Harsh Braking by Truck Drivers: A Comparison of Thresholds and Driving Contexts Using Naturalistic Driving Data

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ABSTRACT

Frequent harsh braking is an example of risky driving behaviour by truck drivers. This study explored how threshold values on longitudinal deceleration affect the detection rate of harsh braking events across driving contexts. Naturalistic driving data from the EU project UDRIVE was used to study the behaviour of 24 Dutch truck drivers. Harsh braking events were identified through longitudinal deceleration using an initial threshold of 3.0 m/s^2. The maximum deceleration in each event was used to stratify the events, covering a range of threshold values found in previous studies. In total 2031 events were found. For each speed limit the mean event rate was calculated across drivers. The event rate at urban roads (30, 50 km/h) was significantly higher than at rural roads (60, 80 km/h), which in turn was significantly higher than at highways (100, 120+ km/h). Drivers with a high event rate at urban roads also showed a high event rate at rural roads and highways, but only for thresholds up to 4.0 m/s^2. Finally, we found distinct event rate distributions when we manipulated the threshold value. Our results suggest that driving context influences harsh braking behaviour, and that drivers have distinct driving styles. We discuss the implications for in-vehicle monitoring systems and driver coaching.

Keywords: Harsh braking, Event detection, Trucks, Naturalistic Driving, Speed limits.

1 INTRODUCTION

Heavy goods vehicles (HGV) were involved in 15% of the 25939 fatal road accidents in Europe in 2014 (Volvo Trucks, 2017). The number of deaths and injuries in traffic can be reduced by preventing risky driving behaviour. Although HGV drivers are experienced drivers that generally know how to drive safely and efficiently, they may not always use their safe driving skills to the full extent. For example, FMSCA (2016) investigated the causation of 967 accidents involving HGV in the United States. In 55% of the cases a critical reason for the accident could be attributed to the truck driver, such as failure to recognize hazards (e.g., due to driver inattention) and making wrong decisions (e.g., driving too fast, misjudging the speed of other vehicles, close following).

Safe driving behaviour can be stimulated by coaching and by giving feedback on risky driving behaviour (Horrey et al., 2012; Bell et al., 2017). Frequent harsh braking is an example of risky driving behaviour, and the focus of this study. If a truck driver is inattentive, driving too fast, or following too close, and a critical situation is imminent, then the driver will likely have to brake harshly to avoid a crash. For this reason, harsh braking events are often used to locate safety critical events in Naturalistic Driving (ND) data (e.g., Hanowski et al., 2005; Olsen et al., 2009; Zovar et al., 2014). Ideally drivers anticipate the occurrence of a critical situation, so that they do not have to brake (harshly) at all. Thus, harsh braking is a factor related to driving performance at which truck drivers can be coached. In-vehicle monitoring systems (IVMS) support coaching and giving feedback by collecting behavioural variables, such as driving speed, fuel consumption, use of cruise control, as well as acceleration and deceleration. Truck drivers can be made aware of their progress by, e.g., comparing their performance with other drivers in the same fleet (Toledo et al., 2008).

Harsh braking events are typically identified by comparing longitudinal deceleration against a threshold value. The problem is that there is no agreement on the threshold beyond which one speaks of a harsh braking event. In studies on the effect of coaching on driver behaviour, for example, Hickman & Hanowski (2011) report a threshold of 4.9 m/s^2, whereas Bell et al. (2017) have used a threshold of 2.3 m/s^2. With regard to ND studies, the NDTS project (Olson et al., 2009) uses a threshold of 1.96 m/s^2 to identify safety critical events, whereas the DDWS FOT project (Olson et al., 2009) uses a speed-dependent threshold of 3.4m/s^2 when driving above 24 km/h and 4.9m/s^2 below 24 km/h. The EuroFOT project (Malta et al., 2012) also uses a speed-dependent threshold that decreases linearly from 5.4m/s^2 to 3.6m/s^2 when the speed increases from 50km/h to 150km/h. A higher threshold will yield a lower number of harsh braking events per kilometre driven. However, little is known on whether a manipulation of the deceleration threshold yields consistent results across drivers.

Furthermore, it is likely that the driving context influences how often harsh brake events are registered. Highways and rural roads are generally more predictable than urban roads, due to their absence of pedestrians and cyclists (Wegman & Aarts, 2005). In addition, highways generally feature intersections where traffic merges in the same driving direction, whereas rural roads more often feature crossing traffic. Yet, little is known on the interaction between driving context and deceleration threshold values, either.

Our objective was to explore how deceleration threshold values affect the harsh braking event rate, and how this event rate varies as function of the driving context. Accordingly, a study was performed on the truck database of the UDRIVE project (van Nes et al., 2018).

2 METHOD

In the UDRIVE project, a fleet of trucks was equipped with multiple video cameras and sensors, through which continuous driving data were collected. We have implemented a trigger on the driving data to detect harsh braking events, which were subsequently aggregated per truck driver.

2.1 Truck drivers

Twenty-four Dutch truck drivers (23 males, 1 female) from four Dutch transport companies drove an instrumented Volvo FM distribution truck. Their age ranged from 25 to 71 years old (M = 49.5, SD = 11.7). In the period between 2015 and 2017 a total of 32831 records were collected with a travel distance between 1 and 561 km (M = 12.6 km, SD = 19.6 km, Mdn = 7.3 km).

2.2 Detection of harsh braking events

The truck database includes CAN data (e.g., driving speed, longitudinal acceleration, pedal use) sampled at 10 Hz, and local speed limits sampled at 1 Hz. Harsh braking events were identified with the following characteristics. First, we compared longitudinal deceleration against a threshold of at least 3.0 m/s^2 . The resulting data segments were marked as an event if at their onset the brake pedal was depressed and the driving speed was at least 5 km/h. Multiple events within a two seconds time window were merged. For each event we recorded the deceleration peak value and the posted speed limit at the event onset. Events with speed limits that are not part of the Dutch speed limit system (e.g., 90 km/h) were excluded from subsequent analysis, as were events of which no speed limit data were available.

2.3 Data analysis

For each driver and at each speed limit we calculated the event rate as the number of harsh braking events divided by the distance driven at the corresponding speed limit. A relatively liberal threshold value for longitudinal deceleration was selected on purpose with the aim to yield a large initial set of events. The registered peak value of deceleration was then used to group the events into five categories, based on the following cut-off values: 3.0 m/s^2, 3.5 m/s^2, 4.0 m/s^2, 4.5 m/s^2, and 5.0 m/s^2. This approach allowed us to examine the event rate at distinct thresholds for longitudinal deceleration.

3 RESULTS

A total of 2031 harsh braking events were identified over a distance of 227000 km. We first examine the effect of speed limits on event rate, followed by differences across drivers.

3.1 Harsh braking events across speed limits

Figure 1 displays the mean harsh braking event rate as a function of speed limit. Each stack within a bar represents the event frequency in the range set by two subsequent cut-off values. Most events were identified on 50 km/h roads, followed by 70 and 80 km/h roads. However, 30 km/h roads yielded the highest event rate, because the distance covered was small. Except for 60 km/h roads, the event rates decreases as higher cut-off values are chosen.

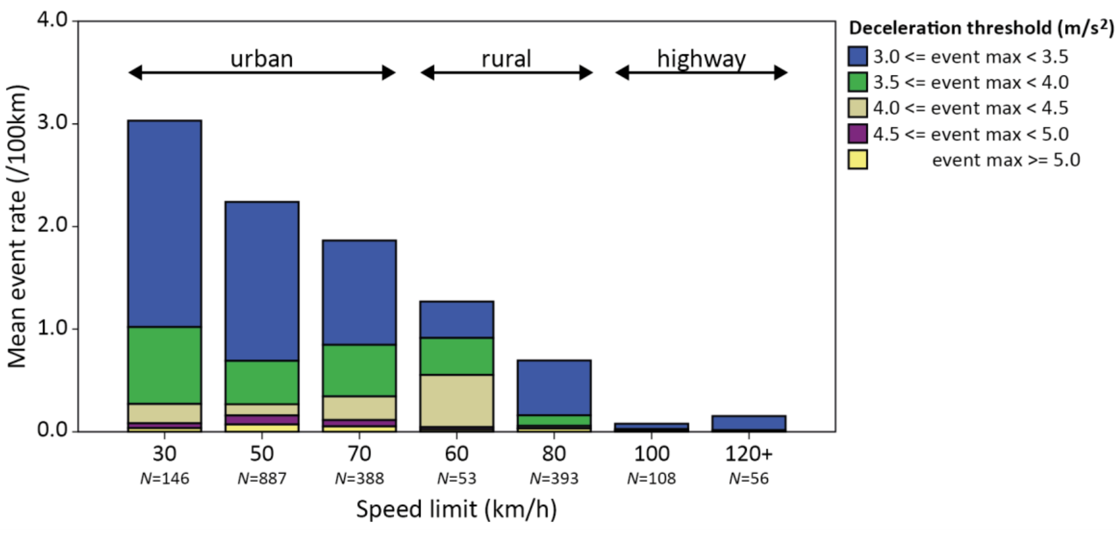

Figure 1 – Mean harsh braking event rate as function of speed limit. *N* = number of events. NOTE: Speed limits 60 and 70 km/h are reversed. Speed limits 120 and 130 km/h are merged due to their similar road design.

Looking at the total bar height, there appear to be three clusters of speed limits with a similar event rate at a cut-off value of 3.0 m/s^2. The highest event rates are found in urban areas (speed limits: 30, 50, 70 km/h). In rural areas (speed limits: 60, 80 km/h) the event rate is approximately 2-3 times lower than in urban areas, and at highways (speed limits: 100, 120+ km/h) the event rate is about one tenth that of rural areas (note: trucks were restricted at a driving speed of 85 km/h). At rural roads and highways the distribution of event rate across drivers was significantly different from the normal distribution. Therefore, a Friedman ANOVA was performed, which yielded a significant effect on speed limit cluster, $\chi^2(2) = 36.55$, $p < .001$. Two Wilcoxon signed ranks tests were used for post-hoc comparisons. A Bonferroni correction was applied, such that the significance was tested against an alpha of .025. The event rate at urban roads (*Mdn* = 1.92 events/100km) proved to be significantly higher than at rural roads (*Mdn* = 0.48 events/100km), $T = 1$, $p < .001$. Likewise, the event rate at rural roads was significantly higher than at highways (*Mdn* = 0.018 events/100km), $T = 0$, $p < .001$.

3.2 Harsh braking events across drivers

We examined differences between drivers within speed limit categories, and across speed limit categories. Figure 2 shows the event rate across drivers for urban roads. The drivers were ordered based on their event rate at the lowest cut-off value (i.e., 3.0 m/s^2). If a higher cut-off value had been chosen, this order would have changed drastically. Similar patterns were found at rural roads and highways (the corresponding figures are omitted due to limited space). To summarize, drivers differ in how often and how harshly they brake, and harsh braking intensity appears to be unrelated to harsh braking frequency.

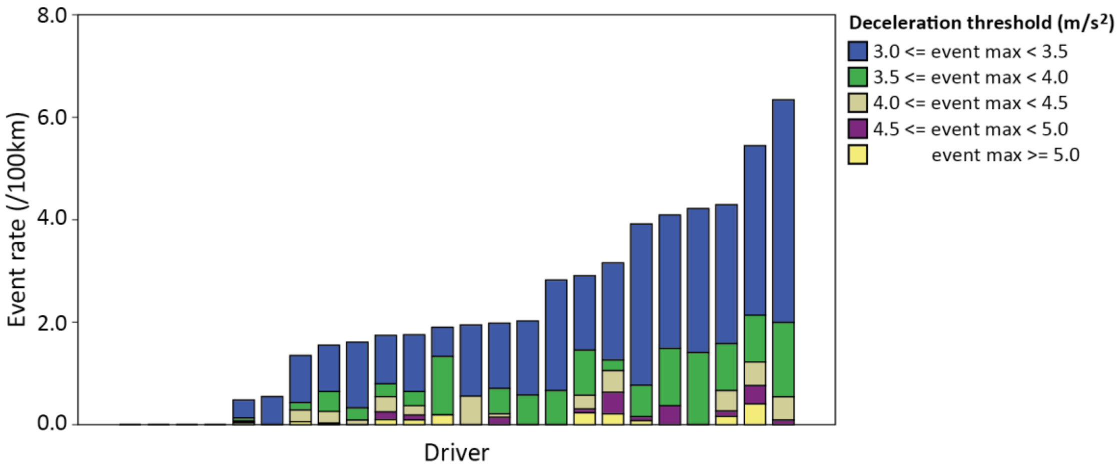

Figure 2 - Harsh braking event rate across drivers within urban areas (speed limits: 30, 50, 70 km/h).

To compare between drivers across speed limit clusters, we have calculated the correlation between event rates at each cut-off value. Significant positive correlations were found between each speed limit cluster at the lowest cut-off value, see Table 1. When the cut-off value is increased, however, the magnitude of the correlations and their significance declines. This finding suggests that drivers differ in where they perform very harsh braking manoeuvres, at least when the driving context is operationalized in terms of urban, rural and highway speed limit clusters.

Table 1 - Pearson correlation on event rate between driving contexts, stratified across cut-off values (m/s^2).

	Cut-off ≥ 3.0			Cut-off ≥ 3.5			Cut-off ≥ 4.0			Cut-off ≥ 4.5			Cut-off ≥ 5.0		
Location	**U**	**R**	**H**	**U**	**R**	**H**	**U**	**R**	**H**	**U**	**R**	**H**	**U**	**R**	**H**
Urban	1	.68**	.67**	1	.51*	.58**	1	-.15	.46*	1	.25	.38	1	-.09	.18
Rural	.	1	.73**	.	1	.39	.	1	-.10	.	1	-.15	.	1	-.13
Highway	.	.	1	.	.	1	.	.	1	.	.	1	.	.	1

NOTE: U = Urban, R = Rural, H = Highway. * $p < .05$, ** $p < .01$.

4 DISCUSSION

The objective of this study was to explore the impact of deceleration threshold values on the detection of harsh braking events across driving contexts. Most truck drivers in the UDRIVE database have been found to perform harsh braking manoeuvres, yet the event frequency varies across drivers. Some drivers show many harsh braking events, but the magnitude of deceleration in each event is modest. Other drivers perform relatively few harsh braking manoeuvres, but for those drivers the magnitude of deceleration is much larger. Consequently, when drivers are ordered according to their harsh braking event rate, the ordering changes when the threshold is shifted from a liberal to a more conservative value. The implication of this finding with regard to driver coaching is that the interpretation of individual driver performance compared to fleet performance depends on the threshold that is chosen to identify harsh braking events.

With regard to driving context, the momentary speed limit significantly influenced the frequency of harsh braking events. At urban roads (speed limits: 30, 50, and 70 km/h) the event rate was approximately twice as high compared to rural roads (speed limits: 60 and 80 km/h). In turn, the event rate at rural roads was approximately ten times higher than events found at highways (speed limits: 100, 120, and 130 km/h). Seeing that some drivers might drive more in urban areas and others more on the highway, a comparison between individual driver and fleet performance should be corrected for the driving context in which harsh braking events are collected. Alternatively, harsh braking behaviour could be evaluated separately for each context.

Our study examined driving behaviour by Dutch truck drivers, which may limit the generalizability of our findings towards other countries. For example, the event rate at highways (*Mdn* = 0.018 events/100km) reported in this study is in line with the event rates reported in the US study of Hickman and Hanowski (2011) for a long-haul carrier (*M* = 0.0123 events/100km) and a short-haul carrier (*M* = 0.025 events/100km). For urban and rural roads, however, our event rate was two to three orders of magnitude larger. This difference could be explained if the data in the US study were mainly collected on highways, including the short-haul carrier, but such information was not reported. An alternative explanation could be that traffic on urban roads differs between US and Dutch cities. US residents typically commute by car, whereas relatively many Dutch residents use their bicycle. Consequently, the number of interactions between truck drivers and cyclists is likely higher in Dutch urban areas than in US urban areas, which in turn may account for an increased harsh braking event rate.

Another limitation of our study is that most records in the UDRIVE database covered a distance smaller than 10 km, which is a fraction of trips driven by long-haul trucks. Long, monotonous trips increase fatigue and reaction time (Ting et al., 2008), which may increase the number of harsh braking events. However, all trips in the present study yielded maximally one event, including trips covering a large distance. Furthermore, the event rate has been stratified across speed limits, and expressed as proportion of the distance driven. Therefore, a potential bias introduced by trip distance has been mitigated to the best possible extent.

Previous studies on harsh braking behaviour report a wide range of deceleration threshold values. Some studies used a low value to find a large number of events (i.e., high sensitivity), followed by a manual validation of actual harsh braking events (Bell et al., 2017). This approach may be too time-consuming for use in automated commercial in-vehicle monitoring systems. Other studies have used a relatively high threshold value to decrease the number of false positives (i.e., high specificity), which may be more attractive for automated processing, yet it comes at the risk of missed events. The optimal balance between sensitivity and specificity remains a subject for future research. Until then, our study serves as a reminder that an arbitrarily chosen threshold will likely influence feedback on the performance of individual drivers in relation to their peers.

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