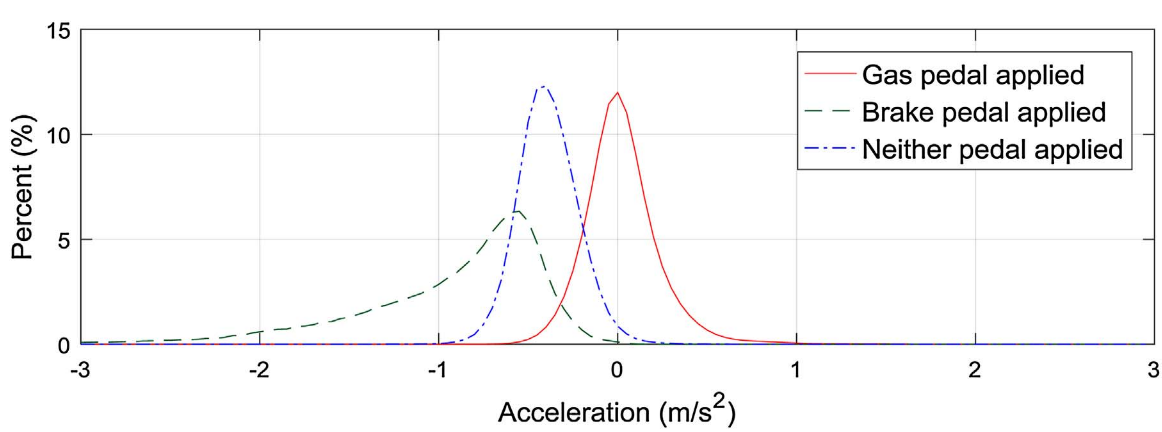


Fig. 2. Distributions of acceleration (histogram bin width: 0.05 m/s^2).

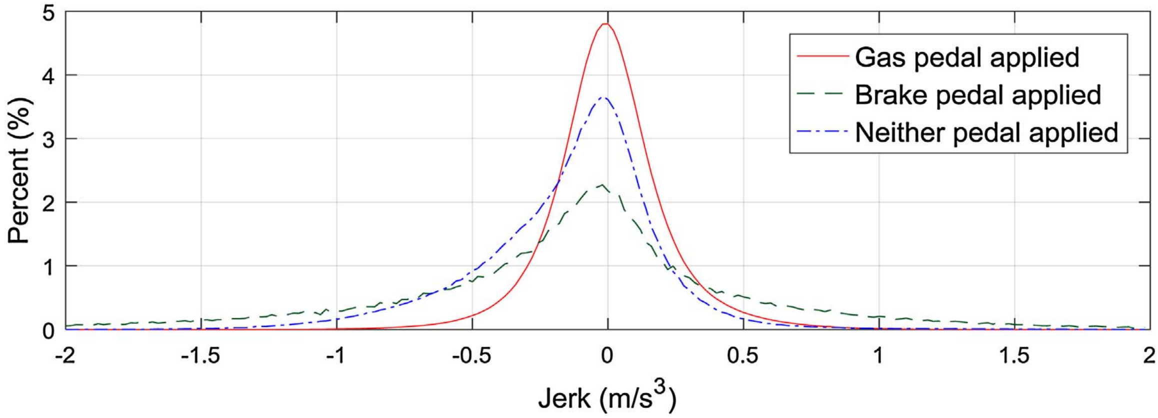


Fig. 3. Distributions of jerk (histogram bin width: 0.02 m/s^3).

Table 1
Summary of the acceleration and jerk statistics.

		Mean	SD	Percentile		
				1 st	50th	99th
Acceleration (m/s^2)	Gas pedal applied	0.05	0.21	−0.39	0.03	0.74
	Brake pedal applied	−0.92	0.57	−2.85	−0.76	−0.15
	Neither pedal applied	−0.36	0.17	−0.75	−0.37	0.07
Jerk (m/s^3)	Gas pedal applied	0.01	0.22	−0.57	0.01	0.66
	Brake pedal applied	−0.13	0.79	−2.60	−0.07	1.91
	Neither pedal applied	−0.13	0.35	−1.12	−0.08	0.69

3.2. Drivers' frequencies of using large jerk

In this section we aimed to validate the performance of the two jerk-based metrics in identifying aggressive drivers. The large positive jerk was defined as a jerk value greater than 1.07 m/s^3, which is the 99.9th percentile of the jerk distribution associated with gas pedal operation (from all drivers). The large negative jerk was defined as a jerk value smaller than −1.47 m/s^3, which is the 99.9th percentile of the jerk values (from largest to smallest, from all drivers). Both metrics were calculated in the unit of number of events per 100 miles of driving.

3.2.1. Age and gender effects

The 88 drivers that were included in this paper were classified into an aggressive group and a normal group using the three driver classification methods (described in Section 2.3 above). Table 2 shows the number of drivers in each group broken down by their age group and gender.

Firstly, Fisher's exact tests were conducted to examine the age and gender effects on drivers' classification into the aggressive group (i.e., their association with speeding, tailgating, or crash/near-crash). The results show that (1) when the drivers were classified by their speeding behavior (Method I), the proportion of aggressive drivers was significantly higher among the younger drivers than older drivers ($p < 0.01$). There was no significant difference between the younger and middle-aged drivers ($p = 0.19$), or between the middle-aged and older drivers ($p = 0.07$). In terms of gender, the proportion of aggressive drivers was significantly higher among the male drivers than female drivers ($p < 0.05$); (2) when the drivers were classified by their tailgating behavior (Method II), the proportion of aggressive drivers was significantly higher among the younger drivers than both middle-aged drivers ($p < 0.01$) and older drivers ($p < 0.001$). There was no significant difference between the middle-aged and older drivers

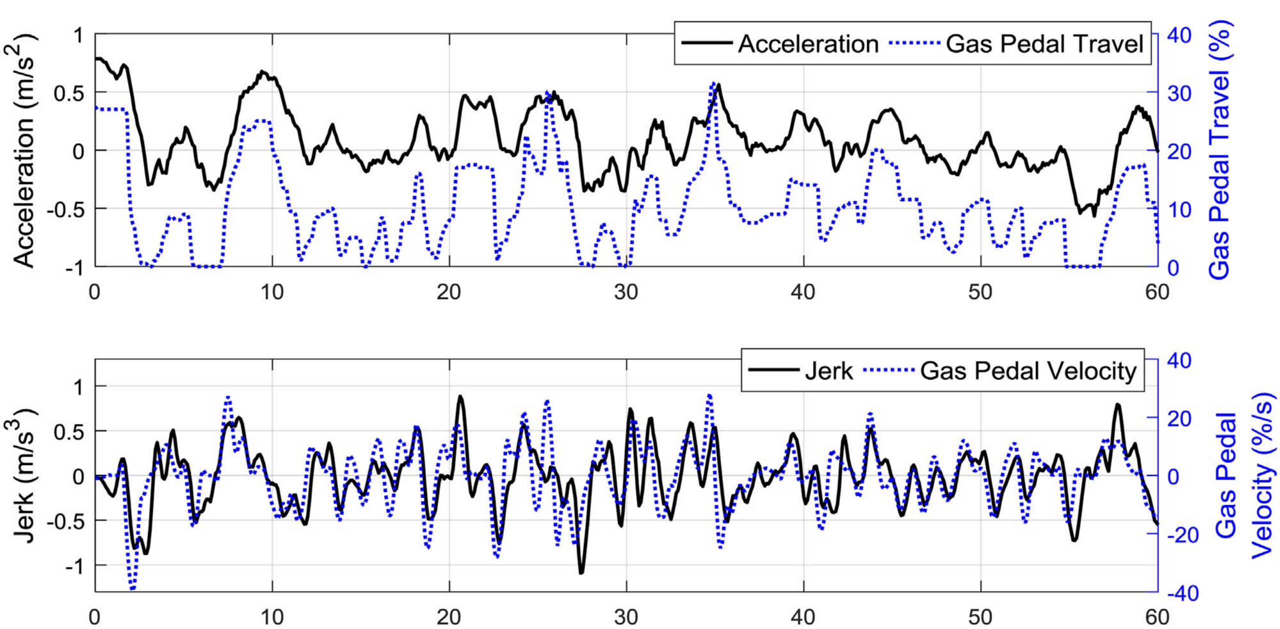


Fig. 4. Correlations between acceleration and gas pedal travel (top figure) and between jerk and gas pedal velocity (bottom figure) from a 60-s sample data.

Table 2
Aggressive driver breakdown by age group and gender.

		Method I		Method II		Method III	
		Not speeding (N = 66)	Speeding (N = 22)	Not tailgating (N = 66)	Tailgating (N = 22)	Without near-crash (N = 60)	With near-crash (N = 28)
Younger (20–30)	Male	8	9	6	11	7	10
	Female	11	4	9	6	12	3
	subtotal	19	13	15	17	19	13
Middle-aged (40–50)	Male	11	6	15	2	13	4
	Female	15	2	14	3	9	8
	subtotal	26	8	29	5	22	12
Older (60–70)	Male	12	1	13	0	11	2
	Female	9	0	9	0	8	1
	subtotal	21	1	22	0	19	3
subtotal – Male		31	16	34	13	31	16
subtotal – Female		35	6	32	9	29	12

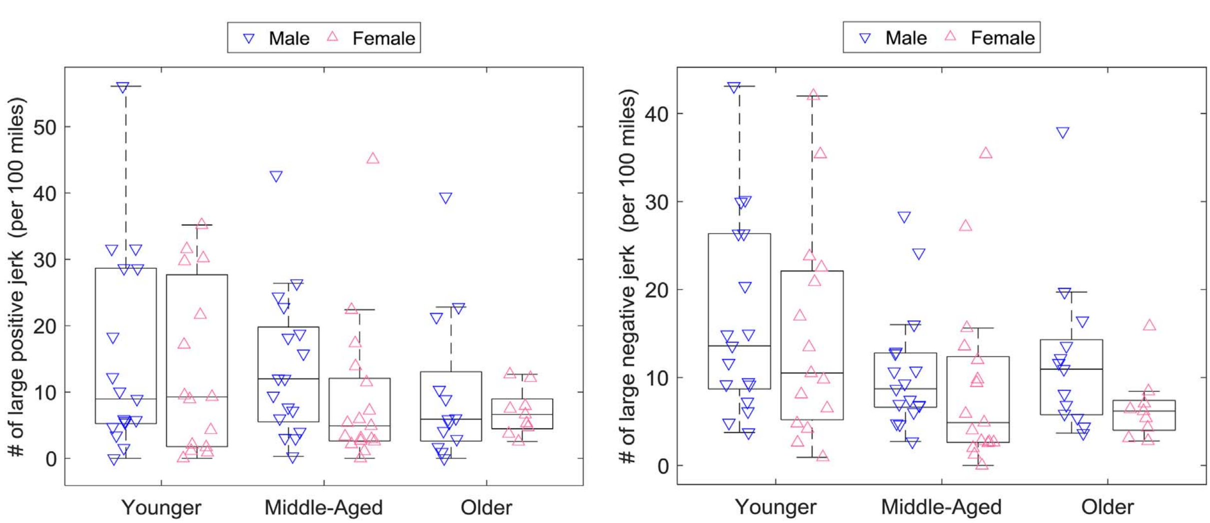
(p = 0.14). There was also no significant difference between male and female drivers (p = 0.63); and (3) when the drivers were classified by their involvement in crashes or near-crashes (Method III), the proportion of aggressive drivers was significantly higher among the younger drivers than older drivers ($p < 0.05$). There was no significant difference between the younger and middle-aged drivers (p = 0.80), or between the middle-aged and older drivers (p = 0.12). In terms of gender, There was no significant difference between male and female drivers (p = 0.65), although within the younger driver group, male drivers had significantly higher proportion than female drivers ($p < 0.05$). No such significance was found within the middle-aged or older driver group.

Secondly, the age and gender effects on the two jerk-based metrics were examined. The two jerk-based metrics were calculated for each driver (Fig. 5). Normality tests show that the frequencies in each group did not follow a normal distribution (all $p < 0.001$). Since the normality assumption of ANOVA (analysis of variance) is violated, a nonparametric method of adjusted rank transform test (Leys and Schumann, 2010) was firstly used to test the interaction effects between age and gender. Then the Kruskal-Wallis (K-W) test by ranks (nonparametric equivalent of one-way ANOVA) was used to examine the main effects. The results show that there was no significant interaction between age and gender for both the frequency of using large positive jerk ($F(2, 82) = 0.502$, $p = 0.607$) and using large negative jerk ($F(2, 82) = 0.232$, $p = 0.794$). The K-W tests show that for the frequency of using large positive jerk, there were no significant differences in the metric among the three age groups (all $p > 0.05$). For the frequency of using large negative jerk, younger drivers were associated with significantly higher values compared to both middle-aged drivers (χ^2 (1) = 8.04, p = 0.001) and older drivers (χ^2 (1) = 4.24, $p < 0.05$). There were no significant differences between the middle-aged and older drivers (χ^2 (1) = 0.45, p = 0.50). In terms of gender, there was no significant difference in the frequency of using large positive jerk between the male and female drivers. However, the male drivers were associated with significantly higher frequency of using large negative jerk (χ^2 (1) = 4.46, $p < 0.05$) compared to their female counterparts.

3.2.2. Speeding vs. non-speeding drivers

In this section we aimed to examine whether the two jerk-based metrics are different between the speeding and non-speeding drivers. Fig. 6 shows the vehicle speed distributions for all drivers (Fig. 6a) and individual drivers (Fig. 6b). In general the drivers spent significant amount of time traveling faster than the posted speed limit (70 mph on most freeways in the dataset).

For each driver the percentage of time speeding was calculated using Equation (2) in the previous section. The resulted percentage ranges from 0 to 17.3% (mean = 1.4%) for the 88 drivers. The top 25% (N = 22) drivers ranked by this percentage were put into a "speeding" group. The remaining drivers (N = 66) were put into a "non-speeding" group. The two jerk-based metrics for the drivers in the two groups are shown in Fig. 7. Normality tests show that the metrics in each group did not follow a normal distribution (all $p < 0.001$). The K-W tests show



(a) Number of large positive jerk by gas pedal (b) Number of large negative jerk by brake pedal

Fig. 5. The use of large jerk in driver gender and age groups.

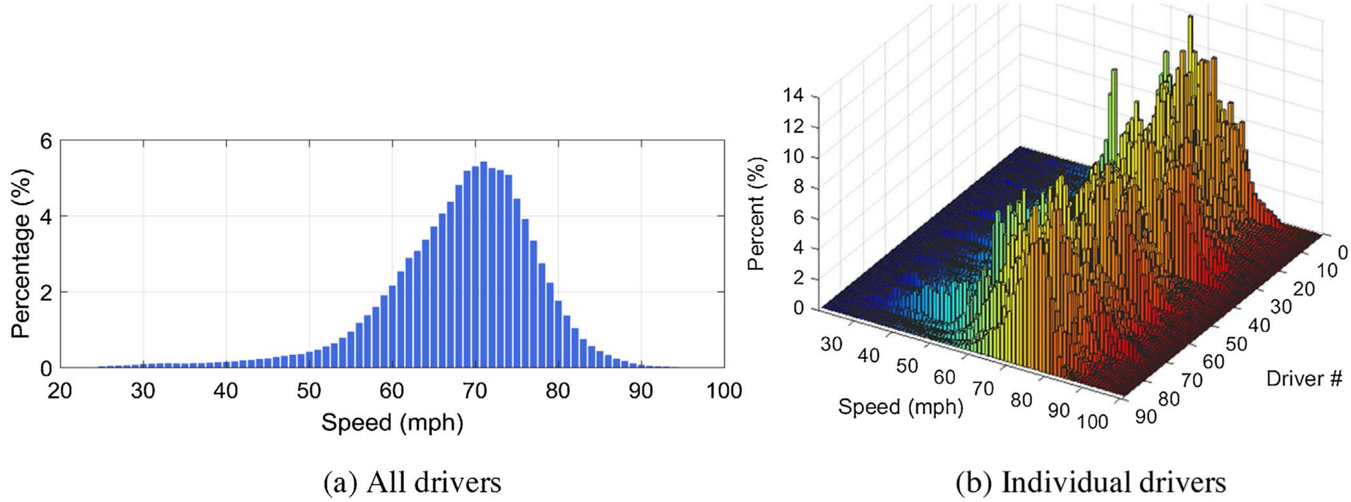


Fig. 6. Distributions of vehicle speed.

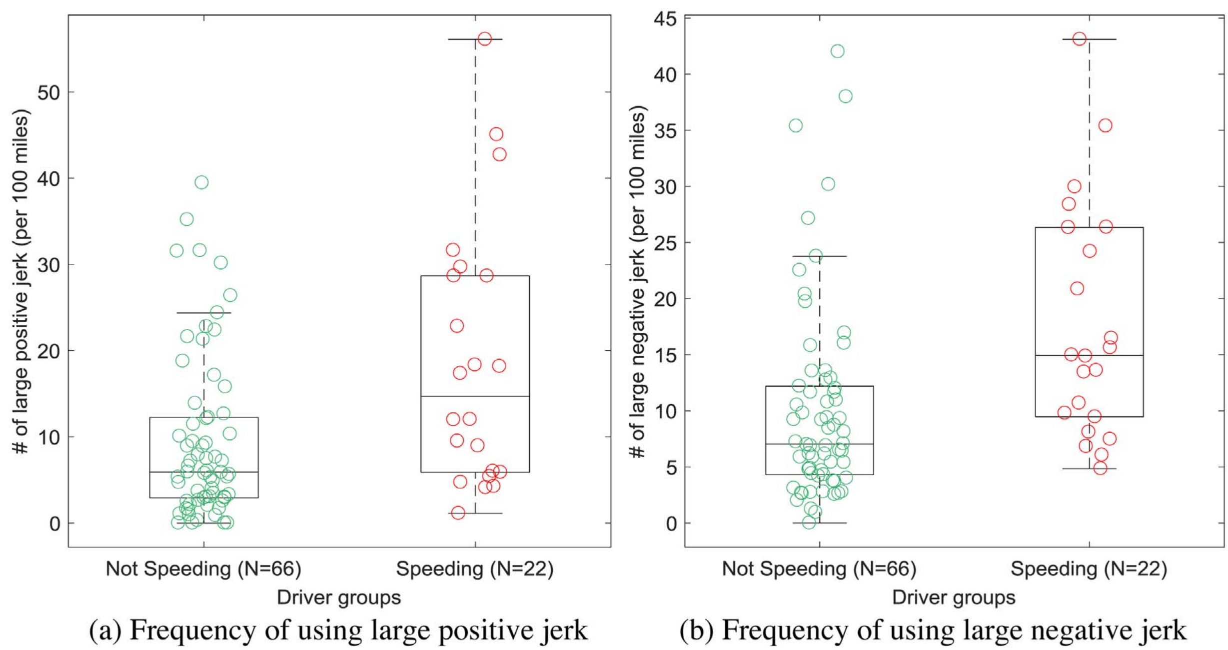


Fig. 7. The frequencies of using large jerk between two driver groups in terms of speeding.

that the drivers in the speeding group were associated with significantly higher frequencies of using both large positive jerk (χ^2 (1) = 8.64, $p < 0.01$) and large negative jerk (χ^2 (1) = 12.64, $p < 0.001$).

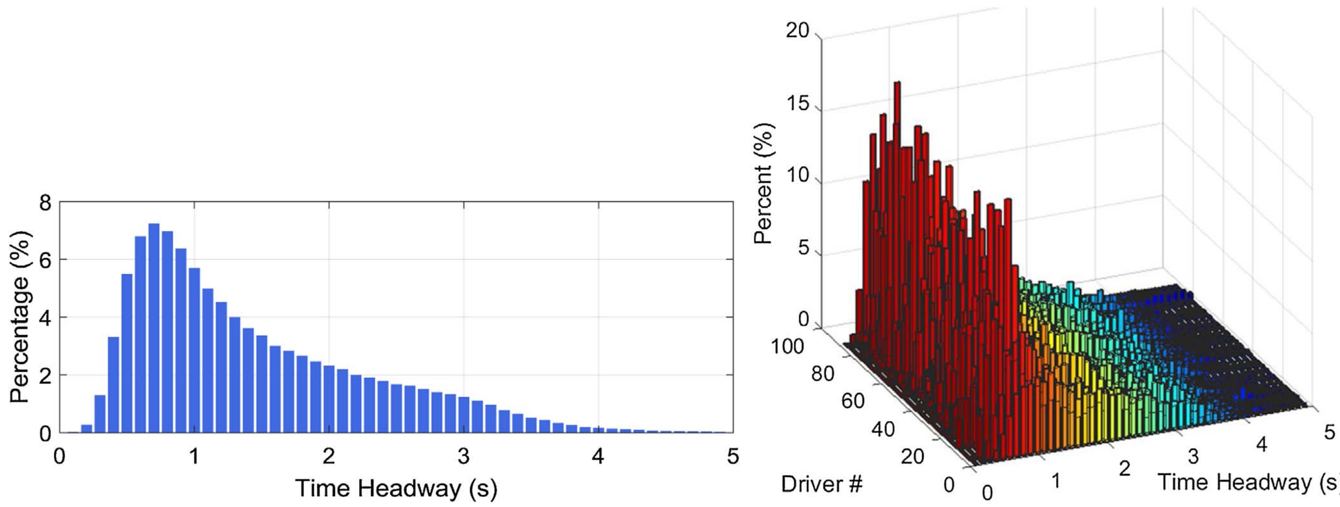
Additional K-W tests were conducted within a gender or age group (with the exception of the older driver group in which only one driver fell into the aggressive group). The results show that among the male drivers (N = 47), the speeding drivers (N = 16) were associated with significantly higher frequencies of using both large positive jerk (χ^2 (1) = 5.78, $p < 0.05$) and large negative jerk (χ^2 (1) = 5.24, $p < 0.05$). Among the female drivers (N = 41), the speeding drivers (N = 6) were associated with significantly higher frequency of large negative jerk (χ^2 (1) = 4.58, $p < 0.05$). However, there was no significant difference of large positive jerk (χ^2 (1) = 2.33, $p = 0.13$). Among the younger drivers (N = 32), there was no significant difference between the speeding and non-speeding drivers for both the frequency of using large positive jerk (χ^2 (1) = 5.78, $p = 0.09$) and large negative jerk (χ^2 (1) = 2.66, $p = 0.10$). Among the middle-aged drivers (N = 34), the speeding drivers were associated with significantly higher frequency of large positive jerk (χ^2 (1) = 5.79, $p < 0.05$) and marginally higher frequency of large negative jerk (χ^2 (1) = 3.34, $p = 0.07$).

3.2.3. Tailgating vs. non-tailgating drivers

In this section we aimed to examine whether the two jerk-based metrics are different between the tailgating and non-tailgating drivers. Fig. 8 shows the distributions of the time headway to the vehicle in front (if presented) for all drivers (Fig. 8a) and individual drivers (Fig. 8b). In general the drivers spent significant amount of time with a time headway of less than 1 s.

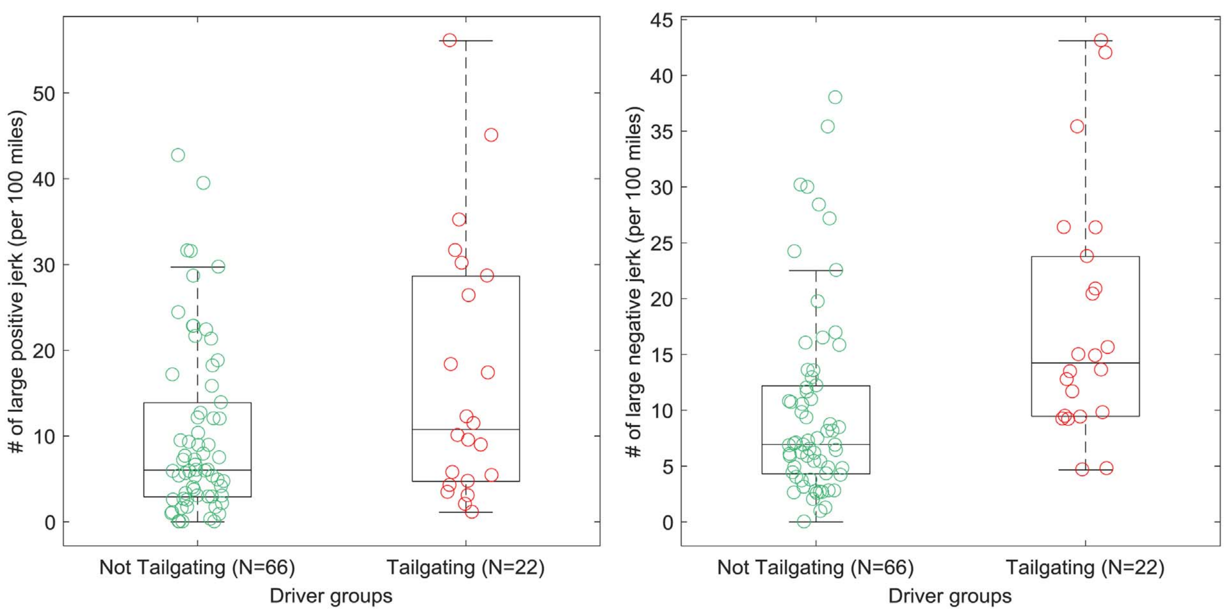
For each driver the percentage of time tailgating was calculated using Equation 3 in the previous section. For the 88 drivers this percentage ranges from 0 to 14.0% (mean = 1.9%). The top 25% (N = 22) drivers ranked by this percentage were put into a “tailgating” group. The remaining drivers (N = 66) were put into a “non-tailgating” group. The two jerk-based metrics for the drivers in the two groups are shown in Fig. 9. Normality tests show that the frequencies in each group did not follow a normal distribution (all $p < 0.001$). The K-W tests show that the drivers in the tailgating group were associated with significantly higher frequencies of using both large positive jerk (χ^2 (1) = 4.75, $p < 0.05$) and large negative jerk (χ^2 (1) = 13.20, $p < 0.001$).

Additional K-W tests show that among the male drivers, the



(a) All drivers (b) Individual drivers

Fig. 8. Distribution of time headway.



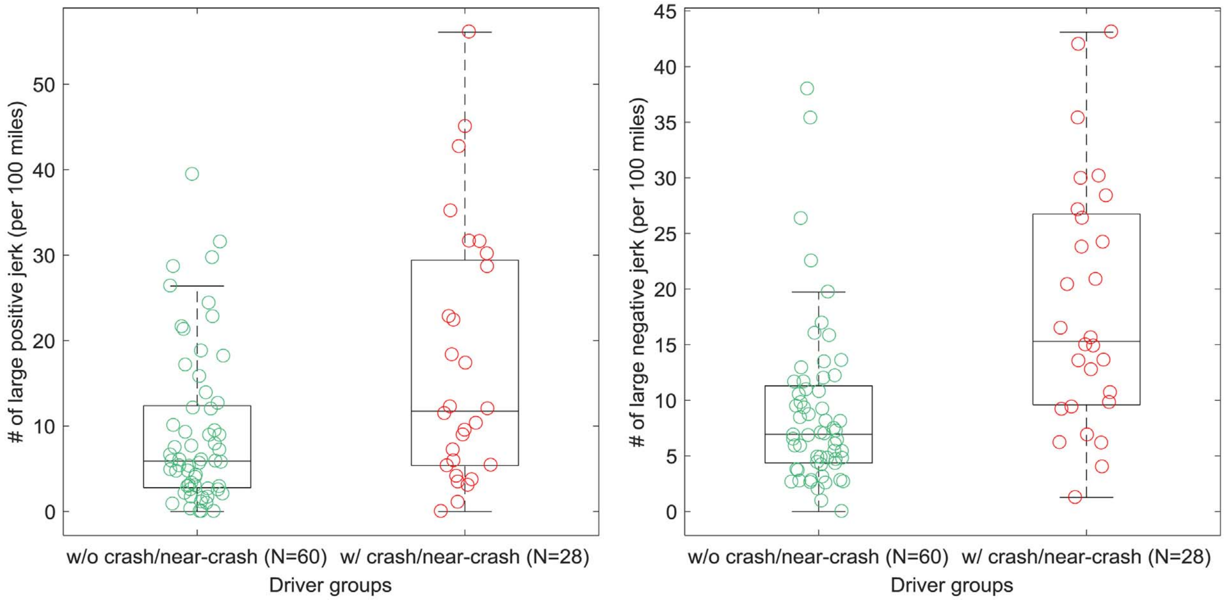
(a) Frequency of using large positive jerk (b) Frequency of using large negative jerk

Fig. 9. The frequencies of using large jerk between two driver groups in terms of tailgating.

tailgating drivers (N = 13) were associated with significantly higher frequency of large negative jerk (χ^2 (1) = 5.00, $p < 0.05$). However, there was no significant difference of large positive jerk (χ^2 (1) = 0.65, p = 0.42). Among the female drivers, the tailgating drivers (N = 9) were associated with significantly higher frequencies of using both large positive jerk (χ^2 (1) = 4.27, $p < 0.05$) and large negative jerk (χ^2 (1) = 8.22, $p < 0.01$). Among the younger drivers, the tailgating drivers were associated with significantly higher frequency of large negative jerk (χ^2 (1) = 5.05, $p < 0.05$). However, there was no significant difference of large positive jerk (χ^2 (1) = 0.21, p = 0.65). Among the middle-aged drivers, the tailgating drivers were associated with marginally higher frequency of large positive jerk (χ^2 (1) = 3.72, p = 0.05). However, there was no significant difference of large negative jerk (χ^2 (1) = 1.42, p = 0.23).

3.2.4. *Higher vs. lower crash-risk drivers*

In this section we aimed to examine whether the two jerk-based metrics are different between the drivers with higher and lower crash risk. The entire IVBSS dataset were used to identify the potential safety-critical events, which was set to be marked if the vehicle longitudinal deceleration was greater than −0.6 g. A total of 209 events were identified from the dataset. A review of the forward-facing camera videos of the events were then conducted to identify the crashes and near-crashes. After the review, two crashes and 56 near-crashes were identified. The other 151 events were considered non-critical as there was not an imminent crash risk. Examples of the non-critical events include tire strikes, hard braking for red lights, stop signs, missed turns, or crossing animals, etc. The 58 crashes and near-crashes were from 28 (32%) out of the 88 drivers, and they were put into a "higher crash risk" group. The remaining drivers (N = 60, those who did not have any crash or near-crash in the IVBSS dataset) were put into a "lower crash risk" group. The two jerk-based metrics for the drivers in the two groups are shown in Fig. 10. Normality tests show that the frequencies in each group did not follow a normal distribution (all $p < 0.001$). The K-W tests show that the drivers in the higher crash risk group were associated with significantly higher frequencies of using both large



(a) Frequency of using large positive jerk (b) Frequency of using large negative jerk

Fig. 10. The frequencies of using large jerk between two driver groups in terms of crash risk.

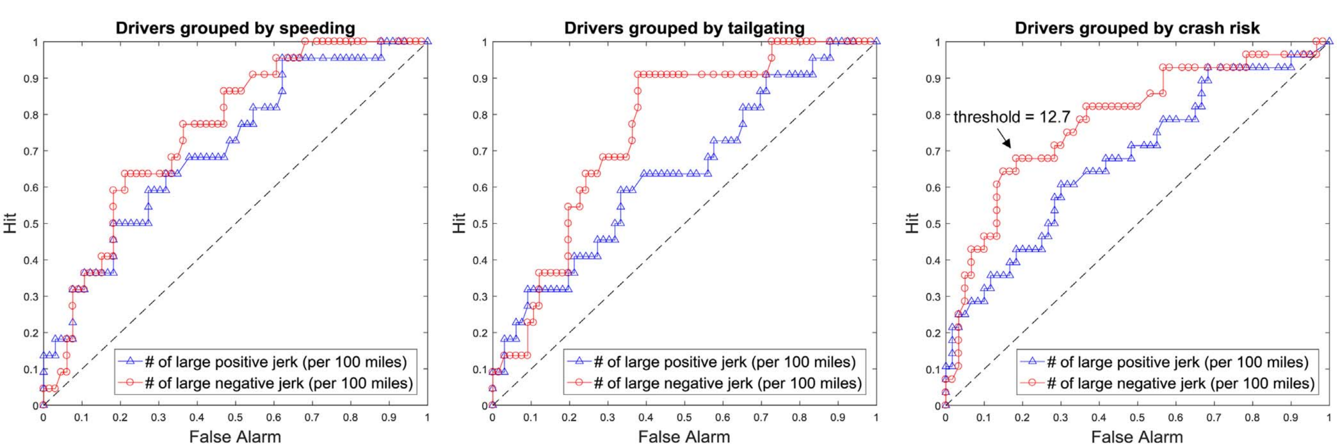
positive jerk (χ^2 (1) = 5.48, $p < 0.05$) and large negative jerk (χ^2 (1) = 18.4, $p < 0.001$).

Additional K-W tests show that for either male or female drivers, the ones with crash/near-crash were associated with significantly higher frequency of using large negative jerk (male drivers: χ^2 (1) = 12.72, $p < 0.001$; female drivers: χ^2 (1) = 6.36, $p < 0.05$). However, there was no significant difference of the frequencies of using large positive jerk (male drivers: χ^2 (1) = 2.33, $p = 0.13$; female drivers: χ^2 (1) = 2.82, $p = 0.09$). Among the younger drivers, the ones with crash/near-crash were associated with marginally higher frequencies of using large positive jerk (χ^2 (1) = 3.26, $p = 0.07$) and significantly higher frequencies of using large negative jerk (χ^2 (1) = 9.54, $p < 0.01$). Among the middle-aged drivers, the ones with crash/near-crash were associated with significantly higher frequencies of using large negative jerk (χ^2 (1) = 7.70, $p < 0.01$). However, there was no significant difference of large positive jerk (χ^2 (1) = 2.65, $p = 0.10$).

3.2.5. Receiver Operating Characteristic (ROC) analysis

The performance of utilizing the two jerk-based metrics as classifiers to identify aggressive drivers was further examined using a ROC analysis. The ROC curves of the two metrics are shown in Fig. 11. The ideal performance of a classifier is at the upper left corner of the chart which represents 100% true positive (hit) and 0% false positive (false alarm). The diagonal line represents a classifier with no useful information and using a strategy of random guessing.

All the ROC curves in Fig. 11 are in the upper triangular region away from the diagonal line, meaning the metrics perform better than random guessing and thus contain useful information about aggressive drivers. For example in Fig. 11c, with a threshold of 12.7 for the frequency of using large negative jerk (meaning if a driver uses more than 12.7 large negative jerk per 100 miles, that driver would be classified as with higher crash risk), it could successfully identify 68% of the "true" higher-crash-risk drivers, while misclassify 18% of the "true" lower-crash risk drivers (the overall accuracy is 77% for 88 drivers). The Area Under the ROC Curve (AUC) was also calculated which indicates the probability that the classifier will rank a randomly chosen positive instance (an aggressive driver in our case) higher than a randomly chosen negative instance (a normal driver in our case) (Fawcett, 2006). The AUC of the two curves in Fig. 11a are 0.71 and 0.74, indicating that for a randomly chosen speeding driver and a



(a) Drivers grouped by speeding (b) Drivers grouped by tailgating (c) Drivers grouped by crash risk

Fig. 11. ROC curves of utilizing the frequency of using large jerk to identify aggressive drivers.

Table 3
Significant levels of the K-W tests with varying parameters in the analysis.

	Frequency of large positive jerk use					Frequency of large negative jerk use				
Window width of the Savitzky-Golay filter (s)	0.2	0.6	1.0	1.4	1.8	0.2	0.6	1.0	1.4	1.8
Large jerk threshold (m/s^3)	4.41	1.99	1.07	0.87	0.78	-4.91	-2.18	-1.47	-1.27	-1.15
Speeding (75+ mph)	n.s.	n.s.	n.s.	*	*	n.s.	n.s.	*	**	*
Speeding (80+ mph)	n.s.	n.s.	n.s	*	*	n.s.	n.s.	**	**	**
Speeding (85+ mph)	n.s.	*	**	***	***	*	**	***	***	***
Speeding (90+ mph)	n.s.	*	**	***	**	*	**	**	**	**
Tailgating (< 0.3 s)	n.s.	n.s.	*	**	***	n.s.	*	**	**	**
Tailgating (< 0.4 s)	n.s.	n.s.	*	**	**	n.s.	**	***	***	***
Tailgating (< 0.5 s)	n.s.	n.s.	*	**	*	n.s.	**	***	***	**
Tailgating (< 0.6 s)	**	**	*	**	*	*	***	***	***	***
Crash/near-crash vs not	*	*	**	**	**	**	***	***	***	***
younger vs middle-aged	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	*	**	**
younger vs older	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	*	*	n.s.
middle-aged vs older	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
gender	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	*	*	*

*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$, n.s.: not significant.

randomly chosen non-speeding driver, the metric of the frequency of using large positive (/negative) jerk had a probability of 0.71 (/0.74) of ranking the speeding driver higher than the non-speeding driver. Similarly, the AUC of the two curves in Fig. 11b are 0.64 (large positive jerk) and 0.74 (large negative jerk). And the AUC of the two curves in Fig. 11c are 0.68 (large positive jerk) and 0.77 (large negative jerk).

3.3. Sensitivity analysis

A sensitivity analysis was conducted to examine whether the above findings are consistent with varying parameters in the filter settings of the jerk calculation and the driver classification methods. Five different time window width (ranging from 0.2 to 1.8 s) of the Savitzky-Golay filter which was used in the jerk calculation were tested. When a different width of the time window was used, the large jerk threshold was always set using the 99.9th percentile value of the jerk distribution. In addition, varying threshold values to define speeding and tailgating were also tested. When a different threshold value was used, the same method was used to put the top 25% drivers (N = 22) ranked by the percentage of time speeding (or tailgating) into the aggressive group, and the remaining drivers (N = 66) in to the normal group. The only exception was when 90 mph was used, only the top 21 drivers were put into the speeding group, because they were the only ones who ever drove above 90 mph.

The results of the sensitivity analysis are shown in Table 3 using the significant levels of the K-W tests. As can be seen, the significance of the two jerk-based metrics were largely persistent with larger time window of the Savitzky-Golay filter (e.g., 1.0, 1.4 or 1.8 s). When smaller time windows were used (e.g., 0.2 or 0.6 s), the results generally become not significant. This is likely due to the increased noise introduced in the jerk calculation. With varying threshold values of defining the speeding and tailgating, the significance of the two jerk-based metrics were largely persistent. Although when defining the speeding drivers, the significant levels seem higher when more "extreme" threshold values (i.e., 85 and 90 mph) were used.

4. Discussion

This paper investigated the characteristics of vehicle jerk by using vehicle sensor data from an existing naturalistic driving study, and whether vehicle jerk can be potentially used to identify aggressive drivers. Our initial analysis show that the vehicle jerk distributions have distinct characteristics depending on drivers' gas and brake pedal operations. The jerk distribution when the driver was applying the brake pedal has a wider range on both the positive and negative side compared with the jerk distribution when the driver was applying the gas pedal. And when the driver was applying the gas pedal, the jerk reflects how fast the driver's foot was pressing the gas pedal (i.e., gas pedal velocity). These findings seem to suggest that large positive jerk are largely resulted when the driver was releasing the brake pedal rather than pressing down the gas pedal. Considering the majority of the time the driver was pressing the gas pedal, we proposed two jerk-based metrics associated with different pedal operations: (1) driver's frequency of using large positive jerk when pressing the gas pedal, and (2) driver's frequency of using large negative jerk when pressing the brake pedal. To validate the performance of the metrics the drivers in the dataset were divided into an aggressive group and a normal group based on their behaviors of speeding, tailgating, or their involvement in crashes or near-crashes in the dataset. The results show that drivers in the aggressive group using any of the three classification methods were associated with significantly higher values of the two jerk-based metrics. A ROC analysis further demonstrated the efficacy of the metrics in identifying aggressive drivers. Between the two metrics, the frequency of using large negative jerk seems to have a better performance in identifying aggressive drivers. This results may be explained as the (aggressive) drivers who were speeding, tailgating, and with higher crash risk also tend to operate the vehicle less smoothly by pressing the gas and brake pedals in a more abrupt manner.

The results also show that the younger driver group had significantly higher proportion of speeding drivers, tailgating drivers, and higher-crash-risk drivers. Male drivers had significantly higher proportion of speeding drivers compared to female drivers. In terms of the jerk-based metrics, younger drivers used significantly more large negative jerk compared to either middle-aged or older drivers, and male drivers used significantly more large negative jerk compared to their female counterparts. These results were consistent with the majority of the existing studies on age and gender differences in driving behaviors with the consensus that younger drivers and male drivers tend to be more aggressive (Tavris et al., 2001; Turner and McClure, 2003). Possible explanations for the differences may be related to the higher levels of sensation-seeking and risk-taking for younger and male drivers (SIRC, 2004; Roberti, 2004).

The potential applications of this paper include developing quantitative surrogate safety measures to identify aggressive drivers and monitor aggressive driving. These safety measures could be potentially used for in-vehicle safety systems or other countermeasures with the goal of preventing or mitigating the unsafe situations that may arise from aggressive driving. Examples of such in-vehicle systems or functions include providing real-time or post-ride performance feedback to the drivers or management, and potentially providing warnings to the surrounding drivers/vehicles using the connected vehic501–507le technologies.

There are several limitations in the current study. First, only the driving data on freeways were used. Freeway driving was selected mainly because of its relative simplicity compared to other driving scenarios (e.g., local roads with intersections) and the convenience of measuring the drivers' speeding behaviors (by assuming a fixed speed limit). It would be meaningful in the next step to expend the analysis to other road types and driving scenarios. Secondly, only two specific jerk-based metrics were examined. It would be meaningful to examine other jerk-based metrics, including the ones from other related studies, such as the time duration of large jerk (Huang and Wang, 2004), the standard deviation of jerk within a time window (Murphey et al., 2009), or the magnitude of peak-to-peak jerk (Bagdadi and Varhelyi, 2013). Thirdly, our method of identifying the drivers with higher crash risks was limited to the IVBSS dataset, which has a fairly short data collection phase (40-days or average about 700 miles for each driver). And unfortunately we did not have access to other information relevant to drivers' crash risk such as their long-term driving records. From the dataset we indeed identified 2 crashes and 56 near-crashes from 28 out of the 88 drivers, but they may not be the most accurate representation of the drivers' crash risk if more information become available. Lastly, while aggressive driving can be exhibited in a variety of behaviors, speeding, tailgating, and their involvement in the crash/near-crash were chosen to label the aggressive drivers for the purpose of validating the proposed metrics. It would be meaningful in the next step to develop more comprehensive measures that may incorporate aspects of aggressive driving such as weaving through traffic, improper or erratic lane change, or failure to yield right of way, etc.

5. Conclusions

This paper investigated the characteristics of vehicle longitudinal jerk by using vehicle sensor data from an existing naturalistic driving study. The main objective was to examine whether vehicle jerk contains useful information that could be potentially used to identify aggressive drivers. Our results firstly show that there are unique characteristics of vehicle jerk in drivers' gas and brake pedal operations. The distribution of the jerk associated with the brake pedal operation has a wider range on both negative and positive side compared to the jerk associated with the gas pedal operation. In addition, we found that when the gas pedal was pressed, the jerk is positively correlated to the speed the driver was pressing the gas pedal. For these reasons we developed two jerk-based metrics that account for both the gas and brake pedal operations: (1) the frequency of using large positive jerk when pressing the gas pedal, and (2) the frequency of using large negative jerk when pressing the brake pedal. To validate the performance of the two metrics, aggressive drivers in the dataset were identified using three methods: (1) their behavior of speeding, (2) their behavior of tailgating, and (3) their association with crash or near-crash in the IVBSS dataset. The results show that the aggressive driver group in any of the three methods were associated with significantly higher values of the two jerk-based metrics. A ROC analysis further demonstrated the efficacy of the metric. The results show that those aggressive drivers defined using any of the three methods above were associated with significantly higher values of the two jerk-based metrics. Between the two metrics the frequency of using large negative jerk seems to have better performance in identifying aggressive drivers. A sensitivity analysis shows the findings were largely consistent with varying parameters in the analysis. The potential applications of this work include developing quantitative surrogate safety measures to identify aggressive drivers and aggressive driving, which could be potentially used to, for example, provide real-time or post-ride performance feedback to the drivers, or warn the surrounding drivers or vehicles using the connected vehicle technologies.

Acknowledgments

This work was funded in part by the Toyota Class Action Settlement Safety Research and Education Program. The conclusions are those of the authors and have not been sponsored, approved, or endorsed by Toyota or plaintiffs' class counsel. The authors would also like to thank Mary Lynn Buonarosa for proofread the manuscript.

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