Jerky driving—An indicator of accident proneness?

Omar Bagdadi\textsuperscript{a,b,∗}, András Várhelyi\textsuperscript{b}

\textsuperscript{a} VTI, Swedish National Road and Transport Research Institute, Borlänge, Sweden
\textsuperscript{b} Department of Technology and Society, Lund University, Lund, Sweden

ARTICLE INFO

Article history:
Received 9 December 2009
Received in revised form 17 January 2011
Accepted 8 February 2011

Keywords:
Accident involvement
Safety critical driver behaviour
Acceleration profiles
Jerks

ABSTRACT

This study uses continuously logged driving data from 166 private cars to derive the level of jerks caused by the drivers during everyday driving. The number of critical jerks found in the data is analysed and compared with the self-reported accident involvement of the drivers. The results show that the expected number of accidents for a driver increases with the number of critical jerks caused by the driver. Jerk analyses make it possible to identify safety critical driving behaviour or “accident prone” drivers. They also facilitate the development of safety measures such as active safety systems or advanced driver assistance systems, ADAS, which could be adapted for specific groups of drivers or specific risky driving behaviour.

© 2011 Elsevier Ltd. All rights reserved.

1. Introduction

Identifying risky or “accident prone” drivers could facilitate more effective traffic safety work and allow measures to be tailored for a specific driver group.

Parker et al. (1995), using a Driver Behaviour Questionnaire, found that higher levels of reported violations were associated with greater accident involvement. The types of violations considered were: breaking the speed limit, not stopping at red lights, close following, unofficial races and drinking and driving. Such violations imply that if a disturbance in a traffic situation occurs, i.e. deviates from the expected occurrence, the change in longitudinal or lateral movement of the vehicle will be jerky. Hence, jerkiness in driving may be an indication of a more risky driving style and a higher probability of accident involvement. A risky driving style in terms of jerkiness is defined as the amount of critical jerks a driver causes while driving.

Measuring acceleration profiles in everyday driving shows that most of the braking results in average acceleration rates of $-3.1 \text{ m/s}^2$ and average jerks (the rate of change of acceleration) of $-3.6 \text{ m/s}^3$ (Nygård, 1999). However, normal driving may also include more powerful but still planned braking, which would cause more extreme acceleration values. Using video recordings of serious traffic conflicts to study deceleration rates in normal braking situations, van der Horst (1990) found that only about 20% of the vehicles involved had acceleration rates between $-4.0 \text{ m/s}^2$ and $-7.7 \text{ m/s}^2$ during conflict situations. The study also showed that when braking in a normal situation, for example at a railway crossing, the acceleration rate was lower than $-4.0 \text{ m/s}^2$, which put it in the same range as for braking in conflict situations (near-accidents). Since several other studies (Várhelyi, 1998; Nygård, 1999; Wahlberg, 2000) have shown similar results, it is apparent that using acceleration as the only means of separating normal braking from braking in conflict situations is insufficient. The acceleration profiles in normal situations are rather similar to the acceleration profiles experienced in conflict situations, and it is therefore necessary to use a complementary indicator of traffic conflicts.

Safety critical driving behaviour decreases the safety margins for drivers when they compensate for erroneous or risky driving caused either by themselves or by other road users (Risser, 1985). Depending on the amount of safety margin left, the severity of the situation may be classified into three categories, accidents, near-miss or serious traffic conflict and slight or potential conflicts. According to Hydén (1987), it is possible to detect safety critical driving behaviour by studying fluctuations in the acceleration and deceleration profiles. This hypothesis was also addressed by Nygård (1999), who found a significant difference at the beginning and end of a jerk representing normal braking compared to braking in conflict situations. During these start and stop phases the lowest value of acceleration derivatives of normal braking registered was $-8.0 \text{ m/s}^2$, while conflict situations showed derivatives ranging from $-9.9 \text{ m/s}^2$ down to $-12.6 \text{ m/s}^2$. This difference in the acceleration data was not observed for potential conflicts, which may be explained by the definition itself; i.e. a potential conflict is an event that a driver could adapt his/her driving to, and therefore avoid any sudden action which causes a jerk.
Participating drivers per age group.

<table>
<thead>
<tr>
<th>Age groups</th>
<th>18–24</th>
<th>25–44</th>
<th>45–64</th>
<th>65+</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male drivers</td>
<td>7</td>
<td>35</td>
<td>56</td>
<td>14</td>
<td>112</td>
</tr>
<tr>
<td>Female drivers</td>
<td>3</td>
<td>21</td>
<td>28</td>
<td>2</td>
<td>54</td>
</tr>
<tr>
<td>Total</td>
<td>10</td>
<td>56</td>
<td>84</td>
<td>16</td>
<td>168</td>
</tr>
</tbody>
</table>

2. Method

2.1. Objective

The objective of this study is to analyse continuously registered driving data from 166 passenger cars and compare the jerkiness, i.e. jerk rate, derived from the registered driving data and the drivers’ self-reported accident involvement, in order to ascertain whether or not there exists a relationship between jerky driving and accident proneness.

2.2. Subjects

This study analyses driving data that was collected in a large-scale field trial in Lund, Sweden, between 2001 and 2003 (Várhelyi et al., 2004). The trial was carried out to evaluate the effects of Intelligent Speed Adaptation (ISA) on driver behaviour.

It involved over 200 passenger cars equipped with an ISA system and data loggers, which recorded driving data such as the actual speed of the vehicles with a 5 Hz sample rate by means of a CAN (Controlled Area Network) bus. The ISA functionality uses the speed and position of the vehicle to inform the driver about speed limits, and to give warnings if the driver exceeds the speed limit, by comparing the driving data with the digital road map incorporated in the ISA equipment.

The ISA system was not activated at the beginning of the trial, except for recording driving data for approximately 1 month. This data, which serves as a baseline for the drivers’ behaviour, i.e. how they normally drive, contains time stamped driving data for each participating vehicle (Várhelyi et al., 2004).

The recruitment of the drivers was carried out through a questionnaire sent to more than 3800 private car owners, randomly selected from a register of car owners in Lund. Of the responding drivers, 625 were interested in participating in the trial. Due to the limited amount of available equipment and technical issues that evolved during installation, only 246 private cars were included in the trial (Várhelyi et al., 2004). The recruitment questionnaire focused mainly on the car owners’ opinions and attitudes regarding mobility, speed limits, traffic safety issues and previous accident involvements.

Table 1 shows that fewer female drivers participated in the field trial, especially when it came to elderly drivers, i.e. over 65 years of age, resulting in a somewhat skewed distribution of the drivers.

Of the 246 drivers initially participating in the trial, a total of 80 drivers are excluded from further analysis in this study, due to incomplete driving data and erroneous data recorded in the database.

2.3. Data collection

The accident involvement of the participating drivers is gathered from the self-reporting questionnaires. These show that, of the initial 246 participating drivers, 47 reported being involved in at least one accident during the previous 3 years. The corresponding number of drivers was 33 for the final 166 drivers included in this study.

Self-reports of accidents, which are an alternative to official accident records based on police and hospital reports, provide the possibility of gaining further information about the accidents than stated in the police reports. Still, the use of self-reports is not without criticism and several studies have attempted to validate self-reports. In a study dating back to 1976, Smith (1976) found that self-reports often contained more accidents than the official state records, but also left out some of the accidents recorded in the latter.

The reason for leaving out accidents from self-reports is believed to be a combination of bias, caused by social desirability, and incorrect memory recall (Meadows and Stradling, 1996; Chapman and Underwood, 2000). In addition to having trouble remembering the correct year of an accident, there is the issue of forgetting the event altogether. Normal events that are not considered extra stressful or arousing during driving are very quickly forgotten, while near-accidents are remembered for a longer period of time (Chapman and Underwood, 2000). According to Chapman et al. (2000), the time until a person forgets a certain event is related to the amount of stress the event causes. However, there seems to be a limit to the stress level that a person can handle before memory impairment hinders the recalling of, for instance, a severe accident (Loftus and Burns, 1982).

Comparing self-reports and official records of accidents, McGwin et al. (1998) found a moderate level of correlation and concluded that the discrepancy was caused by an incorrect recall of when the accidents occurred. This correlation was somewhat higher than that found in a similar earlier study (Marottoli et al., 1997). However, the time period of interest differed between the studies. As McGwin used a longer period of 5 years compared to a 1 year time period of interest used by Marottoli et al., which supports the conclusion by Chapman et al. (2000) that people have difficulties remembering what year an accident occurred and hence incorrectly leave certain accidents out. If the time period of interest increases, it is more likely that more accidents during any part of the time period will be included in the reports. Hence, a period of 3 years has been chosen for this study.

The recorded driving data is analysed in order to compare the acceleration profiles of drivers with a prior accident history to the profiles of drivers who reported no previous accident involvement.

A threshold level of $-9.9 \text{ m/s}^3$ is used for the jerks as an indicator of safety-critical driving behaviour. This threshold is the same as used by Nygård (1999) for identifying serious traffic conflicts, based on speed data from an instrumented vehicle during a field study where 70 drivers were accompanied by a trained observer (Kulmala et al., 2000). Nygård calculated the acceleration profiles from the speed data using the three point rule of numerical derivatives, while the jerks, i.e. second derivatives of the speed data, were calculated using Euler’s backward differential method of numerical derivative (Benko et al., 2009).

2.4. Data processing

Although the threshold value of $-9.9 \text{ m/s}^3$ is set to select serious conflicts (Nygård, 1999), the sample rate by which the speed data is recorded, i.e. raw data, as well as the chosen method for calculating the derivatives, can affect the threshold value. Nygård (1999) used an initial sampling frequency of 5 Hz for the speed data, which was then filtered to remove noise, and produced a less fluctuating acceleration profile curve. The filtering of the raw speed data is done by averaging the speed data with a three-point moving average. A higher sampling frequency gives a better resolution of the derivatives, which results in higher peaks due to the smaller time difference between samples. Unfortunately, a higher sampling frequency comes at the cost of a higher degree of noise in the measured data, while a lower sampling...
frequency has the opposite effect, i.e. lower resolution and less noise.

The recording equipment is able to record speed at a sampling rate of 5 Hz. Due to technical difficulties and other unknown factors, however, the actual sampling rate varied from 5 Hz down to 1 Hz and sometimes even missed long periods of driving. This resulted in data records of varying quality, which needed to be processed before further analysis.

The first action of data processing is to remove any spikes and treat missing values, and thereafter smooth the raw data to minimize the effect of fluctuations in the measurements due to technical causes. The smoothing of the raw data is done automatically using a weighted exponential smoothing method [formula (1)] (Rakha et al., 2001), implemented in Matlab 2008r:

$$x_t^s = \alpha x_t + (1 - \alpha)x_{t-1}^s$$  \hspace{1cm} (1)

where $x_t$ is the raw data at time $t$, $x_t^s$ is the smoothed data at time $t$, $\alpha = 0.4$ (weighting constant).

Using the same method with a dynamic step variable, the first and second derivatives of the speed are calculated from the resulting speed data. The next step in the process is to count all critical jerks that are equal to or below the threshold value of $-9.9 \text{ m/s}^3$.

The difference in sample rate results in piecewise smoother acceleration profiles for the periods where the step size is greater than 0.2 s, which affects the amplitude of the jerks. A more smoothed acceleration profile results in higher absolute values of the jerks, suggesting that a less abrupt braking has occurred. Therefore, it is reasonable to assume that the resulting number of critical jerks below the threshold value is fewer than in reality. However, this cannot be easily resolved by changing the threshold value in order to classify those jerks that have a higher absolute value as critical, since this would also classify jerks calculated with a step size of 0.2 s, which is the same as the step size used to determine the threshold value, as critical and thus erroneously as safety-critical driving behaviour.

### 2.5. Statistical analysis

It is assumed that the number of accidents in traffic is Poisson distributed for an entity, $Y \sim \text{Poisson}$. Let $E(Y) = \mu$ denote the expected number of accidents; it follows that the probability of experiencing a certain number of accidents, denoted $y$, is:

$$P(Y = y) = \frac{\mu^y}{y!}e^{-\mu}$$ \hspace{1cm} (2)

Due to the low number of participants in this study, the number of drivers who had had more than two accidents is over represented; thus a dichotomous variable expressing accident involvement is created. Since the accident variable is considered to be binomial distributed, a binary regression model is required. However, the logit regression model would result in a biased result, as the number of drivers in the cohorts involved in accidents is more than 10%. Therefore, a complementary log–log link function is used instead of the logit function. The complementary log–log regression model can be derived from the Poisson probability model accordingly:

$$P(Y \geq 1) = 1 - P(Y = 0) = 1 - \frac{\mu^0}{0!}e^{-\mu} = 1 - e^{-\mu}$$

$$\ln(-\ln(1 - P(Y \geq 1))) = \ln(-\ln(e^{-\mu})) = \ln(\mu)$$ \hspace{1cm} (3)

Models using $\ln(-\ln(e^{-\mu}))$ link function are interpretable as models for the hazard function given by the standard formulation:

$$\ln(-\ln(e^{-\mu})) = \beta_0 + \sum \beta x_i$$

Which gives:

$$\ln(\mu) = \beta_0 + \sum \beta x_i$$ \hspace{1cm} (4)

Here, $\mu$ is the expected number of accidents, $\beta_0$ is the intercept coefficient and $\beta_i$ is the regression coefficient estimating the effects of $X_i$, which represent the explanatory variables, jerk rate, age and gender. For the analysis, the age of the drivers is classified into four age categories: 18–25, 26–45, 46–65 and over 65.

### 3. Results

Of the 166 participants 33 reported that they had been involved in at least one motor vehicle accident. While a higher proportion of those reporting accident involvement, compared with those not reporting such involvement, were female (24 versus 18%, p-value < 0.023), there were no significant differences in accident reporting between the age groups. The self-reported accident involvement, in terms of accidents/no-accidents category, is distributed between male and female drivers for each respective age category according to Table 2.

<table>
<thead>
<tr>
<th>Age</th>
<th>Drivers involved in accidents</th>
<th>Drivers not involved in accidents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Male</td>
<td>Female</td>
</tr>
<tr>
<td>18–25</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>26–45</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>46–65</td>
<td>11</td>
<td>6</td>
</tr>
<tr>
<td>Over</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>20</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 2 Sample size of drivers by gender, age and accident involvement.

where $\mu$ is the expected number of accidents, $\beta_0$ is the intercept coefficient and $\beta_i$ is the regression coefficient estimating the effects of $X_i$, which represent the explanatory variables, jerk rate, age and gender. For the analysis, the age of the drivers is classified into four age categories: 18–25, 26–45, 46–65 and over 65.

Several complementary log–log regression models have been examined in order to exclude variables with no explanatory value from the model. The final model includes the explanatory variables with a p-value < 0.05, but age groups (p-value > 0.4 for all age groups) are excluded as an explanatory variable from further analysis. In addition, the difference in exposure in terms of driving distance between the drivers is accounted for in the analysis. The results from the regression model $\ln(\mu) = \beta_{\text{jerk rate}} + \beta_{\text{gender}} + \beta_{\text{gender*jerk rate}}$ shown in Table 3 estimate the relationship between accident involvement and the significant explanatory variables jerk rate and gender. The model includes both main effects as well as the interaction term Gender*jerk rate.

The model shows a positive correlation between jerk rate and an increase in the expected number of accidents. The results in Table 3 show that the expected number of accidents a driver will be involved in increases by 1.13 over a period of 3 years, i.e. the hazard rate, for each additional critical jerk. The model does not show statistical significance for either gender or the interaction term gender*jerk rate. However, excluding the interaction term from the model causes the gender variable to become statistically significant ($e^{\beta_{\text{gender}}} = 2.37$, p-value < 0.022). Exclusion of the interaction variable has only a minor effect on the main effect of jerk rate ($e^{\beta_{\text{jerk rate}}} = 1.15$, p-value < 0.000).

Although Table 3 shows that there is no statistically significant interaction effect between female drivers and jerk rate, a statistical regression analysis stratified by gender shows that the main effect of jerk rates is higher amongst female drivers than male drivers ($e^{\beta_{\text{jerk rate}}} = 1.42$, p-value < 0.014, $e^{\beta_{\text{jerk rate}}}_{\text{male}} = 1.13$, p-value < 0.000), where $e^{\beta_{\text{jerk rate}}}$ is the main effect of jerk rate amongst female drivers and $e^{\beta_{\text{jerk rate}}}_{\text{male}}$ is the main effect of jerk rate amongst male drivers.

### 4. Discussion

This study attempts to ascertain whether there is a relationship between jerkiness in driving, in terms of jerk rate, and drivers’ accident involvement as a first step in developing a new method for
identifying safety critical driving behaviour. Identifying safety critical driving behaviour or “accident prone” drivers could facilitate the development of safety measures such as active safety systems or advanced driver assistance systems, ADAS, that could be adapted for specific groups of drivers or specific risky driving behaviour.

The results from the regression model support the contention that there exists a relationship between jerk rate and self-reported accident involvement. Although the data sample is relatively small, the regression model shows that the expected number of accidents increases by approximately 1.13 over a period of 3 years for each additional critical jerk the driver causes.

The model also indicates that the gender of the drivers has no correlation with self-reported accident involvement, and that the gender-jerk rate interaction term included in the model has no statistically significant interaction effect. However, a gender-stratified analysis shows a greater main effect of jerk rate on the hazard ratio for female drivers, suggesting that jerk rate is a better indicator of safety critical driving behaviour amongst female drivers. Thus, the small number of participating drivers may explain the lack of statistical significance of the interaction term.

Uncertainties around accident reporting make it difficult to obtain data with which to draw statistically significant conclusions about accident involvement in relation to different driver characteristics such as age or gender, especially in field trials with relatively few participants. In addition, based on the assumption that self-reports under-report certain types of accidents (Smith, 1976), accidents with lower severity are likely left out to a greater extent than more serious accidents (Chapman and Underwood, 2000). Maycock et al. (1991) points out that male drivers have a higher accident liability than women at all ages, which supports the argument that the number of reported accidents by men should be higher. Therefore, drawing a general conclusion about the correlation between accident and gender, based on the results of this study, is not recommended.

However, accidents in fact do cluster, and this clustering is more prevalent than expected by chance (Visser et al., 2007), confirming that accident proneness exists. Ulleberg and Rundmo (2002) found that certain personality traits, especially drivers’ attitudes towards traffic safety, were correlated with self-reported accidents. It is also considered that a person’s attitude towards traffic safety or risk-taking is difficult to change, since it is influenced by other stable personality traits such as sensation seeking and locus of control (Yagil, 2001; Ulleberg and Rundmo, 2003). Even though accident involvement is likely to be affected by other variables such as exposure, being able to identify safety critical driver behaviour instead of actual accident involvement would most likely aid in developing new improved safety measures, and also be useful in the analysis of the effectiveness of the safety measures.

There are several weaknesses in this study, mostly caused by quality issues in the data set, limiting the number of possible analyses. Hence, future research on jerks needs to include a more comprehensive analysis of driving behaviour and possible confounding variables.

The technical difficulties during the field trial resulted in a large amount of erroneous driving data, such as false zero speed or unrealistic high speed recordings and lack of data records. The original sampling frequency in the data used in this study is 5 Hz, which is on the verge of being too low. Unfortunately, the resulting sampling frequency is lower on average, affecting the quality of the calculated acceleration profiles and the calculation of the rate of change within these profiles. However, the situation is handled using dynamic step sizes for the calculations of the rate of change, but, as the sampling frequency is not optimal, the acceleration profiles are not as accurate as they could be, which in turn affects the amplitude of the rate of change. The chosen threshold of $-9.9 \text{ m/s}^3$ is based on driving data sampled at 5 Hz and smoothed with a three-point moving average. The occasional difference in sampling frequency most likely affects the number of jerks classified as critical, and results in fewer critical jerks than there would have been if the recording of the driving data had been more accurate.

Using a sampling frequency as low as 5 Hz affects the resolution of the acceleration profile and is a major problem when it comes to sampling distortion and further calculation, for example the calculation of the rate of change, i.e. jerks, based on the sampled data. In future trials the sampling frequency should be at least 10 Hz, preferably 20–50 Hz in order to decrease the risk of sampling distortion, due to noise, that could otherwise affect the data during the necessary smoothing and filtering of the raw data.

An important issue to address is that the method chosen to measure the acceleration profiles and to calculate the rate of change affects both the absolute value of the jerks and the threshold level used to classify jerks as critical. Previous studies concerning measurements of acceleration profiles use different methods, which makes it difficult to compare their results. Therefore, the next step in the development of a method for identifying safety critical driving behaviour is to improve the measurement method, which is an important step in obtaining more accurate and reliable data for the analysis of jerk characteristics in different traffic safety-related events.

5. Conclusion

This study has shown that jerks may be used as a measure of safety critical driving behaviour and accident prone drivers. Thus, a method based on jerks may prove to be very useful for identifying and analysing safety critical driving behaviour and facilitating the development of traffic safety measures such as driver support systems tailored for specific driver groups.

References


Table 3

<table>
<thead>
<tr>
<th>Variables</th>
<th>β-Coefficient (95%CI)</th>
<th>Hazard ratio (95%CI)</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jerk_rate</td>
<td>0.12 (0.06–0.19)</td>
<td>1.13 (1.06–1.21)</td>
<td>0.000</td>
</tr>
<tr>
<td>Gender (female)</td>
<td>0.23 (−0.86 to 1.32)</td>
<td>1.26 (0.42–3.77)</td>
<td>0.677</td>
</tr>
<tr>
<td>Gender*Jerk_rate</td>
<td>0.23 (−0.06 to 0.52)</td>
<td>1.26 (0.94–1.67)</td>
<td>0.122</td>
</tr>
<tr>
<td>Intercept</td>
<td>−16.63 (−17.20 to −16.07)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


