Analyzing and Modelling Drivers' Deceleration Behaviour from Normal Driving

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ABSTRACT

Most research in vehicle automation has mainly focused on the safety aspect with only limited studies on occupants' discomfort. In order to facilitate their rapid uptake and penetration, autonomous vehicles (AVs) should ensure that occupants are both safe and comfortable. Recent research however revealed that people felt uncomfortable when AVs braked. This may be due to their robot-like braking performance. Existing studies on drivers' braking behaviour investigated data either from controlled experiments or driving simulators. There is a dearth of research on braking behaviour in normal driving. The objective of this paper is therefore to examine drivers' braking behaviours by exploiting naturalistic driving data from the Pan-European TeleFOT (Field Operational Tests of Aftermarket and Nomadic Devices in Vehicles) project. On a fixed route of 16.5km long, 16 drivers were asked to drive an instrumented vehicle. A total of about eleven million observations were analysed to identify the profile, value and duration of deceleration events. Since deceleration events are nested within trips and trips within drivers, multilevel mixed-effects linear models were employed to develop relationships between deceleration value and duration and the factors influencing them. The results indicate that the most used profile of the deceleration behaviour follows a hard braking at the beginning when detecting a danger and then becomes smoother. Furthermore, they suggest that the speed, the reason for braking and the deceleration profile mostly affect the deceleration events. Findings from this study should be considered in examining the braking behaviour of AVs.

INTRODUCTION

Research on autonomous vehicles (AVs) has attracted a significant interest from the research community worldwide in recent years. Fundamentally, vehicle automation aims to eliminate or decrease human involvements from the routine tasks of driving *(1)*. Ensuring human-like driving performance is however a basic condition for the wide acceptance of (semi)autonomous vehicles *(2)*.

Despite the remarkable research and development progress in the area of (semi)autonomous vehicles over the last decade, there is a concern that occupants may not feel comfortable due to the unnatural driving performance of the current technology which sometimes differs from the average human driving *(2)*. Driver comfort is understood as a state which is achieved by the removal or absence of uneasiness and distress. Even though many factors may affect driver's comfort (such as lateral and longitudinal acceleration, time headway etc.), one of the most important is the braking. In other words, a (semi)autonomous vehicle should decelerate in the style which could avoid mental discomfort to the people both inside and outside of the vehicle. Regarding the braking performance, stress and nervousness are apparent if the timing at which the vehicle automatically brakes differs from the driver's own judgment or whether the level of deceleration is greater than the driver's expectation or the deceleration profile does not follow the one that the driver is used to *(3)*. It is therefore imperative to fully understand drivers' braking behaviour with respect to the level of braking, the duration of braking and the deceleration profile in the context of normal driving.

It should however be noted that hard deceleration is sometimes necessary in the case of emergency situations in order to avoid a collision. As a result, passenger tolerance to longitudinal deceleration would influence the design of the vehicle's braking system *(4)*. An efficient approach in designing (semi)autonomous vehicle would be to monitor and identify how human drivers perform the driving tasks and then analyse and characterise such behaviours with the aim of developing various thresholds so as to implement them into the system *(5)*. Vehicle automation with respect to braking is then possible to be designed in such a way that it emulates human behaviour.

This paper therefore focuses on the analysis of the deceleration events observed within *normal driving* with the aim of identifying the braking behaviours under different driving and operational conditions. The definition of normal driving is 'subjective' and there is no generic one in the literature. Moreover, perceptions of normal driving differ from country to country. In this paper, normal driving means that the drivers execute the driving tasks under 'normal' driving conditions i.e. the absence of any safety critical events such as 'near misses' or 'crashes'. In particular, the paper aims to develop a statistical relationship between braking patterns, human factors, traffic and road network conditions. The purpose of this analysis is to inform vehicle manufacturers about the deceleration behaviour observed during normal driving so as to ensure comfortable and safe braking operations.

The rest of the paper is organised as follows: firstly, the existing literature and its main findings are reviewed. This is followed by a presentation of the data used in the analysis. After that, the estimation of the deceleration profile and the statistical analysis are presented and the results are discussed. Finally, the last section summarises the main conclusions of the study.

LITERATURE REVIEW

The analysis of the braking behaviour has gained attention in the literature over the past decades. A braking event is normally described using the deceleration value, the speed at the beginning and at the end of the event, the perception/reaction time and the duration *(6)*. The aim of this review was to synthesise existing studies on drivers' braking behaviour and identify thresholds related to comfortable braking performance. A gap in knowledge was also identified.

Braking behaviour was studied during the design and implementation of Adaptive Cruise Control (ACC). It is perhaps the most studied feature of advanced vehicle systems *(1; 5; 7)*. Goodrich et al. *(5; 7)* tried to identify the braking behaviour and apply the results to the design of ACC. In both studies a driving simulator and a controlled test track were used. The braking behaviour was characterised by the perceptual trajectory using time-to-collision (TTC) versus time headway. In their first study Goodrich et al. *(5)* conducted a series of experiments from which they concluded that in order to produce a comfortable performance, ACC designers need to develop controllers that emulate a trajectory, which does not violate the smooth counter–clockwise characteristics of the human–generated one. In the second study it was further postulated by Goodrich et al. *(7)* that in order to achieve a human interaction with the ACC system which results in safe and comfortable vehicle dynamics, the automated braking behaviour should match that of a skilled human operator. Consequently, the design and programming of the advanced vehicle system can benefit from a careful analysis of the human actions and the interaction between human and automation.

Some studies have dealt with the factors which affect the braking behaviour (*3*; *8-10*). For instance, Rakha et al. *(8)* conducted a study to analyse field data and to characterise driver deceleration rates at the onset of a yellow-phase transition on high-speed signalised intersection approaches. The study concluded that deceleration rates are sensitive to the roadway grade, the age, and the gender of the driver. In contrast to Rakha et al. *(8)* who examined braking behaviour during normal driving, Loeb et al.'s *(9)* study was conducted in a simulator and analysed the differences in emergency braking performance between novice teen drivers and experienced adult drivers. Their results showed significant differences both in performance and quality of braking between novice teens and experienced adults, with novice teens decelerating on average 50% less than experienced adults on the same scenarios, indicating a poor response. Haas et al. *(10)* evaluated driver deceleration and acceleration behavior at stop sign–controlled intersections on rural highways in southern Michigan. Their results seemed to indicate that drivers showed wide variability in rates of acceleration and deceleration and that the initial speed had a strong and statistically significant dependence on the deceleration rate while the other examined factors (e.g. driver demographics and time-of-day) had not. Finally, Kazumoto et al. *(3)* conducted a discriminant analysis on factors which influence the braking behaviour of drivers. The factors were the speed of the following vehicle, the distance between the two examining vehicles, the relative velocity, the TTC, the rate of change of visual angle. They found that the rate of change of visual angle, which is the inverse of TTC, is the most closely related factor to a driver's judgment about when to apply the brakes.

On a more theoretical base, a categorisation of the factors that influence braking behaviour includes driver factors such as awareness, expected/unexpected need of action and experience, vehicle factors, and situational factors such as external environment (i.e. other road users, weather and traffic conditions) *(11)*. Another classification relates to initiating and mediating factors *(12)*. Initiating factors have immediate effect on the driver's comfort and are based on the driver's direct interaction with the system, the environmental cues and the actual risk. On the other hand, mediating factors are more subjective but they may have a greater influence on how the driver feels when the brake is applied. These factors emerge from exposure to a system in conjunction with perceived risks, motivational factors (e.g. willingness to use automation), attitudes/biases (e.g. driving styles, trust in automation, and overall system use) and experiences.

There are some studies focussing on modelling deceleration behaviours. For example, Wu et al. *(13)* examined occupants' comfort during longitudinal deceleration events. They generated a brake comfortable car-following model for longitudinal acceleration considering the friction coefficient between the car and the road surface. Moreover, Chiang et al. *(1)* presented a complete Longitudinal Automation System where it accelerates and decelerates based on the recognized target distance from the detected leading vehicle. In the study by Bennet and Dunn *(14)*, in which driver deceleration behaviour at the exit ramp on a motorway (freeway) in New Zealand was monitored, the deceleration rate was discovered to be proportional to the initial speed such that higher speed drivers decelerate harder over a short period of time. Therefore, they developed equations for predicting deceleration behaviour of vehicles as a function of approach speed and cumulative time.

As mentioned above, one approach to the design of automated systems is to formulate the human behavior and then train the autonomous system to adopt it. For example, in two separate studies, Wada et al. *(1*5-*16)* formulated mathematical models that closely mimic the deceleration patterns of an expert driver, as a proxy for comfortable braking patterns; the difference is that the second study specifically examined the last-second braking. Adopting a similar approach to Wada et al., Lefevre et al. *(17)* developed a learning–based model for the longitudinal control of an AV which goes a step further by reproducing different driving styles from different drivers.

Different thresholds for describing a deceleration event have been used in the literature. For instance, Naito et al. *(18)* and Miyajima et al. *(19)* set a threshold rate of 0.3g (=2.94 m/s^2) for describing and categorising deceleration events in emergency braking. Wu et al. *(13)* set a lower threshold value of 2 m/s^2 for comfortable longitudinal deceleration. In Japan the threshold for detecting deceleration events is usually between 0.2g and 0.4g (i.e. 1.96 m/s^2 and 3.9 m/s^2 respectively) *(18)*. The Institution of Transportation Engineers proposed a threshold deceleration rate of 3.0 m/s^2, while the AASHTO set the threshold for comfortable deceleration at 3.4 m/s^2 *(20)*.

In light of the above literature review, it is apparent that studies on drivers' braking behaviour observed in normal driving are limited. It is unclear how deceleration profiles, values and durations affect the level of occupants' comfort and how they relate to different roadway infrastructure and traffic operational conditions. This study aims to fill in this knowledge gap by analysing drivers' braking behaviour from normal driving.

DATA

The data used in this paper was obtained from the TeleFOT project which is a large scale collaborative European field trial under the seventh framework programme *(21)*. The objectives of the TeleFOT project are related to the safety and mobility as well as economic and fuel efficient driving.

In this study, data from the detailed Field Operational Tests (FOTs) was analysed. Specifically, the sample was composed of 16 drivers (6 males and 10 females) with an average age of 40 years, varying from 23 to 59 years old. Information on the driver (subject number, age, gender, driven miles per year) was reported in the summary sheet of the file. The participants were asked to drive along a specific 16.5 km long route in the Leicestershire area of England, as depicted in Figure 1a, after driving for a couple of hours to familiarize with the car. The route was chosen carefully to have a good mixture of different road elements such as roundabouts, T-junction, cross-junction, traffic light, mid-block crossings and the existence of dynamic obstacles (e.g. other vehicles, pedestrians, cyclists). This was to capture braking behaviours that significantly vary due to the road element. There were 27 trips conducted in which data-logging occurred, as some drivers performed multiple trips.

An instrumented vehicle capable of recording driver behaviour, vehicle kinematics and driving environment (e.g. traffic density, road elements) was employed. Since a single vehicle was used in the experiment, the influence of vehicle related factors (e.g. engine size, vehicle power and braking performance) need not be considered. The vehicle was equipped with four video cameras (forward road view, driver face, backward road view, driver reaction from the passenger seat), GPS, speedometer and accelerometer (see Figure 1b). The sampling frequency was 100 Hz for the duration of the entire trip with an average driving time of 30 minutes per trip. This resulted in a total of 10.8 million observations. The data was processed by software (with a built-in noise filter) developed by Race Technology (Figure 1) *(21)*.

Given the range of data types captured by the instrumented vehicle, it was possible to analyse the deceleration events (i.e. the deceleration value and the duration) based on different influencing factors related to the driver (e.g. age, gender and experience), vehicle kinematics (e.g. the initial speed before the event), traffic (e.g. *low*, *medium* and *high* traffic density) and road infrastructure. Various descriptive statistics were generated to understand these factors. The average deceleration value was found to be -2.42 m/s^2 and the maximum value was -5.17 m/s^2, while the average duration was 2.85 sec and the maximum duration was 23.55 sec.

Speed (m/s), deceleration (m/s^2), GPS coordinates (m), time (s) and video frames were essential for the analysis and were extracted using the Race Technology program. On contrary, traffic density and road environment (road elements) were determined qualitatively by viewing the videos related to the deceleration events.

Most of the deceleration rates observed in this study are relatively low as can be seen in Figure 2(a) and this may be due to the nature of the FOT which reflects driver's normal braking and does not include any safety critical events. Therefore the threshold was set at 2m/s^2 for this study, which is the lowest value found in literature to detect deceleration events.

The beginning of deceleration event is defined from the time onwards where deceleration values are greater or equal to 0.5 m/s^2. That threshold was defined in order to exclude random noise to the actual event, since a deceleration rate which is equal to -0.3 m/s^2 may just be part of normal driving and not of a deceleration event. The Matlab software package R2016a was used for the detection of the deceleration events, which satisfy those thresholds. A total of 574 deceleration events were detected within the data (Figure 2a). The Matlab software was also used to compute the duration of braking events (see Figure 2b), the maximum deceleration rate (m/s^2) and the travelled distance (m) of each event.

For the deceleration events, the average initial speed was 40 km/h (25 mph), with 80% of the events starting at speeds between 5 m/s (11 mph) and 15m/s (33 mph). The mean duration and mean deceleration value for different initial speeds are presented in Figure 2(c-d) and Table 1 and it can be concluded that the higher the initial speed the longer and harder the deceleration event.

As far as the traffic density is concerned, most of the deceleration events (66%) occurred in low traffic density conditions, 29% in medium traffic conditions and only 5% in high density conditions. The mean of the maximum deceleration values for different traffic densities did not indicate that a relationship exists between the observed rates and the traffic density (see Table 1). Moreover it can be noted that gender does not affect the deceleration value but affects the duration as males seem to decelerate in a shorter time than females. Also younger drivers seem to decelerate in a harder way, both greater deceleration value and shorter duration.

The deceleration events for each reason of braking are: 102 for roundabouts, 169 for T-junctions, 50 for cross-junctions, 35 for mid-block crossings and 181 for obstacles. As can be seen from Table 1 the reason for braking affects slightly the deceleration value and more the duration of the event, with the durations for mid-block crossings and dynamic-obstacles being relatively shorter. Finally some influence is noted between the deceleration event and the fact that a road element is signalised or not, which is that for non-signalised road elements the deceleration value is greater than for signalised. Moreover, the mean duration of the deceleration events for the non-signalised elements is smaller indicating harder braking.

METHODOLOGY

Estimation of the Deceleration Profile

The literature review yields a variety of deceleration models (from really simple, constant deceleration to more complex linear and polynomial models *(6)*). Within this study three different functions are tested to represent the deceleration profile for each event, which can be assumed as typical braking patterns. The first one is the simplest and has linear relationship between deceleration value (d) and elapsed deceleration time (t). The function is $d = a_1 \times t$ (linear equation). In real traffic this reflects to the driver braking gradually. The second function is $d^2 = 2 \times a_2 \times t$ (Parabola 1) and in real traffic represents the situation where the driver brakes firmly at the beginning of the event due to a sudden obstacle appearing, followed by a gradually smoother braking since there is plenty of space to stop. Finally, the last function is $t^2 = 2 \times a_3 \times d$ (Parabola 2) and depicts a wrong judgement of the driver, who brakes smoothly at the beginning considering enough space to stop the vehicle, though this is followed with a hard brake due to lack of space and time (Figure 3a).

To judge which of the three abovementioned functions fits best to each deceleration event firstly the appropriate coefficients and then the sum of the square of the Euclidean distance for the three functions are calculated using the Matlab software package R2016a. Therefore the function with the minimum sum of the square of the Euclidean distance is considered to be the most appropriate to represent the deceleration profile of that event. The results of the analysis were that 51 out of 574 deceleration profiles fitted best to the linear equation, 488 to the Parabola 1 and 35 to the Parabola 2, which means that the majority of the braking events were hard at the beginning of the event and then became smoother. Using the average of the coefficients of each event for the best fitted function, the reference functions were created and illustrated in Figure 3b.

Statistical Method

The objective is to develop a statistical model which can explain the relationship between the deceleration events under normal driving conditions and the factors affecting them. Three types of factors are considered: (1) driver factors (e.g. age, gender and driving miles per year), (2) factors relating to the trip (e.g. traffic density, cause of braking, trip duration, road elements,) and (3) factors related to the deceleration event. Since each driver had one or two trips and each trip had multiple deceleration events, it is obvious that the deceleration behaviour can be modelled using three level analyses i.e. the driver level, the trip level and the event level as can be seen in Figure 4.

Deceleration events from the same driver may have some common characteristics, for instance if a driver is aggressive it is more possible to decelerate hard and jerkily (large deceleration value and short duration). In addition, the deceleration events are nested within trips, which may indicate some correlation among the events from the same trip (i.e. within-cluster correlation). On the other hand, there might be a variation between deceleration events from different drivers or / and different trips (i.e. between-cluster variation). Therefore, a statistical model is needed to jointly control both within- and between-cluster variations. The use of a multilevel mixed-effects linear regression model, and specifically a three-level random-intercept and random-coefficient model, is more suitable because it allows for dependency of deceleration characteristics for the same driver and within the same trip and examines the variation of deceleration characteristics for different drivers and different trips by the same drivers. Also it deals with the problem of consistency due to the fact that not all drivers have executed multiple trips. A three-level random-effects linear regression model can be developed for a single explanatory variable (*x*) as *(22)*:

Event-level (level 1):

$$Y_{ijk} = \beta_{0jk} + \beta_{1jk}x_{ijk} + e_{ijk} \tag{1}$$

Trip-level (level 2):

$$\beta_{0jk} = \delta_{00k} + u_{0jk}; \quad \beta_{1jk} = \delta_{10k} + u_{1jk}; \tag{2}$$

Driver-level (level 3):

$$\delta_{00k} = \gamma_{000} + \vartheta_{00k}; \quad \delta_{10k} = \gamma_{100} + \vartheta_{10k} \tag{3}$$

The composite equation can be expressed as:

$$Y_{ijk} = \gamma_{000} + \left(\gamma_{100} + u_{1jk} + \vartheta_{10k}\right)x_{ijk} + \vartheta_{00k} + u_{0jk} + e_{ijk} \tag{4}$$

In which Y_{ijk} is the deceleration value (max) for event *i*, trip *j* and driver *k*, γ_{000} is the final model intercept, u_{0jk} is the random trip-level intercept, ϑ_{00k} is the driver-level random intercept, e_{ijk} is the event-level residual, Level-1 (event) variance of e_{ijk} is σ_e^2, Level-2 (trip) variance of u_{0jk} is $\sigma_{u_0}^2$ and Level-3 (driver) variance of ϑ_{00k} is $\sigma_{\vartheta_{00}}^2$, γ_{100} is the fixed slope coefficient for explanatory variable *x*, u_{1jk} is the random trip-level slope coefficient for *x*, and ϑ_{10k} is the random driver-level slope coefficient for *x*. All random components are assumed to follow a normal distribution with a mean of zero and a constant standard deviation. Equation (4) represents a three-level random-effects linear regression model for a single explanatory variable but this can be similarly extended for multiple explanatory variables. This model can be estimated using the maximum likelihood (ML) estimation method.

RESULTS AND DISCUSSION

Deceleration characteristics denoted by the maximum deceleration value and the duration were analysed using the statistical model discussed in the previous section. Two statistical analyses were conducted. In the first one the dependent variable was the maximum deceleration value (Model 1), whereas in the second the dependent variable was the duration of the event (Model 2). The explanatory variables were kept the same in both models that include trip duration, age, gender, driven miles per year, initial speed, traffic light, deceleration profile, reason for braking (approaching roundabout, T-junction, cross junction, mid-block crossing or dynamic obstacle), traffic density and travel distance. The modelling results and the associated discussions are presented in this section.

Initially a three-level mixed model was tested for both dependent variables i.e. deceleration value and duration. The results indicated that the three-level mixed model was not appropriate for our data, since the intra-class coefficient of the driver level was too low (close to zero) in both analyses. This was further supported by the results of the likelihood Ratio (LR) test, comparing the three-level mixed model to the two simpler two-level mixed models (i.e. driver level and trip-level). Separate models were therefore developed for trip-level and driver-level, and the results revealed that the slightly better model is the two–level mixed model based on the trips. Having only one or two trips for each driver may be the reason why the three-level mixed model was not suitable. The LR test was conducted again in order to examine whether a trip effect in the deceleration event exists, and the results revealed that there is overwhelming evidence for both analyses in favour of a two-level mixed model over a simple regression model at the 0.05 significance level.

Two types of multilevel model were estimated: (1) random-intercept model and (2) random- intercept and random-slope model. Each of the variables has been examined to determine whether or not the effect of the variable (i.e. the slope coefficient) varies across the trips by conducting the LR test. Only the standard deviation associated with the slope coefficients of the initial speed for Model 1 and the distance for Model 2 was found to be statistically significant. The results for both multilevel models are presented in Table 2. The overall intra-class correlation (ICC) for Model 1 is 0.0325 indicating that 3.25 per cent of the variation in the deceleration value is explained by the multilevel or hierarchical data structure, whereas for Model 2 the ICC was greater and equal to 0.5082 indicating that 50.82 per cent of the variation in the duration is explained by the multilevel or hierarchical data structure. Both models show reasonable a goodness-of-fit.

The most statistically significant variables affecting the deceleration events have been found to be the initial speed, the distance and the estimation of the deceleration profile (fit 1, 2 and 3). Since the initial speed has a random effect on the deceleration value, it can be calculated that in 78.25% of the data, it affects negatively the deceleration value, meaning that the increase in the initial speed (i.e. the speed at which a driver starts to apply the brakes) decreases the maximum deceleration (i.e. the absolute value is increasing as the deceleration is negative). However, the initial speed has an opposite effect on the duration, meaning that a greater initial speed leads to a longer deceleration event. Regarding the travel distance of the event, a 1 m increase in the available distance reduces the absolute value of the deceleration by 0.0035 m/s^2 and increases the duration of the event by 2.7255sec but only for 82.12% of the data since it has a random effect on the deceleration duration. In terms of the deceleration profile, not obtaining the most common deceleration profile (fit 2) reduces the deceleration value from 0.2347 to 0.358 and increases the duration by 0.567 and 0.4957 for fit 1 and 3 respectively.

The initial speed effect for trip j is estimated as -0.0113+ u_{1j} for model 1 and the distance effect as 0.0832+u_{1j} for model 2, and the between trip variance in these slopes is estimated as 0.0002 and 8.8671 for Models 1 and 2 respectively. For an average trip, a decrease of 0.0113 in the deceleration value and an increase of 0.0832 sec in the deceleration duration are predicted when increasing initial speed by 1 m/s and distance by 1 m.

Another statistically significant variable is the reason for braking. This variable was included in the model as a categorical variable with 5 categories with the category of braking due to a dynamic obstacle as the reference category. It can be observed from Table 2 that braking due to a reason other than dynamic obstacle leads to an increase in the deceleration value and the duration i.e. smoother braking and this may be because the dynamic obstacle mostly describes the unexpected and sudden braking, except for the braking due to approaching to mid-block crossing. For example if the driver brakes because there is a cross-junction instead of a dynamic obstacle the deceleration value reduces by 0.0731m/s^2 and the duration of the event increases by 0.4263sec. Traffic density (i.e. low, medium and high) was included in both analyses as a categorical variable with low density as the reference category, but it was not statistically significant.

The factors associated with the human characteristics were included in the model as categorical variables. More specifically, the age of the driver had four distinct categories, with age 50 to 60 as the reference category; gender had two categories, with the male drivers as the reference one; and the driven miles per year had four categories, with the driven miles 5.000-10.000 as the reference. As the results indicate, none of the human factors variables was statistically significant. This is perhaps because the number of drivers (16 different drivers) was small and the number of events varied from driver to driver.

Summarising this research revealed that the initial speed, the distance, the deceleration profile and the reason for braking are the most significant variables affecting the deceleration events. It is concluded that as the initial speed increases the braking becomes harder. Moreover, regarding the reason for braking, the results show that drivers can tolerate a harder and shorter braking when the reason for braking is a dynamic obstacle (vehicle, pedestrian or bike), but not when it is due to a roundabout or junction; for these smoother braking is preferred in order to feel comfortable. The limitation of this study lies on the fact that the number of drivers was small and considerably less than the number of events, the sample of drivers was not selected to represent the population at large, and the number of events varied from driver to driver, so collecting data from more drivers could show significant associations with the human factors variables.

Furthermore, it is concluded that the most used deceleration profile, which is assumed to make drivers feel comfortable while braking (i.e. with the absence of uneasiness and distress since the data doesn’t include any safety critical events), is the one where the driver brakes firmly at the beginning of the event followed by a gradual smoother braking (i.e. defensive driving). This may stem from the fear people feel when detecting a danger and the uncertainty about having enough space and time to avoid it. In addition the findings of this study show that driver deceleration cannot be effectively modelled by applying average rates since the deceleration value and duration vary a lot depending on the vehicle kinematics and the reason for braking. The results highlight the importance of studying the braking behaviour and the perspectives in AVs area to simulate the human driving behaviour. Furthermore, in order for AVs to be widely accepted and for people to feel comfortable and safe in them, designers need to give careful attention to deceleration events.

CONCLUSIONS

This paper studies the deceleration events, observed from normal driving and models the braking behaviour. Hence, a rigorous statistical analysis of the data was conducted and multilevel mixed effects models were utilised. The most used deceleration profile, which is felt natural and comfortable, was defined. The results revealed that the deceleration events with respect to the deceleration value and the deceleration duration are interdependent during the same trip. Moreover, the initial speed, the distance, the estimation of the deceleration profile and the reason of braking are the most significant variables affecting those events. This paper concentrated on the comfort of autonomous vehicles, by imitating human behaviour and incorporated various driving scenarios. It is important for the acceptance of the autonomous vehicle to guarantee not only the safety of the passengers but also the comfort in order to gain their trust. To accomplish that, the aforementioned results should be taken into consideration when designing an autonomous vehicle. A larger study with more data will be conducted to help generalize the results and to possibly reveal more factors that affect the deceleration behaviour.

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TABLE 1 Average deceleration statistics based on different factors

	Mean values	
	Maximum deceleration value (m/s^2)	**Duration (sec)**
Gender: male	-2.447	2.64
female	-2.423	2.83
Initial speed: 0-5	-2.385	0.94
5-10	-2.379	2.08
11-15	-2.442	3.04
16-20	-2.399	4.48
21-25	-2.570	6.01
>25	-2.697	8.23
Traffic density: low	-2.426	2.70
medium	-2.422	3.17
high	-2.379	2.82
Age: 20 - <=30	-2.490	2.48
30 - <=40	-2.486	2.39
40 - <=50	-2.374	2.91
50+	-2.388	2.80
Traffic light: Signalised	-2.480	3.44
Unsignalised	-2.380	2.57
Reason of braking:		
Roundabout	-2.375	3.94
T-junction	-2.407	3.34
Cross- junction	-2.355	2.54
Mid-block crossing	-2.500	1.53
Dynamic-obstacle	-2.406	1.91

TABLE 2 Multilevel mixed-effects linear regression models

Dependent variable	**Model 1: Deceleration value (Max)**		**Model 2: Duration**	
Fixed effect	Coefficient	t-stat	Coefficient	t-stat
Initial speed	-0.0113	-2.3	0.0832	8.2
Deceleration profile:				
1	-0.2347	-3.85	0.5670	3.78
2 (Reference)				
3	-0.3580	-4.98	0.4957	2.67
Reason of braking:				
Roundabout	0.0921	1.91	0.1199	1.05
T-junction	0.0299	0.73	0.4018	3.91
Cross-junction	0.0731	1.16	0.4263	2.76
Mid-block crossing	-0.1653	-2.15	0.0993	0.53
Dynamic-obstacle (reference)				
Distance	0.0035	2.7	2.7255	4.59
Intercept	-2.3883	-75.19	2.4564	11.76
Random effect parameters				
Variance of Initial speed	0.0002		-	
Variance of Travel distance	-		8.8671	
Variance of Intercept	0.0051		0.8522	
Variance of Residual	0.1525		0.8247	
Statistics				
Number of observations	568		568	
Number of groups	26		26	
Intra-class correlation (ICC)	0.0325		0.5082	
Log-likelihood ratio index	0.1		0.35	

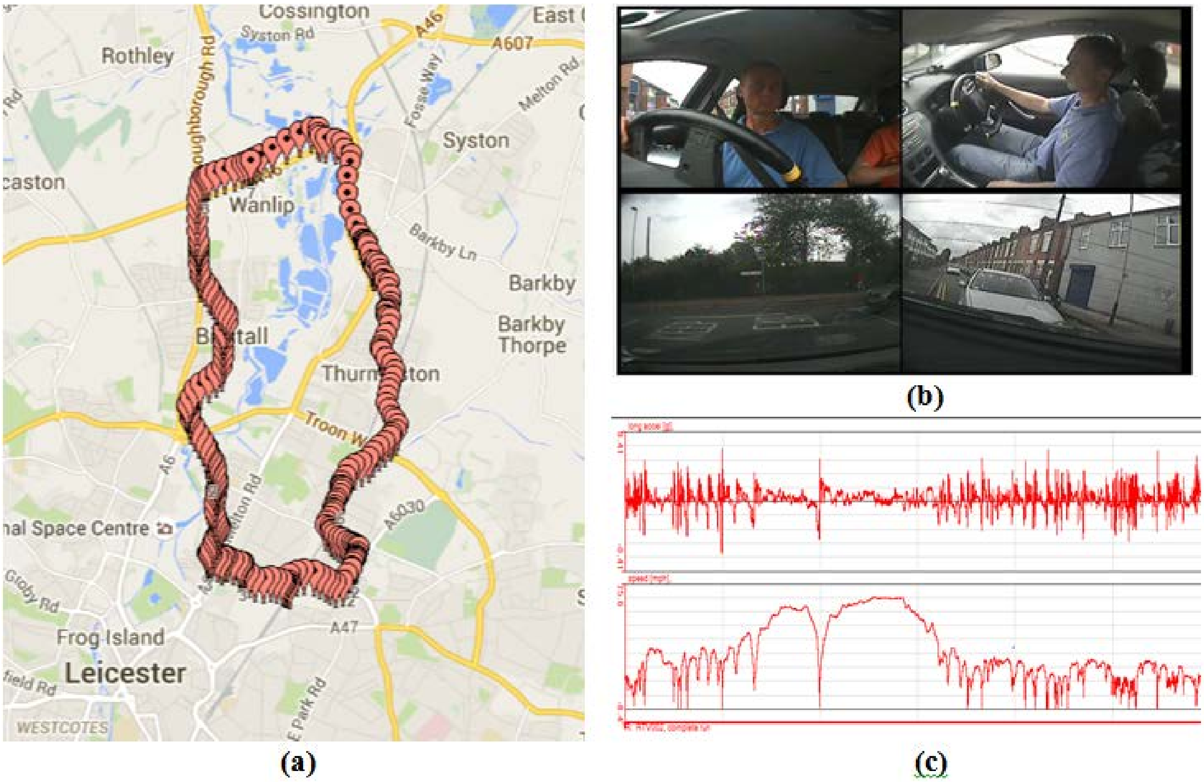
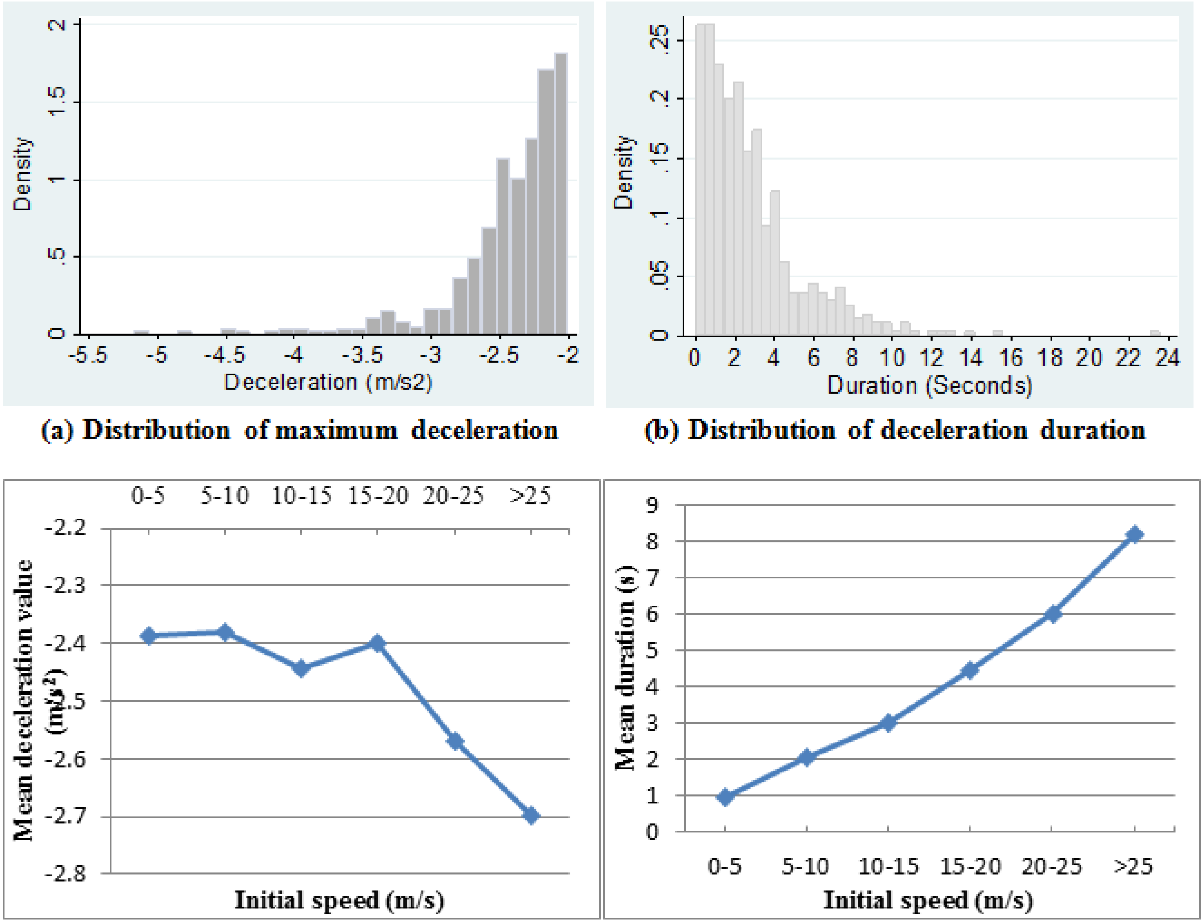


FIGURE 1 The route of the field test (a), the view from the 4 cameras (b) and the acceleration-time and speed-time diagram for the whole trip from the Race Technology programme (c).



(a) Distribution of maximum deceleration **(b) Distribution of deceleration duration**

(c) Speed vs Mean Deceleration **(d) Speed vs Mean speed**

FIGURE 2 Characteristics of extracted deceleration events.

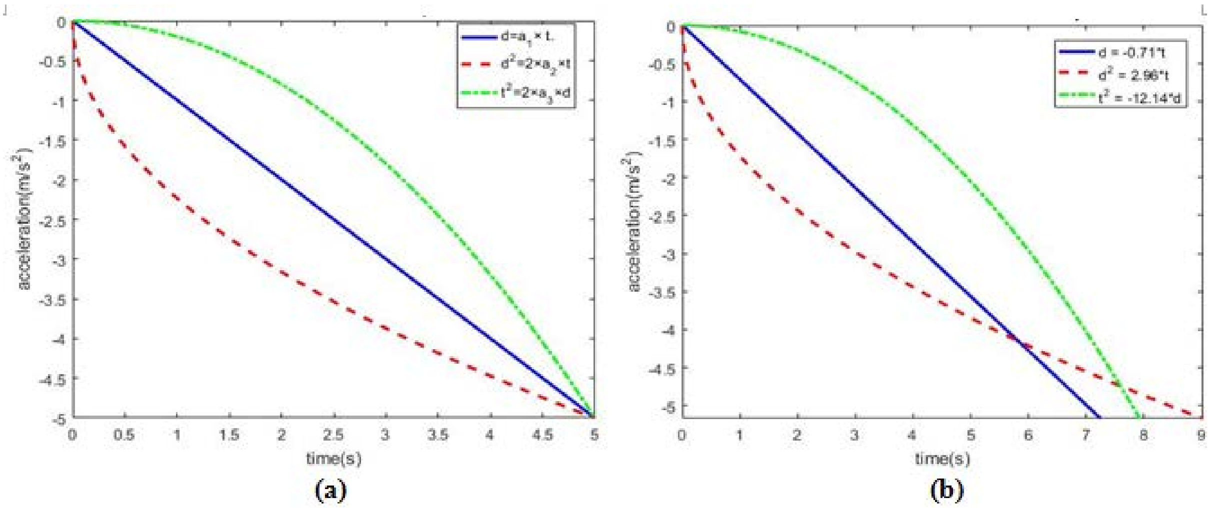


FIGURE 3 Different functions for the deceleration profile (a) and Reference Functions for the deceleration profiles (b).

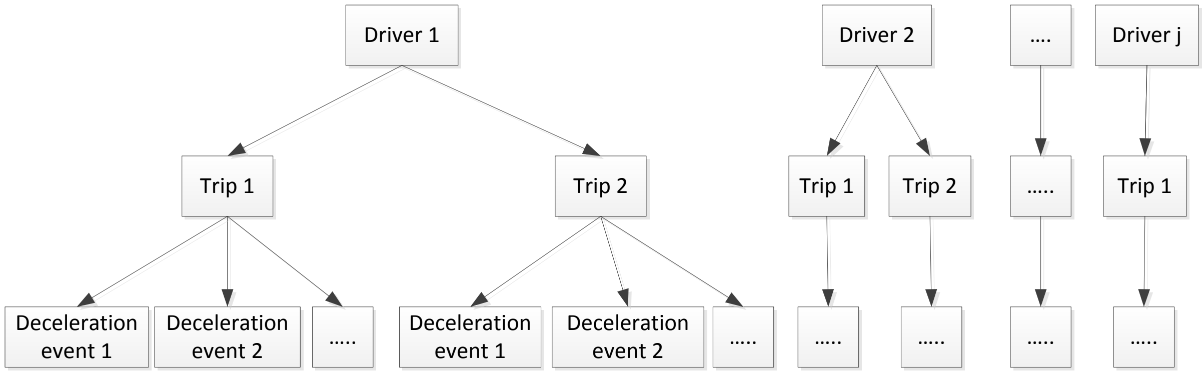


FIGURE 4 Multi-level model for Deceleration events.