Detecting Deviation from Normal Driving Using SHRP2 NDS Data

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ABSTRACT
Normal driving is naturally the first stage of the crash development sequence. Investigating normal driving can be proved useful for comparisons with safety critical scenarios and also crash prevention. The better we understand it, the more effectively we can detect deviations and stop them before they culminate in crashes. This study utilises Naturalistic driving data from the Strategic Highway Research Program 2 (SHRP2) to look into normal driving scenarios. Indicators' thresholds were assumed with influence by the literature and then the values were validated based on real world data. The paper focuses on the methodology for deriving indicators representative of baseline, uneventful driving. With the approach that is presented here, reliable thresholds for variables can be introduced, capable of detecting the deviation on its very early onset.

Keywords: Naturalistic driving studies, normal driving, SHRP2 data, crash progression, indicators, threshold validation

INTRODUCTION

More than 1.25 million people die each year from road traffic crashes worldwide *(1)*. Despite the fact that the situation has been significantly improving in Europe relative to other regions, traffic crashes and their outcomes constitute an extremely serious social problem. As a result, there has been a massive development of new sensors and systems aiming to address the negative impacts of transport on society in relation to safety, congestion and fuel economy. More specifically, the automotive industry, together with the universities, has been developing "intelligent" vehicles for the purpose of enhancing road safety. One of the fundamental functions of such a safety system is to detect hazardous situations and safety critical events and intervene automatically before they result in unwanted mishaps *(2)*.

Traditionally, road traffic safety analysis has relied mostly on crash statistics as the main data source. Over the years, however, numerous problems associated with crash data have been widely documented *(3)*. The most important aspects are: (i) crashes are under-reported, and (ii) the information on pre-crash traffic conditions and the behavioural aspects of road users are rarely available.

Therefore, different surrogate safety measures have been employed to better understand the complex mechanism of crash occurrence *(4)*. *Safety critical events (SCE)* from normal driving conditions (i.e. an event where a crash is about to happen but does not actually happen due to an intervention either by a human or a system) constitute one of these measures *(5)*.

Detecting SCE and investigating them in an effort to understand the evolution of the crash process would likely lead to the reduction of crashes. More specifically, a vehicle-based system that could automatically detect the deviation from normal driving by examining real-time kinematics data and prevent it in the first stage of the crash development process, before it culminates in a crash, could be fundamentally beneficial to road safety since collision risks in normal driving are lower than in emerging situations *(6)*. This is challenging as fundamental research efforts are required for in-depth and substantial understanding of normal driving.

Despite the fair existence of studies about unsafe and risky driving, there is a lack of definition of *normal driving*. While several studies refer to criteria in order to detect SCE and hazardous situations during normal driving, there is inadequate research about normal driving itself. Moreover, the starting point of the very initial deviation from normal driving, the manner that this can be measured using the variables that characterise normal driving and how this measurement changes within the stages of the crash development are rarely investigated.

Fundamental questions remain: what do we really mean with the term normal driving? How can we define and measure (in quantitative terms) normal driving? Olson et al. *(7)* refer to the normal driving as "baseline, routine and uneventful" driving. Similarly, Klauer et al. *(8)* calculate the risk due to distractions in safety critical events and in "normal, baseline driving". Normal is defined as something usual, typical, standard, ordinary or conventional *(9)*, but how could this be quantified? What are the acceptable kinematics of a typical driving scenario and how much does it depend on specific operational conditions? The benefits of answering these questions are two-fold: first of all, an understanding of normal driving is essential in order to effectively detect the onset of hazardous situations so as to prevent crashes. Secondly, since (semi)autonomous vehicles are expected to be introduced in the market shortly, there has to be an in-depth inquiry regarding their adaptation to meet driving styles and comforts of different users. There is dearth of research in this area and this paper therefore constitutes an attempt for understanding and quantifying normal driving through naturalistic driving studies (NDS).

LITERATURE REVIEW

The purpose of this review was to synthesize existing studies on the crash development process as well as to identify indicators representing baseline driving. This leads to the knowledge gap in the approaches for detecting the onset of deviation from normal driving.

Crash development sequence

Researchers investigated the correlation between several factors associated with the development of a crash. This enabled the implementation of methods aiming to avert and control crashes at various points within the crash development *(10).*

Partitioning the crash sequence is important not only because intricate crash causation can be untangled, but also effective prevention strategies can be suggested *(11)*. Tingvall et al. *(12)* documented the so-called integrated safety chain where the system was designed backwards from a possible event. The chain included four stages starting from the deviation from normal driving, continuing with the emerging situation, critical situation and concluding to the stage where crash event is unavoidable. Figure 1 shows a visual representation of the crash development stages.

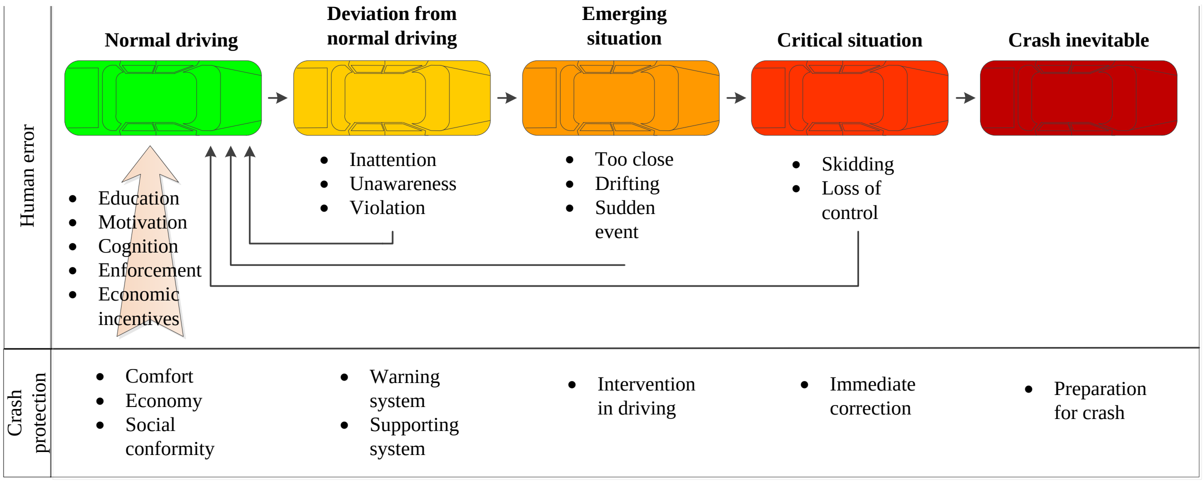


FIGURE 1 Stages of the crash development (adapted from *(12)*)

Investigating the normal driving conditions could be the key for detecting hazardous situations at their onset in a very early stage of the crash sequence. Hence, the crashes or at least their consequences could be mitigated. While the connection between the crash contributing factors at different stages is poorly understood, due to incomplete and inaccurate pre-crash information, NDS seem to provide a deep insight on the crash progression.

Naturalistic Driving Studies (NDS) as a subject of crash development investigation

NDS are based on a wide ranging collection of data regarding the driver, the vehicle, and the environment and these data sets enable researchers to understand the development of a crash or near-crash and their investigation. Dingus et al. *(13)* provided a definition of naturalistic as "Unobtrusive observation; observation of behaviour taking place in its natural setting" whereas Pande *(14)* referred to it as the data derived from observing 'natural' driving behaviour.

Through naturalistic driving datasets, it is possible to examine the different stages of the crash development that include the pre-crash, the during-crash, and the post-crash phase.

Recent research has exploited NDS data for: (i) crash surrogate analysis, (ii) crash risk analysis using crash surrogates, and (iii) crash sequence analysis *(11)*.

Data from NDS have been successfully applied to analyse road safety issues using different statistical or other methods. Dozza & González, *(15)* stated that automatic video processing can significantly help in recognizing SCE from extensive video data. On the contrary, Wu and Jovanis *(16)* claimed that with a statistical multi stage modelling framework it is possible to screen and define SCE without any video screening. Furthermore, Dozza et al. *(17)* developed a method for NDS data analysis called chunking where the data is divided into equivalent segments in order to provide robust parameter calculation and increase statistical sensitivity.

On a driver level analysis, Wu et al. *(18)* found that young drivers have more possibilities to get involved in crashes or crash-related events. One method to identify high risk drivers is the detection of critical jerks (i.e. hard braking) as Bagdadi *(19)* referred to an association between the frequency of the critical braking events and crash involvement. By taking into account the vehicle mass and the relative speed of the vehicles, the severity of an event can be also estimated *(20)*. Similarly, Zheng et al. *(3)* found that the speed at the onset of braking has a strong relationship with near-crash events. Therefore, driving speed at the time of braking plays an important role in the progression of a SCE. Later, Wu & Thor *(11)* developed an approach (termed as a safety frontier concept) for comparing and dissecting the differences in the crash sequence that lead to different outcomes. Last but not least, Jovanis & Wu *(21)* presented a flexible exposure-based analysis structure that can include driver, event and environment characteristics and detect baseline hazards.

Indicators for normal driving

A range of different indicators were used to measure the driving risks and possibly detect imminent hazardous situations. These primarily include: braking, longitudinal acceleration, lateral acceleration (left and right) and time-to-collision (TTC). Dingus et al. *(13)* examined a number of indicators and found that forward TTC has a high false alarm rate. The best overall indicator was found to be longitudinal acceleration.

TTC distributions have been applied in several studies (e.g. *(32)*) to pinpoint traffic safety impacts *(33)*. There is still no general agreement among researchers regarding the critical value of TTC although a few studies suggested a value of 1.5 seconds as a threshold *(34)*. It is envisaged that this indicator would also play a significant role in detecting any deviation from normal driving.

The standard deviation of the lateral position (SDLP) within a driving lane is one of the most prevalent performance metrics, and describes the degree of driver's vehicular control independent of driving condition. A typical standard deviation of lane position for baseline driving is just under 0.2 m, approximately 0.18 m for driving on the road and approximately 0.23 m for simulators (*35*).

There are many indicators that could characterise driving and have been also used in several naturalistic driving studies in order to identify events in the latest stage of their progression. However, the comprehension of normal driving patterns that will constitute the basis for detecting any hazards in an early stage of an event development remains a challenge. This study will attempt to fill this gap.

METHODOLOGY

The main purpose of this study is to identify a range of indicators and validate their thresholds so as to detect a deviation from normal driving. It is also important to see whether the thresholds are consistent across different operational conditions (e.g. speed, traffic density) and driver groups (e.g. male vs female and young vs other drivers). For these purposes, a methodology consisting of four steps is developed. This is briefly explained below:

Step 1: Identify indicators that can be used to detect the deviation from normal driving;
Step 2: Determine threshold values of the variables (as identified in Step-1) by exploiting the values from existing studies. These can be termed as 'Initial Thresholds'. It is apparent from the literature that a combination of variables needs to be considered;
Step-3: Examine whether the 'Initial Thresholds' are applicable in detecting the deviation from normal driving: This is a challenging task and one of the best ways to achieve this task is to employ NDS data. This has three sub-tasks:

Step-3(i): Obtain NDS data (SHRP 2) and identify 'normal driving' (using the definition in the literature);

Step-3(ii): Analyse the data to calculate real values of the indicators from normal driving;

Step-3(iii): Examine whether the thresholds are consistent across different driver groups (male vs female; young, middle-aged and older; etc.). This may require the use of non-parametric tests.

Step – 4: Modify the "Initial Thresholds" based on the findings in Step-3.

Step-1: Identification of indicators

The first step is to identify variables that can characterise normal driving. Some of the aforementioned variables utilised in different studies can be employed to trigger a SCE flag. The kinematic search criteria used in those studies for the identification of SCE are summarised in Table 1 below. The criteria used in previous studies can provide a useful basis for determining the corresponding thresholds for normal driving.

Step-2: Determination of Initial Thresholds

It is noticeable that the identification of a safety critical event is not dependant on a single indicator rather a combination of different indicators. The use of multiple indicators would certainly increase the overall correct detection rate of critical events by increasing the discrimination power. Likewise, the detection of normal driving would also require similar indicators, perhaps with different threshold values (see Figure 1).

For instance, it can be seen from Table 1 that the TTC values for the case of a safety critical event (SCE) is generally assumed to range from 1.75 seconds to 2 seconds. The initial threshold value of TTC to represent normal driving can be expected to be equal or more than 2 seconds. However, the threshold value varies as it depends on other indicator values as well, i.e. speed or yaw rate. Longitudinal deceleration triggering values randomly fluctuate from -0.2g to -0.65g varying with the speed of the ego-vehicle. The range is large and therefore it is difficult to find a fixed threshold. It however seems that the value for normal driving deceleration should not often exceed -0.6g. Likewise, lateral acceleration values vary from 0.25g to 0.7g and reported to depend on travelling speed of the ego-vehicle. Based on Table 1 and these arguments, the following conservative values are proposed as Initial Thresholds:

- TTC $\geq$ 5 seconds;
- Longitudinal deceleration $\geq$ -0.5g;
- Longitudinal acceleration $\leq$ 0.5g;
- Lateral acceleration (left or right) $\leq$ 0.65g or $\geq$ - 0.65g;

Threshold values for the yaw rate were provided in different units in the literature. It was therefore difficult to identify a threshold value for this variable. .These values are considered to be the first attempt in quantifying normal driving without currently taking into account all the operational conditions, e.g. different speeds and road networks.

Table 1 Kinematic search criteria for Safety Critical Events (SCE)

Study	Longitudinal acceleration (g)	Lateral acceleration (g)	Yaw rate (°/s) or Swerve (°/s^2)	Time-to-collision (sec)
100-car study *(13)*	< - 0.6 & > 0.6	> 0.7	⩾±4° (within 3 sec time window)	TTC_{front} ⩽ 4 TTC_{rear} ⩽ 2
Dacota NDS *(22)*	< - 0.25	> 0.25	n/a	n/a
DDWS FOT *(23)*	⩽ - 0.35 when u*⩾24km/h ⩽ -0.5 when u<24 km/h	n/a	⩾171.9 °/s^2 when u⩾24km/h	TTC_{front} ⩽ 1.8 when u≥8km/h, yaw rate ≤│4°/sec│, & azimuth ≤│0.8°│
Driver Distraction in Commercial Vehicle Operations *(7)*	⩽ - 0.2 when u⩾ 1.6 km/h	n/a	⩾114.6 °/s^2 when u⩾8km/h	TTC_{front}⩽2 when u≥8km/h, yaw rate ≤│6°/sec│, & azimuth ≤│0.12°│
EuroFOT *(24)*	⩽ - 0.6 when u < 50 km/h ⩽(-0.4-0.6)*((u-50) /100) – 6 when 50 ⩽u⩽150km/h ⩽ -0.4 when u>150km/h	(0.7-0.25)*(u/40) +0.25 when u<40km/h > 0.7 when 40⩽u⩽50km/h (0.4-0.7)*((u-50)/50) +0.7 when 50<u⩽100km/h >0.4, u>100km/h	>50 when u< 40km/h (25-50)*((u-40) /10)+50 when 40⩽u ⩽50km/h (15-25)*((u-50) /35) +25 when 50<u⩽ 85km/h >15 whenu>85km/h	TTC<1.75
Naturalistic Teen Driving Study *(25)*	⩽ -0.65	⩾ 0.75	⩾ ±4°/s (within 3 sec time window)	TTC_{front} ⩽4
Naturalistic Truck Driving Study *(26)*	⩽ - 0.2 when u⩾1.6 km/h	n/a	⩾114.6 °/s^2 when u⩾8km/h	TTC_{front}⩽2 when u≥8km/h, yaw rate ≤│6°/sec│, & azimuth ≤│0.12°│
Teen driver study *(27)*	⩽ - 0.5	⩾ 0.54	n/a	n/a
U DRIVE NDS	⩽ - 0.2	n/a	n/a	n/a
SHRP2 NDS *(28)*	⩽-0.65 & ⩾0.5	⩽-0.75 & ⩾0.75	±8°/s (within 0.75sec time window)	n/a

(*u= the speed of the ego-vehicle) (Adapted from *(29)*)

Step-3: Validation of the Initial Thresholds

In order to validate the initial thresholds presented above, one of the best ways is to examine NDS data. For this purpose, comprehensive NDS data collected as part of Safety Highway Research Program 2 (**SHRP2**) naturalistic driving study were obtained through Virginia Tech Technology Institute (**VTTI**). This rich dataset provides many variables that can be used to determine the threshold values of the indicators.

Data preparation

SHRP2 data were obtained from VTTI in the form of four datasets: (i) Time series (i.e. highly disaggregated kinematic data for the ego-vehicle), (ii) Demographic questionnaire of the driver, (iii) Event detailed and (iv) Event ID data key. As the anonymous Demographic questionnaire table and Event ID data key table both include the Participant ID variable, they were the first datasets to be merged. Then, using the File ID as a common point, the Time series table and Event detailed table were also merged into the initial data table to form an aggregated dataset for analysis.

All data was anonymous and strict data protection protocols were followed. Each set of time series data culminated in a SCE or collision and the data for the prior two minutes were requested. For the purposes of this study, only the first minute data of these two minutes of every event were selected and used as representative of the drivers' baseline driving. Given that the crash development lasts for a few seconds, 60 seconds before the event (data from 2 minutes time prior to the event until 1 minute before the event) are safely considered to be uneventful, *normal driving*. However, some events happened on the very start of the trip before the end of two minutes period. These events were excluded.

As most of the variables in time-series data had a sampling frequency of 10 Hz, 600 observations of every event was taken and merged in a final large dataset of 1,084,802 observations representing normal driving scenarios for 979 drivers involved. This dataset gathers data from 1,808 events consisting of 1,420 near-crashes and 387 crashes.

Thresholds across different driver groups

It should also be noted that driving style varies by gender, age, culture and other operational conditions. Therefore, it would be interesting to see how the distributions of the values identified in Step-2 change with these factors. Composite variables of gender and age were computed in order to investigate whether the thresholds are consistent across different geo-demographic profiles, i.e. young drivers and old drivers, males and females, etc. It is believed that the values of a specific indicator, for instance, TTC, would not necessarily be normally distributed. Therefore, two non-parametric tests are employed:

- Mann-Whitney two-sample statistic (also known as the Wilcoxon rank-sum test): this test examines the hypothesis that two independent samples (unmatched data) are from populations with the same distribution *(30), (31).*
- Median performs a nonparametric *k*-sample test on the equality of medians. It examines the null hypothesis that the *k* samples were drawn from populations with the same median.

Step 4: Modification of the Initial Thresholds

The results of the analysis in Step-3 would provide important information whether the initial thresholds need to be modified. It is envisaged that thresholds may vary by the socio-demographic conditions of the drivers. In this task, thresholds will be modified based on the findings in Step-3.

ANALYSIS OF SHRP2 NDS DATA

Data prepared in Step-3 represent over 1 million observations of normal driving from 979 drivers who made over 1,808 trips. These data were analysed to identify threshold values for the key indicators that can be employed to detect the deviation from normal driving. These include: time-to-collision (TTC), longitudinal deceleration (i.e. braking), longitudinal acceleration, lateral acceleration and yaw rate.

Time-To-Collision (TTC)

This is perhaps one of the most important and possibly the most complex indicators used in existing studies to identify a safety critical event. TTC is a continuous variable and it can be calculated for any moment as long as the road users are on the collision course.

TTC is not recorded as a variable in the SHRP2 NDS data that we received. There are however a large number of relevant variables that could be employed. More specifically, the sensor platform within an ego-vehicle is capable of simultaneously tracking up to eight different targets that the ego-vehicle encounters within its radar field of view (range ~ 250m). Each of the targets is individually tracked as Track 0 through 7. With the raw radar variables, these tracked objects can sometimes switch across different tracks making the calculation of TTC difficult. To resolve this, a post-processing method was developed by VTTI in order to ensure that that the same target is being tracked consistently. This is to identify cases where the target vehicle is moving to different lanes while in front of the ego-vehicle or if another new vehicle comes into the radar's field of view. These post-processed range and relative velocity values were used in this study to calculate TTC for which the following process is developed and adopted:

1. Identify whether the ego-vehicle and a target vehicle are stationary;
2. Determine the lead target vehicle from the distances between target vehicles and the front bumper of the ego-vehicle, projected onto the x-axis (longitudinal) of ego-vehicle. The target vehicle with the smallest distance was identified as the lead vehicle;
3. TTC was calculated only if the lead vehicle was identified to be in the same lane of the ego-vehicle. This results in the calculation of minimum TTC (min TTC)
4. Finally, the travel direction of the lead vehicle was identified and TTC was calculated only if the travel direction of the lead vehicle is known or the target is traveling in the opposite direction in relation to the ego-vehicle at the time of first detection and also at all other times that the object is being tracked. It should be noted that the direction of the target was not known for about 70% of the cases in the sample data.

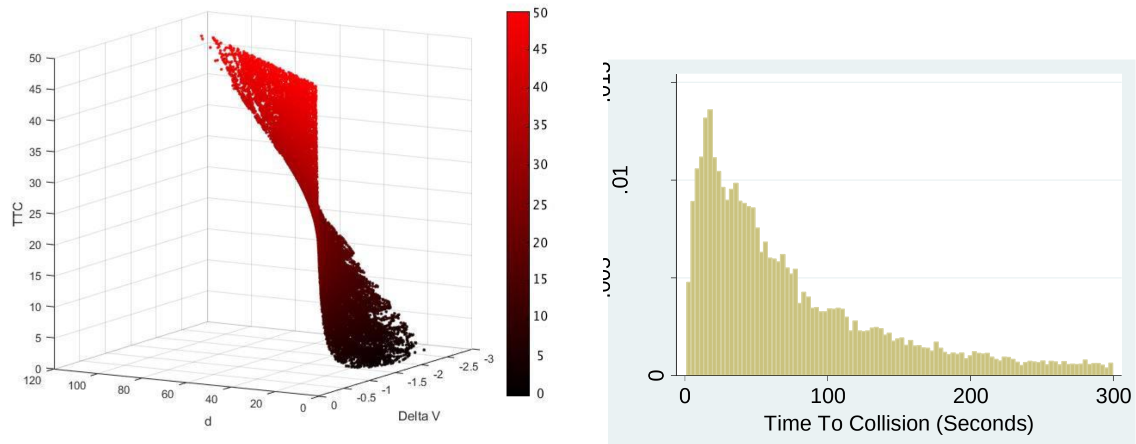
After completing the above process, a new dataset has been created containing only 139,410 observations (about 13% of the total observations initially obtained from the VTTI; these observations represent 1,033 trips, 683 drivers and 689 vehicles) suitable for calculating TTC. This is calculated as follows:

$$TTC_{ld} = \frac{d}{V_t - V_e} = \frac{d}{\Delta\vartheta} \qquad (1)$$

In which: TTC_{ld} is the TTC between the ego-vehicle and the lead target vehicle travelling in the same lane and direction in relation to the ego-vehicle, V_t is the speed (in m/sec) of the lead target vehicle, V_e is the speed of the ego-vehicle, d is the distance (in m) between the lead target vehicle and the front bumper of the ego-vehicle, projected onto the x-axis (longitudinal) of ego-vehicle, $\Delta\vartheta$ is the x-axis (longitudinal) component of range rate (relative velocity) between the lead target and the ego-vehicle. $\Delta\vartheta$ can be directly obtained from the SHRP2 NDS data.

The key values of TTC derived from the dataset are shown in Figure 2:An examination of the calculated TTC values along with the corresponding d and $\Delta\vartheta$ revealed that the primary reasons for some small values of TTC relate to: (i) low values of d (when d<2m), perhaps representing the scenarios when both the ego-vehicle and the target vehicle about to stop at a traffic light or a junction and (2) $\Delta\vartheta$ is large with a relatively small d value; this represents the scenario when the speed of the target vehicle is higher than that of the ego-vehicle at a reasonable space distance between them. The relationship between them is presented in Figure 2(a).

At a particular instant two vehicles are actually considered to be in a collision course if the speed of the ego-vehicle (i.e. the following vehicle) is higher than the speed of the lead target vehicle i.e. $\Delta\vartheta < 0$. Therefore, the conditions applied to obtain reliable values for TTC are: (i) d is larger than 2m and (ii) relative speed ($\Delta\vartheta$) less than 0. This results in a total of 49,739 (only 4.6% of the original data obtained from the VTTI) valid TTC observations which have then employed for further analysis. Some of the TTC values are really large (due to very small $\Delta\vartheta$ and relatively large d indicating that they are in a collision course.



(a) Relationship between d, $\Delta\vartheta$ and TTC *(b) Distribution of TTC (when TTC<300)*

Figure 2 Characteristics of TTC from NDS data

From the final dataset, it was found that TTC was higher than 1.9 seconds for at least 99.9% of the cases. This increased to 3.9 seconds for at least 99% of the cases. The minimum value of the TTC was however calculated to be 1.25 seconds and this was largely due to small d-values (i.e. d was as low as 2m) used in the sample data. The initial threshold value for TTC in detecting any deviation from normal driving was chosen as 5 seconds (See Step-2 in the Methodology section). From this analysis, it has been found that at least 1.8% of the cases have TTC values less than 5 seconds. It has been found that TTC values are related to $\Delta\vartheta$ and d (see Figure 2a). It is therefore very challenging to identify an optimal threshold for TTC and there are other influencing factors. Considering all these factors, it can be concluded that a threshold value of 4 seconds for TTC would provide over 99% confidence level that the corresponding driving may be regarded as ‘normal’.

Non-parametric tests described in the previous section were conducted to examine whether driving behaviours with respect to TTC vary by gender. Both the Wilcoxon rank-sum test and the median test rejected the null hypothesis at the 95% confidence level indicating that their driving behaviours are different. The 1th percentile value of TTC for the female drivers was 2.6 seconds and the same value for the male drivers was 3.1 seconds. Similar results on driving behaviours with respect to TTC were obtained from the same tests for young drivers (16-24) vs other drivers (25+).

Since these scenarios were considered to be 'normal driving in the NDS data, it can be concluded that identifying a single threshold value for TTC is very challenging as this largely depends on other factors.

Longitudinal acceleration-deceleration

Longitudinal acceleration constitutes maybe the most popular kinematic criterion for detecting safety critical events from NDS data. It is recorded as variable in the SHRP2 data; therefore it does not need any additional calculation. The variable presents only 0.5% of missing data, so the analysis was contacted for 1,076,800 observations. In this paper, negative values of this variable are deceleration and the positive ones are acceleration.

From the descriptive analysis of the deceleration and acceleration, we observe that the means are almost equal in an absolute value and close to zero (±0.05). This means that there are almost equally negative and positive values in the sample, so about the same number of decelerations and accelerations events as expected. It is obvious that from the means, it is not possible to make conclusions about the range of the indicators' values.

Examining the percentiles though for the deceleration, we can see that 99.9% of the cases are higher than -0.39g (less negative) while the minimum value reaches -0.75g. However, further investigation reveals that values under -0.5g represent only the 0.018% of the total deceleration values. Regarding the acceleration, 99% of the cases were under 0.25g while the maximum value was 0.52g.

In order to evaluate the differences in distribution of the longitudinal acceleration and deceleration variables between the gender and the age groups, the aforementioned non-parametric tests were conducted. The tests showed that the distribution of both differs in a statistically significant way (95% confidence level) across the categories of age group (16-24, 25+) and the gender. This indicates different acceleration-deceleration patterns between the male and female and between the younger and the other drivers. More specifically, the 0.1^{th} percentile deceleration value was -0.43g for the younger drivers and -0.38g for the other age group, implying that younger drivers brake harder.

Lateral acceleration

Lateral acceleration appears also as a recorded variable in SHRP2 NDS dataset. The results of the descriptive analysis showed that, 99% of the cases are below 0.2g and 99.9% of them are higher than -0.4g. The minimum value is -0.84g, but occurred only once in the dataset and just 6 observations were under -0.65g. The maximum value is 0.68g representing only one case exceeding the 0.65g threshold.

The non-parametric tests reveal that this variable also differs regarding its distribution across the gender and the age groups of the drivers. The 0.1^{th} percentile value was -0.43g for the younger drivers and -0.35g for the others whereas -0.42g and -0.37g was for females and males correspondingly.

Step – 4: Modify the Initial Thresholds based on the findings in Step-3.

The initial thresholds of selected variables were presented according to: a) the thresholds employed in several NDS and b) reasonable assumptions. After the analysis conducted in Step-3, based on SHRP2 NDS data, we are in a position to propose the modified, final thresholds of indicators representing normal driving.

Based on the analysis in Step-3, it is apparent that these indicators depend on many factors and therefore it may be difficult to identify a fixed threshold representing all conditions. In order to elucidate this argument, a 0.1^{th} percentile (except acceleration for which it is actually 99.9^{th} percentile) values of these indicators were derived for different speeds of the ego-vehicle. For example, the 0.1^{th} percentile value of TTC for speed between 40 km/h to 50 km/h is 3.11 seconds indicating that at least 99.9% of the TTC values in the sample are greater than 3.11 seconds. Min TTC changes with speed without a clear trend. Both acceleration and deceleration show a clear pattern. Lateral acceleration indicates random fluctuations.

Table 2 Indicators vary by speed of the ego-vehicle

Speed bin (km/h)	TTC (sec)	Acceleration (g)	Deceleration (g)	Lateral acceleration (g, Left)
0 - <=10	1.27	0.40	-0.37	-0.25
10 - <=20	2.35	0.40	-0.44	-0.39
20 - <=30	1.68	0.35	-0.46	-0.49
30 - <=40	2.43	0.34	-0.45	-0.53
40 - <=50	3.11	0.31	-0.41	-0.39
50 - <=60	3.99	0.26	-0.40	-0.31
60 - <=70	5.24	0.24	-0.35	-0.30
70 - <=80	1.51	0.20	-0.31	-0.28
80 - <=90	7.52	0.19	-0.34	-0.30
90 - <=100	2.14	0.17	-0.29	-0.28
100 - <=110	5.30	0.14	-0.29	-0.19
110+	3.49	0.14	-0.28	-0.23

Based on the findings shown in Table 2, it is recommended that a functional equation should be employed to determine a threshold value for an indicator. These are developed as follows:

Indicator	**Functional forms**	**Goodness-of-fit (R^2)**
Time to collision:	$TTC_{th} = \exp(0.5641 + 0.008352\ \text{Speed})$	0.30
Acceleration:	$Acc_{th} = 0.4203 - 0.0026\ \text{Speed}$	0.98
Deceleration:	$Dec_{th} = -0.4587 + 0.001549\ \text{Speed}$	0.70
Lateral acceleration:	$LAcc_{th} = -0.4328 + 0.00174\ \text{Speed}$	0.4

In summary, it can be concluded that a detection of any deviation from normal driving would not only require the simultaneous measurements of multiple indicators but also the different threshold values per indicator based on traffic conditions and driver demographics. A multivariate analysis utilising vehicle kinematics data for related to normal driving as well as safety critical events is therefore needed to identify the difference in thresholds within and across these indicators. Any future study shall also consider other indicators such as time headway and yaw rate.

CONCLUSIONS

Normal driving is a really broad concept to comprehend and investigate, but this paper has taken a step further in our understanding of driving and the difference in driving patterns between gender and age group. It will contribute to an understanding of the variables for characterising normal driving in order to model the relationships between them and provide a basis for investigation of different driving style patterns in different environments and situations. Moreover, this will introduce a new approach in detecting deviation from normal driving. The deeper the knowledge about it, the more effective detection systems will be developed. Future research can include more variables, i.e. time headway and lateral position and can be also enriched with driver clustering on different characteristics than demographics.

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