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PROACTIVE ASSESSMENT OF ROAD CURVE SAFETY USING FLOATING CAR DATA: AN EXPLORATORY STUDY

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Abstract:

Driving speed is an important risk factor, especially when negotiating horizontal curves. Therefore it may be useful in extracting surrogate measures to proactively safety assessment, a practice consistent with a current shift towards a Safe System approach to addressing road trauma. Review of previous literature indicated two categories of studies: (1) studies focusing on a safe driving perspective, i.e. studies primarily interested in finding the cut-off point in FCD data characteristics between safe and unsafe driving; (2) studies focusing on relating meaningful risk rates (percentages of exceeding the risk thresholds) to specific locations, and thus identify safety critical sites. However, no study was found that specifically focused on the relationship between kinematic characteristics (other than just speed) and road curves.

The presented study focused on exploring the relationship between acceleration and jerk thresholds and crashes occurring on road curves. The first objective was to determine meaningful acceleration and jerk thresholds to utilize in explaining safety performance when negotiating curves. For this purpose floating car data (FCD) from a fleet of company vehicles, driving in rural sections of national roads in the Czech Republic, was collected and used to derive and validate potential surrogate safety measures. FCD presents in-vehicle information with several benefits compared to traditional techniques, such as feasibility of data collection, relatively unlimited spatial coverage, and availability of historical data.

In the analysis, lateral acceleration and longitudinal jerk were found to be the most influential measures of curve safety performance. To sum up, the exploratory study outlined a practical approach to proactive evaluation of road curve safety: FCD data can generate useful surrogate measures of curve safety (acceleration and jerks) associated with crash history. A larger study is required to strengthen robustness of the results and provide confidence necessary for practical application. Potential use cases may include conducting interim evaluations of curve road safety treatments, or in-vehicle monitoring devices for detection of potentially unsafe manoeuvers and providing real-time feedback to drivers based on a combination of identified safety thresholds.

Keywords: *floating car data, surrogate safety measure, horizontal curve, traffic safety*

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1. Introduction

Horizontal road alignment is one of the general design features which have a significant impact on driving and safety. Horizontal alignment consists of tangents (straight sections) connected by horizontal curves. Curves are places of special interest for their higher crash risk compared to straight alignment due to additional centripetal forces exerted on a vehicle, higher driver cognitive workload, and other factors (Hummer et al., 2010; Georgieva and Kunchev, 2015; Gaca and Pogodzińska, 2017). Internationally, 25 to 30% of all fatal crashes occur on curves (PIARC, 2003; Golembiewski and Chandler, 2011; Jurewicz et al., 2015). This amount is even higher in the Czech Republic, where more than one third of total road fatalities occur on curves; particularly critical are curves in rural sections of national roads (Ambros and Valentová, 2016).

Traditionally, road safety management has been reactive, i.e. based on retrospective analysis of Police-reported crash data (Nowakowska, 2012). But recently, in line with a shift towards the Safe System approach to reducing road trauma, as well as automated driving, there has also been increased focus on developing and using surrogate (proactive) safety measures, which are causally and statistically related to crashes and injuries (Tarko et al., 2009). Speed, known as a critical safety factor (OECD/ITF, 2018), is one such measure.

An emerging alternative is using speeds derived from in-vehicle collected floating car data (FCD data, also known as probe vehicle data; Bessler and Paulin, 2013). Compared to traditional speed measurement techniques (radars, loops, etc.), the benefits of FCD data include improved feasibility of data collection, relatively unlimited spatial coverage, and availability of historical data (Jurewicz et al., 2017, 2018). Of additional interest are various measures of deceleration (including rate of change of acceleration or deceleration per unit of time, known as jerk), which have been found to be associated with hazardous situations, i.e. increased crash or near-crash frequency (Dingus et al., 1997; Kiefer et al., 2006; Markkula et al., 2016; Feng et al., 2017).

In this study, we explored the possibilities of proactively assessing the safety of a sample of rural road curves using FCD data. We aimed to answer two research questions:

1) What are the cut-off values of FCD-based kinematic characteristics for assessing hazardous situations due to horizontal alignment (referred to in this paper as risk cut-off studies)?
2) Can the proportion of these hazardous situations help to explain the safety performance of curves on rural roads (referred to in this paper as risk rate studies)?

The following section presents a literature review summary, focusing on both research questions. Section 3 describes the study methods, results, discussion and conclusions.

2. Literature review

Following review summary is divided into two subsections:

– The first lists some examples of studies focusing on a safe driving perspective, i.e. studies primarily interested in finding the cut-off point in FCD data characteristics between safe and unsafe driving.
– The second lists some studies, which focus on relating meaningful risk rates (percentages of exceeding the risk thresholds) to specific locations, and thus identify safety critical sites.

2.1. “Risk cut-off” studies

The research, related to driver behavior, and its risk and safety consequences, has spanned several decades. For example, studying traffic conflicts (near-crashes) started in the late 1960s (for reviews, see Zheng et al., 2014; Johnsson et al., 2018). But still there is no simple answer to the question “What is unsafe driving at an individual level?” (Martens and Brouwer, 2011). Nevertheless, there is evidence some safety critical event algorithms related to speed and acceleration are predictive of crash involvement risk (Sagberg et al., 2015). Particularly interesting to vehicle speed when negotiating curves is lateral acceleration: it has been identified as the primary criterion for the choice of speed in curves (Ritchie et al., 1968), related to higher speeding (Reymond et al., 2001) and higher crash rates (Othman et al., 2012). Also of interest to the present study are jerks, which were found to perform better than acceleration alone in identifying critical situations (Bagdadi and Várhelyi, 2013; Reinau et al., 2016).

In this context, FCD data, linked to specific drivers, present a valuable source for assessing driving performance and driving styles, as well as driving exposure. A common approach is to analyze kinematic vehicle data to detect safety-critical events. For example, so called rapid deceleration events (RDEs) have been successfully used as a surrogate safety metric in studies of older driver safety (Keay et al., 2013; Chevalier et al., 2016, 2017). However, cut-off (threshold) values of these "event triggers" vary significantly in the literature, for example:

- longitudinal deceleration ranges from approx. 0.1 to 0.75 g (Aichinger et al., 2016; Kamla et al., 2019)
- critical jerks vary between 0.06 and 2 g/s (Naude et al., 2017; Pande et al., 2017)

2.2. "Risk rate" studies

Based on cut-off (threshold) values, it is possible to calculate proportions of events, when the threshold was exceeded (i.e. risk rate). The following selection of recent studies illustrates the examples of approaches to subsequent validation:

- Mousavi et al. (2015) conducted sensitivity analysis of 21 different jerk value thresholds; then they compared location jerk rates (percentages) to crash rates.
- Similarly, Pande et al. (2017) assessed the relationship of 10 jerk threshold values (varying from 0.50 to 2.75 ft/s^3, with increments of 0.25) to the crash frequency at the location.
- Reinau et al. (2016) used both speeds and jerks to identify critical locations in a Danish city, which were then visually compared with crash locations.
- In a Czech study, speed consistency (i.e. differences between speeds in tangents and following curves) was used to identify substandard curves, and found curves classified as substandard were statistically related to locations with higher long-term crash frequencies (Ambros et al., 2017).
- Stipancic et al. (2018) conducted network screening in Quebec City, using cut-off acceleration values of ± 2, 3 and 4 m/s^2. The lowest value was found to have the greatest relationship with locations with higher crash frequencies.

2.3. Summary

In spite of the number of reviewed studies related to kinematic characteristics and safety, no study was found that specifically focused on the relationship between kinematic characteristics (other than just speed) and road curves. Based on a literature review, we decided to base this study on examining the relationship between acceleration and jerk thresholds and crashes occurring on road curves. The first objective was to determine meaningful acceleration and jerk thresholds to utilize in explaining safety performance when negotiating curves.

3. Data

Floating car data was collected from a fleet of company vehicles (for details see Ambros et al., 2017). Coverage was limited to rural sections of national (1st class) roads in the Czech Republic, which are mostly two-lane undivided roads (Figure 1).

Fig. 1. Example photographs of two curves in the studied sample (https://mapy.cz/)

A previous Czech study (Ambros et al., 2017) utilized FCD data collected at 4 Hz to obtain speed estimates and assess the consistency of driver speeds across approximately 100 circular curves (without consideration of transition curves). For the present study, we selected 30 of these curves. Since 4 Hz is not sufficient for derivations (acceleration → jerk), additional FCD data was collected at a frequency of 32 Hz. On average, 20 drives through each curve were retrieved. After dividing data into driving directions and excluding some with low number of records, 53 curve-directions (from 29 curves) were available.
The data included time, GPS position, GPS derived speed, acceleration on the X and Y axes (a_x, a_y). Based on data formats provided by the FCD sensors, acceleration may be interpreted as (see Figure 2):
- longitudinal (forward) acceleration represents either accelerating ($+a_x$) or decelerating ($-a_x$)
- lateral acceleration represents either left turns ($+a_y$) or right turns ($-a_y$)

Using acceleration differences (da) and time differences ($dt = 1/32$ s), we calculated jerks as follows:
- longitudinal jerk (j_x) $= da_x/dt$
- lateral jerk (j_y) $= da_y/dt$

Figure 3 illustrates the patterns, provided by speed, acceleration and jerk profile of one sampled drive. The profile includes one potentially hazardous event, indicated by a red rectangle: while it may not be detected from the speed profile, it is visible from the acceleration profile, and even better from the jerk profile.
To relate the mentioned kinematic characteristics to safety, we assigned the following parameters to the curve-directions:
- 6-year frequency of single-vehicle (both casualty and property-damage-only) crashes (N)
- annual average daily traffic volume (I)
- curve length (L)
- curve horizontal radius (R)

Descriptive characteristics of the mentioned variables are provided in Table 1.

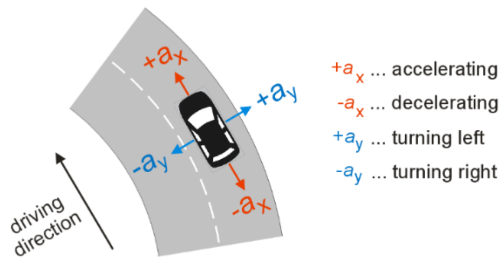

Fig. 2. Definition of axes of longitudinal and lateral acceleration (a_x and a_y) (car icon by Jule Steffen & Matthias Schmidt from the Noun Project, https://thenounproject.com/)

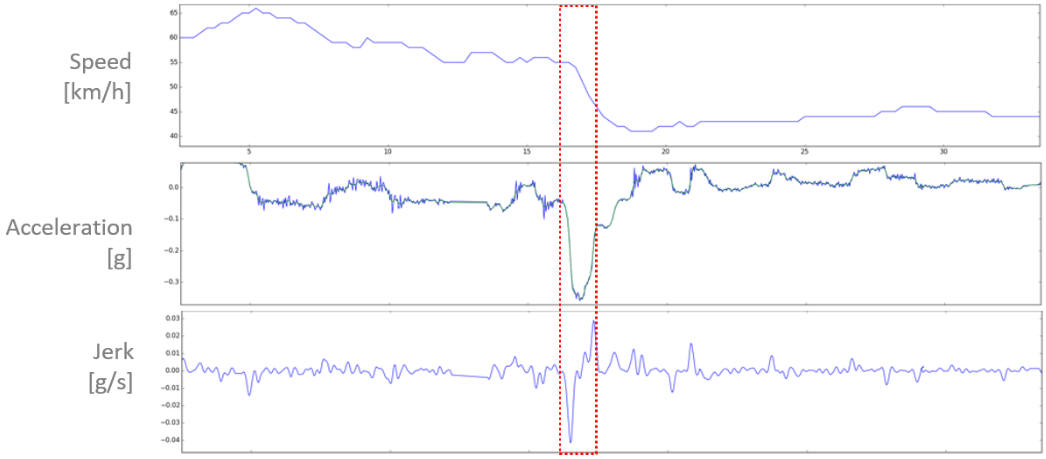

Fig. 3. Example of speed, acceleration and jerk profiles, including a hazardous event (in red rectangle)

Table 1. Descriptive characteristics of collected variables

Variable	Min.	Max.	Mean	Std. Dev.
Crash frequency	0	5	1.04	1.37
Traffic volume [veh/day]	716	6245	3246	1385
Length [m]	53	473	216	122
Radius [m]	53	1034	319	199
Longitudinal acceleration [g]	–0.40	0.39	0.006	0.060
Lateral acceleration [g]	–0.56	0.49	0.002	0.137
Longitudinal jerk [g/s]	–1.14	1.31	0.002	0.070
Lateral jerk [g/s]	–1.10	1.19	0.000	0.097

In accordance with the previously reviewed studies, we prepared several indicators:

- acceleration: longitudinal (a_x), lateral (a_y), absolute value $\left(\sqrt{a_x^2 + a_y^2}\right)$
- jerk: longitudinal (j_x), lateral (j_y), absolute value $\left(\sqrt{j_x^2 + j_y^2}\right)$
- plus absolute values of a_x, a_y, j_x, j_y

We used the minimum, maximum and 85th percentiles (from all collected data) of these indicators. This way, in total 30 variables were created.

4. Analyses and results

4.1. Risk cut-off analysis

To determine the cut-off value, we expressed safety in terms of annual crash rate per 1 million vehicle-kilometres. Then we used pivot tables to find categories, which would indicate a cut-off value.
Reasonable trends were found for 85th percentiles of absolute values of a_y and j_x (see graphs in Figure 4). Thus, the identified cut-off values were $a_y = 0.3$ g and $j_x = 0.1$ g/s. These values are within the range listed in the literature review.

4.2. Risk rate analysis

Risk rate was defined as a percentage of exceeding the risk thresholds. We calculated risk rates (proportion of a number of records, when a_y and j_x exceeding the identified cut-off values to total number of records) and labelled them as a_y-rate and j_x-rate. For example, exceeding the a_y-threshold in 50 cases of 1000 yields a_y-rate = 50/1000 = 0.05 (5%).

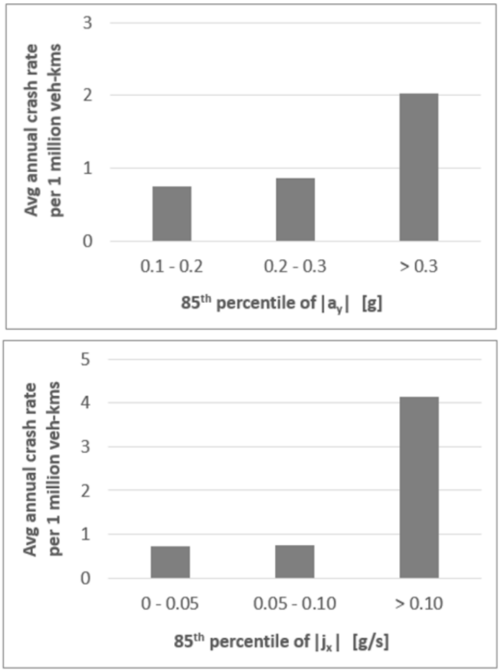

Fig. 4. Cut-off values, identified as the highest categories in graphs of average crash rates

To determine how much the rates contributed to safety performance (crash frequency), we developed two models (also known as safety performance functions):

- "Traditional model" with traffic volume, curve length and radius as explanatory variables.
- "Combined model" with all 30 developed kinematic parameters as additional explanatory variables.

We used generalized linear modelling, with a negative binomial error structure and log link function, i.e. with exposure variables (traffic volume and curve length) in a form of natural logarithms (for more information, see e.g. Ambros et al., 2018):

$$\ln(N) = \beta_0 + \beta_1 \cdot \ln(I) + \beta_2 \cdot \ln(L) + \beta_3 \cdot R + \beta_4 \cdot a_y rate + \beta_5 \cdot j_x rate$$

$$N = \exp(\beta_0) \cdot I^{\beta_1} \cdot L^{\beta_2} \cdot \exp(\beta_3 \cdot R + \beta_4 \cdot a_y rate + \beta_5 \cdot j_x rate)$$

where β_i are regression parameters, estimated by generalized linear modelling in IBM SPSS.

In the first step (developing a traditional model), curve radius was not found to be statistically significant. Both exposure variables (traffic volume and curve length) were significant at approx. 80% confidence level (i.e., $p < 0.2$).
Since a_y- and j_x-rates may be related to traffic volume (I), we checked their correlation. Pearson's correlation coefficients were between 0.2 and 0.3, which indicates "little if any correlation" (Hinkle et al., 2003). Therefore, in the second step (developing a combined model), both exposure (I and L) and rates could be used as independent explanatory variables. Given the small sample size and exploratory character of the study, we decided to accept even lower significance than commonly used 95% levels. Parameters of both models are reported in Table 2. Achieved significance levels included values up to 0.3 (i.e. 70% confidence, as experienced also in other studies, e.g., Turner et al., 2012). Table 2 also lists the goodness-of-fit measures: overdispersion parameter and proportion of explained systematic variation (also known as Elvik's index; Fridstrøm et al., 1995).
All regression coefficients have positive values; i.e., the variables are positively associated with crash frequency. In terms of goodness-of-fit, the combined model seems to outperform the traditional one. This is indicated by the decreased overdispersion parameter value, and increased proportion of explained systematic variation.

5. Discussion and conclusions

Our objective was to explore the possibility of deriving and validating a FCD-based indicator to be used as a surrogate measure of horizontal curve safety. Firstly, using crash rate and pivot tables, we identified critical thresholds of lateral acceleration ($a_y = 0.3$ g) and longitudinal jerk ($j_x = 0.1$ g/s). Secondly, we calculated the proportion of sampled vehicle trips exceeding these cut-off values in each curve-direction, and used it as an explanatory variable. Compared to traditional model, it helped improving the goodness-of-fit.
However, we are aware of several following limitations:

– The studied sample was very small. Also number of drives through each curve was relatively low. This limited possibility of more detailed analyses, for example distinguishing among individual vehicles, curve types, etc.
– The fact that FCD data was collected from company vehicles may have influenced the obtained information.
– For model development, only the traditional explanatory variables were used (traffic volume, length, radius). Future analyses could exploit also other parameters, such as skid resistance, superelevation or vertical alignment characteristics.
– In the developed models, most variables had a lower level of achieved statistical significance, probably due to limited sample size. Nevertheless, the signs of regression coefficients indicated the expected positive associations.
– The two applied goodness-of-fit measures indicated that adding the kinematic parameters as explanatory variables helped improve the model quality. However, it is difficult to find a comparable reference to judge the absolute importance of the reported goodness-of-fit changes. In addition, similar studies, where surrogate safety measures were incorporated into models, used different goodness-of-fit measures (Saleem et al., 2014; So et al., 2016; He et al., 2018).

Table 2. Parameters of the developed safety performance functions

Traditional model				**Combined model**			
Variable	**β_i**	**SE**	**Sig.**	**Variable**	**β_i**	**SE**	**Sig.**
β_0	–5.222	3.105	0.093	β_0	–9.286	4.737	0.050
Ln (volume)	0.414	0.320	0.195	Ln (volume)	0.585	0.443	0.187
Ln (length)	0.370	0.245	0.132	Ln (length)	0.837	0.420	0.046
				a_y-rate	1.746	1.703	0.305
				j_x-rate	4.871	3.742	0.193
Overdispersion	0.237			Overdispersion	0.117		
Syst. var. expl.	70%			Syst. var. expl.	79%		

Note: β_0 – regression constant (intercept); β_i – regression coefficients; *SE* – standard error; *Sig.* – achieved level of statistical significance.

Nevertheless, the exploratory study enabled answering two initial research questions:

1) *What is the cut-off value of FCD-based kinematic characteristics for assessing hazardous curves?* The first analysis (section 4.1) identified cut-off of lateral acceleration ($a_y = 0.3$ g) and longitudinal jerk ($j_x = 0.1$ g/s).
2) *Can the proportion of these hazardous events help in explaining the safety performance?* In the second analysis, risk rates (i.e., percentages of vehicles exceeding the risk thresholds when negotiating the curves) were used as additional explanatory variables, which helped improving quality of the combined safety performance function.

To sum up, this study outlined a practical approach to proactive evaluation of road curve safety using FCD data. Lateral acceleration and longitudinal jerk were found to be the most influential measures of curve safety performance. A practical application of the developed method would be proactive safety assessment of rural curves based on available FCD data. Another potential application would be in conducting interim evaluations of curve road safety treatments (e.g. signs, delineation, etc.). Acceleration and jerks can be measured before and after treatment is implemented, and/or compared with control sites, and an estimated crash reduction factor can be estimated. This would enable monitoring and early intervention for treatments appearing to fail to deliver safety benefits. Other applications may include in-vehicle monitoring devices for detection of potentially unsafe manoeuvers and providing real-time feedback to drivers based on a combination of identified safety thresholds.

This exploratory study found that FCD data can generate useful surrogate measures of curve safety (acceleration and jerks) associated with crash history on rural curves. It is recommended to validate the approach by testing on larger samples (in more curves, from a broader vehicle fleet, in a longer time frame…). The results may help fill the gap in evidence-based studies on proactively evaluating road curve safety.

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