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

Fred Feng[a,*], Shan Bao[a], James R. Sayer[a], Carol Flannagan[a], Michael Manser[b], Robert Wunderlich[b]

[a] University of Michigan Transportation Research Institute, 2901 Baxter Road, Ann Arbor, MI, 48109, USA
[b] Texas A & M Transportation Institute, 3135 TAMU, College Station, TX, 77843, USA

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

* Corresponding author.
E-mail address: fredfeng@umich.edu (F. Feng).

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.