THESIS FOR THE DEGREE OF MASTER OF SCIENCE

A STUDY OF TRUCK DRIVER DECELERATION INITIATION BEHAVIOR

QING CHENG

Department of Applied Mechanics
CHALMERS UNIVERSITY OF TECHNOLOGY
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Department of Applied Mechanics
Adaptive Systems
Chalmers University of Technology
SE–412 96 Göteborg
Sweden
Telephone: +46 (0)31–772 1000

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QING CHENG
Department of Applied Mechanics
Chalmers University of Technology

Abstract

This project aimed to study truck drivers' behavior at deceleration initiation based on data collected in the euroFOT project. It was executed in two steps: statistical description of each driver's typical deceleration behavior under normal conditions and then testing of quantitative models predicting time of deceleration initiation.

The obtained results show that drivers typically achieve harder deceleration by depressing the brake pedal, while milder decelerations are carried out through releasing the accelerator pedal. A rather clear boundary was found: When the average value of acceleration during a deceleration was below -0.2 m/s^2, drivers tended to used the brake pedal. Another interesting statistical observation is that most drivers had an individual, clearly identifiable typical brake pedal position 0.5 s after initiation, and the steady control over brake pedal would last at least for 2 s.

As a preparation for the model testing phase, decelerations were further classified into three scenarios: *lead vehicle stationary* (LVS), *lead vehicle moving* (LVM), and *lead vehicle decelerating* (LVD). However, carrying out such as classification was found non-trivial, and the classification results were found to rely entirely on threshold parameters for which there were no obvious optimum values. In the model testing phase, several models were tested such as a model assuming driver's deceleration initiation is reacting to brake lights of lead vehicle, an inverse time-to-collision (iTTC) model developed by Kiefer et al. [1], a kinematic model proposed by Gipps [2], a classical kinematic equation with constant deceleration, etc. Inspired by Flach's perspective [3] of optical variables, a new optical model was developed based on the constant deceleration kinematic equation. The new optical model seems promising.

Key words: deceleration initiation, deceleration sequence, 2D density plot, deceleration scenario, brake initiation, brake magnitude, Newtonian variables, optical variables.

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Above all, I gratefully dedicate my special thanks to my mother. Thank you for your unconditional love, unflinching sacrifice and unshakable faith in me. I would not have made it this far without you, I love you so much.

Qing Cheng
Göteborg, February 2013

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Chapter 1

Introduction

1.1 Background

More than 40,000 people die very year and more than 1.2 million are injured on European roads [4]. Almost one third of the accidents are rear end collisions. The most common driver behavior in rear end crashes is no maneuver at all [5, 6] which for example can be recognized as failing to react to the visual stimuli [7].

Over the past few decades, significant efforts have been dedicated to improve the traffic safety. One of many directions is the development of in-vehicle active safety systems. Many high-tech active safety technologies are already in existence, such as forward collision control system, lane keeping support, adaptive cruise control system based on radar detectors, sensors [8]. However, the lack of understanding about how to provide assistance to driver with the right information at the right time has been an obstacle to fully exploit the potential of technologies [9]. Meanwhile, with constraints and simplifications, a substantial amount of research and experiments have been conducted to understand (e.g. [1, 3, 10, 7]), to describe(e.g. [2, 11, 12, 13]), and even to predict driver behavior (e.g. [1, 2, 14]). An inevitable question is at what level of confidence such laboratory studies can reflect the real situation.

1.2 The euroFOT project

In 2010, the euroFOT project was initiated to help improve the adoption rate of intelligent vehicle technologies in new vehicles by raising the visibility of their contribution to better driving; testing and assessing the performance of eight key functions, e.g adaptive cruise control, forward collision warning [15]. It is the first large-scale field operational test (FOT) of multiple advanced driver assistence systems in Europe.

The project applied the common European FESTA methodology [16], and followed three major steps: preparing, using, analyzing. In the *preparation* phase, groups of active safety systems were investigated. To identify the effects of the selected systems on driver behavior, performance indicators are needed. Consequently, a comprehensive set of measurements is necessary to compute the performance indicators used to evaluate the systems. The naturalistic data collection in the *using* step, i.e. data collection with logging equipment in normal vehicles of normal drivers, was conducted in two phases: baseline phase and treatment phase. Firstly, in baseline phase all tested functions were deactivated. But there were no restrictions in the remaining phase, so drivers could select themselves whether to use the active safety systems or not. In order to make data analysis efficient in the *analysis* phase, all logged data were transferred to file systems, and made available for the analysis tools, and numerous computations were made in pre- and post- processing. The analysis tool used at AB Volvo is FOT-ware. it was used for video data examination in this thesis project.

1.3 Scope

One of the objectives of AB Volvo in the euroFOT project was to understand the impact of intelligent systems already in use such as adaptive cruise control, lane keeping support. Data were collected from thirty trucks in total, whereof fifteen were 4×2 tractor units, stationed in the Netherlands, driving pan-European transport missions with a focus on central Europe. The other fifteen units, stationed in the United Kingdom, were 6×2 tractor units, limited to national transport missions [8].

The main tasks of this thesis work are to analyze truck driver's deceleration initiation behavior based on euroFOT data, then testing several existing proposals of drivers' deceleration initiation behavior which are already available within and outside of Volvo group. This thesis project is considered as a part of pre-study work for driver model development in the QUADRA project, for the purpose of evaluating active safety systems in computer simulation. The result of this study is expected to supply the development of active safety systems (forward collision warning system) with more statistical observations of driver behavior.

Due to the wide variation in the physical dimensions of on road vehicles and in driver's perceptual input thereof, etc., truck drivers' behavior is expected to differ from passenger car drivers' behavior. However, most previous research related to driver behavior has been based on passenger car setups and more idealized driving scenarios (e.g. [1, 2, 14]). Therefore a comprehensive study of truck driver behavior in real traffic is motivated. With the presence of euroFOT data, it is feasible to identify the most important inputs that trigger the deceleration initiation of a truck driver.

1.4 Objective

In order to obtain a sound, in-depth understanding of deceleration initiation behavior of truck drivers, and to be able to reflect on whether current available models are capable of properly describing the data logged on Volvo trucks, the research work will be elaborated by answering the following questions:

1) What do drivers typically do to initiate a deceleration?

2) Does the deceleration behavior of a driver follow a observable, consistent pattern? If such patterns exist, do patterns of different drivers resemble each other?

3) Typically when does a driver initiate the deceleration, i.e. which are the most influential factors and how does this set of factors affect the behavior of deceleration initiation?

1.5 General work flow

This thesis project focuses on non-critical rear-end decelerations. The rear-end situations can be further classified as *lead vehicle stationary* (LVS), *lead vehicle moving* (LVM), *lead vehicle decelerating* (LVD) [1, 17], whereas non-critical situation stands for a vehicle being either at the state of low risk regarding rear-end collision, at the state of conflict [17]. Based on real data, statistical investigations for 10 randomly selected Dutch drivers and 10 randomly selected UK drivers were performed to learn whether deceleration initiation behaviors of these drivers were similar or not; while in model testing phase, each driver was treated as a case to examine the performance of a particular model. The research was therefore executed as follows:

1. Examining the logged signal measurements.

2. Studying standard and common deceleration behavior of truck drivers from truck manuals and data.

3. Extracting deceleration sequences systematically for each driver.

4. Performing statistical analysis for each driver.

5. Post-processing statistical results for models to be tested, such as defining deceleration situations in compliance with the setup of some models.

6. Model testing and analysis.

1.6 Outline

A literature research of several typical deceleration behavior studies will be given in Chapter 2. It will discuss the topic in two perspectives: Newtonian models and optical models. Chapter 3 will present the work on data extraction and analysis and summarize statistical observations of driver's deceleration initiation behavior. Then these data will be used as inputs to the models in the model testing phase, which will be explained in detail in Chapter 4. In the end of this chapter, the design and testing of a new optical model will be described as well. Finally, conclusions will be given in Chapter 5.

Chapter 2

Literature review

Many studies have focused their research and experiments on rear-end collisions. Some of the studies focused on how Newtonian factors (velocity, acceleration, relative distance, etc.) depict deceleration behavior in terms of physical laws, assuming drivers have instant access to Newtonian factors. While some others examined the problem in the viewpoint of human cognitive processes and proposed models particularly in terms of perceptual factors (optical angle subtended by the lead vehicle, expansion rate of the optical angle, etc.), assuming that visual perceptual information guides deceleration behavior. These two ways to approach the problem will be addressed respectively as Newtonian models and Visual perception models in the rest of this thesis.

2.1 Newtonian models

Gipps [2] constructed a model to define the response of a host vehicle to the behavior of its predecessor in a stream of traffic, assuming the driver is capable of assessing desired maximum acceleration and deceleration of the lead vehicle. The model sets limits on the speed a driver wishes to travel and the most severe braking that the driver is willing to apply.

When the driver travels freely, i.e. no predecessor, driver would first increase acceleration, and then decrease to zero when the vehicle approaches the desired speed. The velocity of the host vehicle in this process V_{free} at the instant of $t + \tau$ is:

$$V_{\text{free}} \leq v_n(t) + 2.5 a_n \tau (1 - v_n(t)/V_n)(0.025 + v_n(t)/V_n)^{1/2} \tag{2.1}$$

where v_n is the speed of vehicle n at time t, τ is the apparent reaction time, a constant for all vehicles, a_n is the maximum acceleration which the driver of vehicle n wishes to undertake, V_n is the speed at which the driver of vehicle n wishes to travel.

When there is a predecessor, a safe velocity of the host vehicle V_{constr} at the instant of $t + \tau$ is:

$$v_n(t+\tau) \leq b_n\tau + \sqrt{\{(b_n^2\tau^2 - b_n[2[x_{n-1}(t) - s_{n-1} - x_n(t)] - v_n(t)\tau - v_{n-1}(t)^2/\hat{b}])\}} \tag{2.2}$$

where b_n is the most severe braking that the driver of vehicle n wishes to undertake ($b_n < 0$), $\hat{b}$ is the estimated b_{n-1}, $x_{n-1}(t) - s_{n-1} - x_n(t)$ is the distance between two vehicles minus the safe region that the host vehicle is not willing to intrude, even when at rest. Therefore:

$$v_n(t+\tau) = \min\{V_{\mathrm{free}}, V_{\mathrm{constr}}\} \tag{2.3}$$

The above equation thus aims to capture a behavior where the driver travels as fast as safety and the limitations of the vehicle permit. Particularly when two terms in the *min* function are equal, the driver starts to change the behavior from maintaining the speed to responding the lead vehicle. The turning point of expected speed could be regarded as the brake initiation. However, it should be noticed that all vehicles in the platoon are identical in the Gipps experiments [2] for validation. With the logged data available from the euroFOT, it is possible to test whether or not the model is capable of describing the complex everyday traffic. Also the estimation of b_{n-1} seems unrealistic, because drivers in general are not so good at estimating distances, absolute velocities, and accelerations of other objects [10]. Instead, Boer [10] concluded that they are capable of accurately estimating visual angles subtended by objects, time to collision, heading, and bearing to salient targets.

2.2 Visual perception models

Visual perceptual information has been found to play an important role by a substantial amount of research in recent years. The most intuitively straightforward instruction to decelerate would be reacting to the brake light of lead vehicle. But in reality, does a driver always react at the very instant when the brake light of lead vehicle goes on? Markkula [7] argued in terms of satisficing that a driver normally applies collision avoidance at some time after the very instant a collision course is established (e.g. brake light goes on), a time which is related to the safety margins of the driver.

The optical variable τ introduced by Lee [11] as an estimation of time to collision (TTC) has been frequently used and studied in a considerable amount of research (e.g. [3, 14]). In Lee's influential article, he further specified the idea of how human

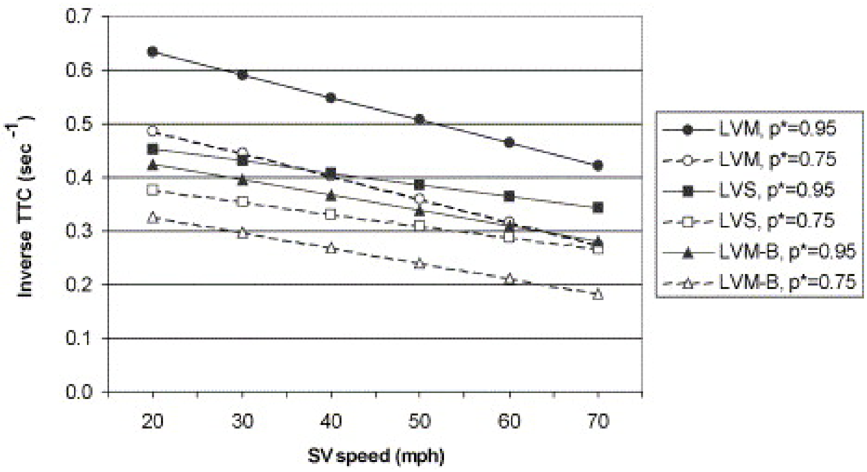

Figure 2.1: *Kiefer's inverse TTC predictions when the probability of hard braking onset scenario p* is set to 0.75 and 0.95. LVM denotes lead vehicle moving at a constant speed, LVM-B denotes lead vehicle decelerating, and LVS denotes lead vehicle stationary. Reprinted from Accident Analysis and Prevention, Vol. 37, Kiefer et al., Developing an inverse time-to-collision crash alert timing approach based on drivers' last second braking and steering judgments, pp. 301, Copyright (2005), with permission from Elsevier.*

adults, animals and human infants avoid impending collision based on the expansion of the visual image on the retina, by registering the value of τ as:

$$\tau = \frac{\theta}{\dot{\theta}} \tag{2.4}$$

where θ is the optical angle subtended by the lead vehicle, it can be expressed as the ratio between obstacle width W and the distance from the obstacle D. $\dot{\theta}$ is the expansion rate of optical angle, the time derivative of the visual angle. Given V as the speed of the vehicle, θ and $\dot{\theta}$ can be further specified as:

$$\theta = \frac{W}{D}; \qquad \dot{\theta} = \frac{W \times V}{D^2} \tag{2.5}$$

In recent years, however, experiments have shown that humans do not only rely on τ to initiate braking. Fajen [14] further explored the visual control strategies in collision avoidance, proposed the concept of global optic flow rate (GOFR), and indicated that driver's brake initiation also relies on other perceptual information than just $\dot{\tau}$ from Lee's braking strategy. Many published studies have found drivers initiate braking differently when the obstacle size is different [18] or at different speed [1].

Experiments carried out by Kiefer et al. [1] suggested that drivers do not use detailed knowledge of lead vehicle deceleration when making hard braking decisions,

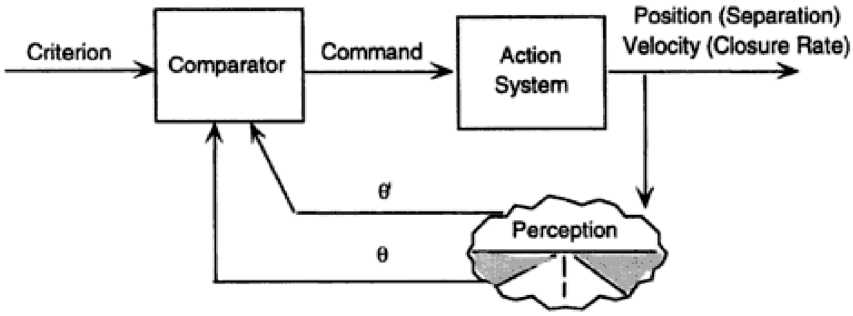

Figure 2.2: *Flach proposed a closed loop control system with visual perceptual feedback: optical angle (θ) and expansion rate ($\dot{\theta}$). Reprinted from Advances in Psychology Series, Vol. 135, Flach et al., Collisions: Getting them under control, pp. 80, Copyright (2004), with permission from Elsevier.*

and demonstrated the dependency relationship between inverse TTC (iTTC) and host vehicle speed, as shown in Figure 2.1. The inverse time-to-collision threshold that decreases linearly with driver speed [1], where p* stands for a priori selected probability value of hard braking onset. The model was developed based on experiments in which the lead vehicle has been the same surrogate target vehicle at all times - a three dimensional mock-up of a passenger car rear end, and the host vehicle has also been a passenger car. However, it has not been tested whether these thresholds are valid also for truck drivers.

Flach et al. [3] proposed the idea of describing the rear end situation with optical variables, particularly θ and $\dot{\theta}$, and then using the variables as the feedback of cognitive comparison process in the course of collision avoidance, as illustrated in Figure 2.2. A state space system was built with variable coordinates θ and $\dot{\theta}$ in an attempt to reflect the states of this feedback control system. Based on the state space system, a linear function of θ and $\dot{\theta}$ succeeded in describing the behavior in a simple laboratory ball-hitting task designed by Smith et al. [3, 18] further argued the validity of using same optical state space system in describing on-road collision avoidance, as demonstrated in Figure 2.3. The dashed line in the figure defines a critical margin, such that the driver must adjust the braking pedal pressure to keep the vehicle's current state at or below. However, θ and $\dot{\theta}$ are only associated with relative speed, i.e. the effect of speed as discussed in other studies was not mentioned. Therefore whether or not the linear relationship is sufficient for interpreting real world collision avoidance is under discussion. Moreover, it is worth to inspect if the timing of brake initiation is associated with the host/lead vehicle speed or not.

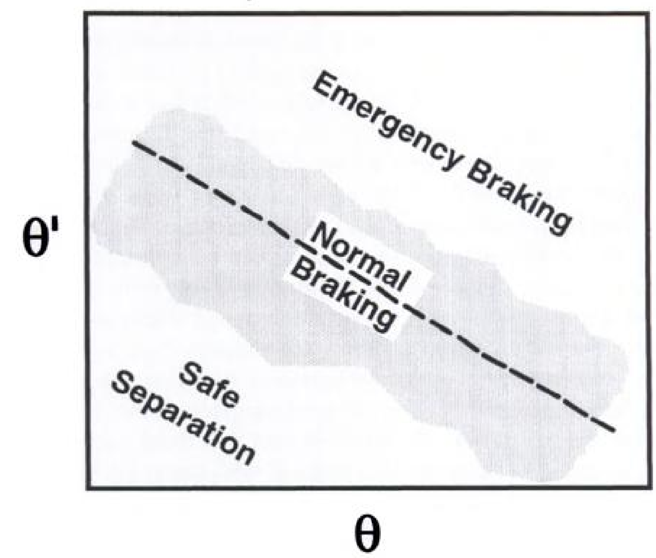

Figure 2.3: *The dashed line with a negative slope is the hypothetical optical criterion for braking to avoid collisions proposed by Flach, which indicates the relationship between a imminent response and the rate of approach. Reprinted from Advances in Psychology Series, Vol. 135, Flach et al., Collision: Getting them under control, pp. 84, Copyright (2004), with permission from Elsevier.*

Chapter 3

Data extraction and analysis

This chapter enumerates the challenges faced before and during the data extraction, and explains how these challenges were handled. An approach to identifying a set of the most relevant data measurements is outlined, and the key moments in a deceleration event are explained. Afterwards, statistical analysis of driver-specific deceleration behavior is described, and then general behavior in deceleration is discussed. Finally, a hypothesis proposed by Markkula [19] was tested using part of the extracted data.

3.1 Data extraction

If a driver behaves in compliance with a pattern, extracted data at an identical moment in similar situations will be similar. Therefore, the concept of a *deceleration sequence* was introduced to patternize the similar situations, and data were organized in separate sequences. A sequence is a fragment or a segment of a trip made by a driver; it represents a complete, successful deceleration maneuver of the driver in a single attempt to avoid collision with the lead vehicle; it holds measured signals of all needed aspects of internal as well as the external environments of the truck. The sample rate of every measurement is 10 Hz.

3.1.1 Signal diagnosis and selection

There are many ways a truck driver can decelerate a truck. Here, the analysis has been focused on logged longitudinal acceleration signal directly (despite its noisiness), rather than any particular means of deceleration such as brake pedal depressing. In addition, since the acceleration signal was recorded on vehicle, the completeness of the measurement was guaranteed. Hence it was used as the basis of all filter methods. However, much of the noise occurred during signal recording did affect the quality of data extraction. The source of noise can be inside vehicle, such as engine, driveline, or external such as rough road surface. Before the actual extraction process was executed, a low pass Gaussian filter was used to smooth the acceleration signal to avoid over-complicated extraction algorithm design yet with acceptable quality. While exposed in the real world, resistances such as air drag, tire friction, as well as mechanical friction would slow a coasting truck down. The average value of acceleration caused by such counteractions was approximately -0.05 m/s^2. Such a value was not a minor observation, but contributed as an acceleration threshold to tighten sequences up and provide more accurate statistics.

Before systematically extracting deceleration sequences, some exploration was carried out to find out the most informative signals that might be associated to deceleration behavior. All relevant signal measurements were plotted in time series for a certain amount of randomly sampled deceleration sequences. In the end, some signal measurements were found to be representative concerning the concept of deceleration: vehicle speed, longitudinal acceleration, TTC, brake pedal position, accelerator pedal position, etc. A typical extracted sequence with some relevant signal measurements is illustrated in Figure 3.1, where driver 8 depressed the brake pedal to decelerate the truck to avoid forward collision.

3.1.2 Sequence extraction

Data obtained from the field operational test were not perfect even after systematic preprocessing in data management in euroFOT [8]. Missing or invalid data were still an issue to be solved before and during the data extraction. More data pre-processing work was required within the context of this project. Therefore filtering mechanisms were employed before and during the data extraction when needed.

The threshold filter is designed to section the longitudinal acceleration signal of an entire trip into two sets of segments (i.e. sequences) and to discard the set above the threshold. Each sequence in the remaining set, from the time when acceleration signal is below the threshold until the truck regains the threshold acceleration value, captures a (possibly partial) deceleration maneuver.

The low pass filter smooths the signal by re-sampling the discrete-time signal at a lower frequency, yet preserves signal features. A Gaussian filter has been adopted for such purposes, which also keeps the signal synchronized with all other raw signal measurements. With a filter standard deviation of 1 s and a filter width of 8 s, the Gaussian filter was found to be able to preserve the essential features of the signal while smoothing out sudden, noise-like, jerky strikes.

The constraints filter filters out sequences which fail to satisfy a number of basic validity constraints (showing that a sequence is indeed a deceleration sequence). The constraints are:

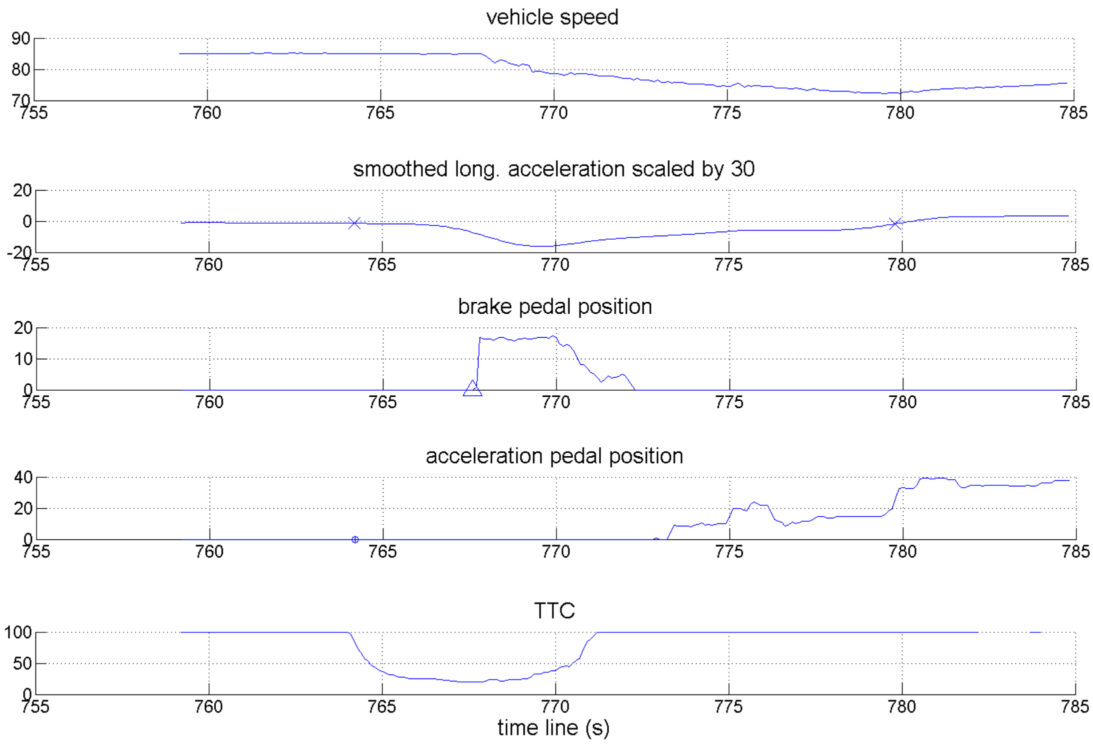

Figure 3.1: *A typical deceleration sequence (from driver 8 in his trip 35936) extracted based on longitudinal acceleration value (the seond plot), where the two crosses on the signal denote the start and the end of the sequence. In this sequence, brake pedal is depressed at the time of 767 s (the triangle in the third plot), then returns to no motion at 772 s, a second later the accelerator pedal is depressed. The plot at the bottom shows that the brake pedal is depressed to prevent further TTC value decrease. When the brake pedal is fully released, the TTC value being 99 suggests there is no threat of a forward collision.*

- An extracted deceleration sequence shall involve at least one of the deceleration methods: releasing accelerator pedal, depressing brake pedal, shifting retarder stalk, combination usage of brake pedal and retarder stalk.

- The lead vehicle information must be fully available in the beginning part of the deceleration sequence (during a time window right before initiating the deceleration, e.g. three-second duration prior to the first crosspoint of the smoothed longitudinal acceleration signal sequence in Figure 3.1, please go to section 3.1 for details).

- The deceleration initiation is indeed in response to the lead vehicle by checking whether or not the observed TTC value reduced accordingly during the time window.

- Make sure the decision to initiate deceleration is without any aid of intelligent safety systems such as warning from forward collision control system, from adaptive cruise control system, by filtering out all the moments that the equipments are actively providing warnings or control interventions.

With a combined usage of these filters, sequence extraction with any specified requirements is achievable, hence statistical investigation is made possible. The employed sequence extraction procedure is given as follows:

1. Checking the data integrity of the trips, i.e. if the signal was successfully logged at all.
2. Applying low pass filter to smooth the acceleration signal for preparation of sequence extraction.
3. Applying threshold filter with the value of -0.05 m/s^2 against the acceleration signal as discussed in previous section to extract all raw sequences.
4. Applying a customized constraints filter to further select all qualified deceleration sequence.

In the experiment, a collection of 500 deceleration sequences was extracted for each driver (those with less than 500 deceleration sequences were discarded).

3.2 Deceleration behavior analysis

Driver behavior in terms of signal measurement can be studied via the signal plots as in Figure 3.1. The deceleration maneuver of the driver in one specific deceleration sequence is clearly depicted in the figure, but it became less useful when trying to have a more general understanding of deceleration behavior of the driver. Therefore, data were grouped according to their attributes (e.g. the average acceleration and deceleration duration) in the sequences and then brought into statistical plot - 2D density plot - in hope of formulating a meaningful, interpretable pattern. Thus, deceleration behavior of each driver became comprehensible. As a result, deceleration maneuvers were summarized statistically.

3.2.1 A case study

Figure 3.2 shows a density plot illustrating all deceleration sequences of one example driver. To achieve such kind of plot, deceleration sequence were sorted into bins, by sequence duration and average longitudinal acceleration during the sequence. As observed from the figure, most of the decelerations are clustered at the lower left corner,

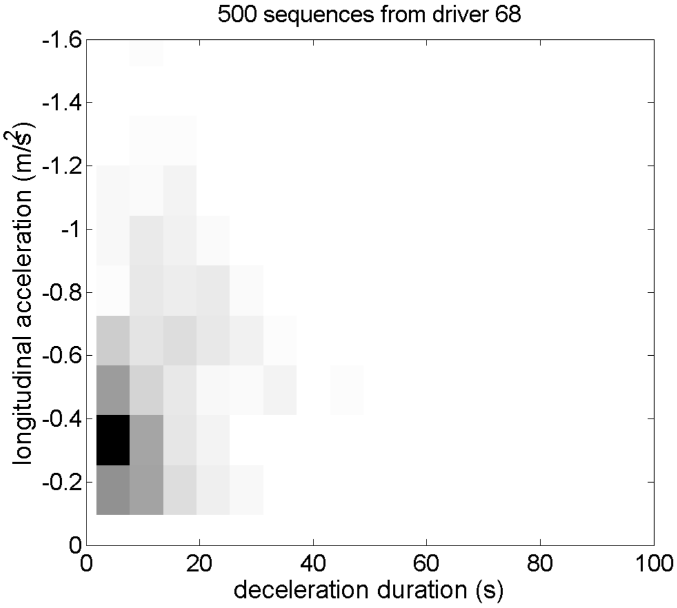

Figure 3.2: *A 2D density plot in terms of deceleration duration and average acceleration for UK driver 68. The darkness of a bin represents the frequency of data points falling within the bin.*

which represent short and light-footed decelerations. Moderate decelerations such as short but hard ones or long but light-footed ones are also visible. However, it was suspected that an extraction only using the longitudinal acceleration signal would also give us unwanted situations where the deceleration was caused by something else (e.g. uphill slopes). Deduced from the truck instruction [20], there are four ways to decelerate the truck: releasing the accelerator pedal, depressing the brake pedal, shifting the retarder (a device used to augment some of the functions of primary friction-based braking system on heavy vehicles) stalk, and a combination usage of brake pedal and retarder stalk. In order to formulate an appropriate definition of deceleration initiation and to recognize the most representative means of deceleration for the modeling part, each of the four ways of deceleration was studied in the same fashion as in Figure 3.2 for every driver.

The set of subplots in Figure 3.3 clearly shows the choice the driver made in different situations: in most case the accelerator pedal is released when a light deceleration is required, whereas the brake pedal is depressed to achieve a deceleration harder than approximately 0.2 m/s^2. Retarder stalk shifting alone as a way to decelerate has not occurred, however, two combination usages of the brake pedal and the retarder stalk are identified. Statistically, the amount of accelerator pedal releasing registered for this

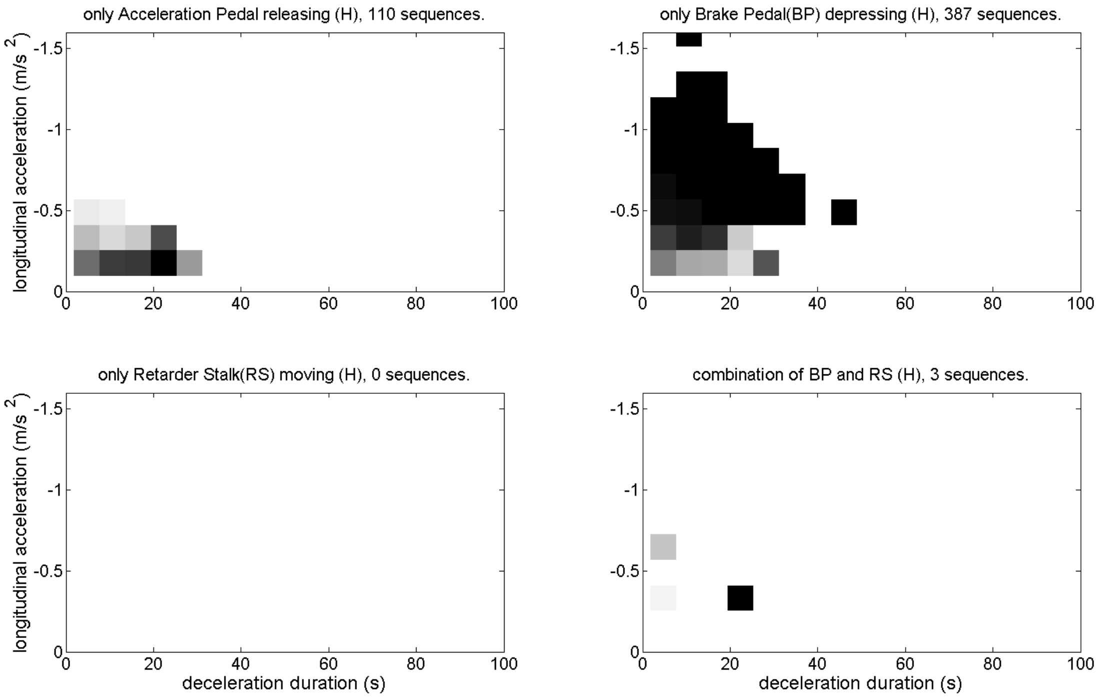

Figure 3.3: *The Same 2D density matrix approach was employed to extract the pattern for each of the four ways of deceleration (releasing the accelerator pedal, depressing the brake pedal, shifting the retarder stalk, shifting retarder stalk while depressing the brake pedal) for driver 68.*

driver is nearly one third of the registered brake pedal depressing.

3.2.2 Generalization

The same approach has been employed to inspect the behavior of every other driver. Then similar kind of behavioral patterns have been visualized statistically for all drivers from UK and the Netherlands as illustrated in Figs. 3.4 and 3.5. When all drivers are grouped together, there seems to be a corresponding division in both of the accelerator pedal releasing statistical plot and the brake pedal depressing plot at around 0.2 m/s^2. Counting on the maximum speed enforced by speed limiters equipped on heavy good vehicles, 90 km/h for DHL fleet in the UK and 85 km/h for Nijhof-Wassink fleet in the Netherlands, as well as the difference in road condition, and possible difference of group driving habits, all statistics were categorized by the drivers' nationality as in Figs. 3.4 and 3.5.

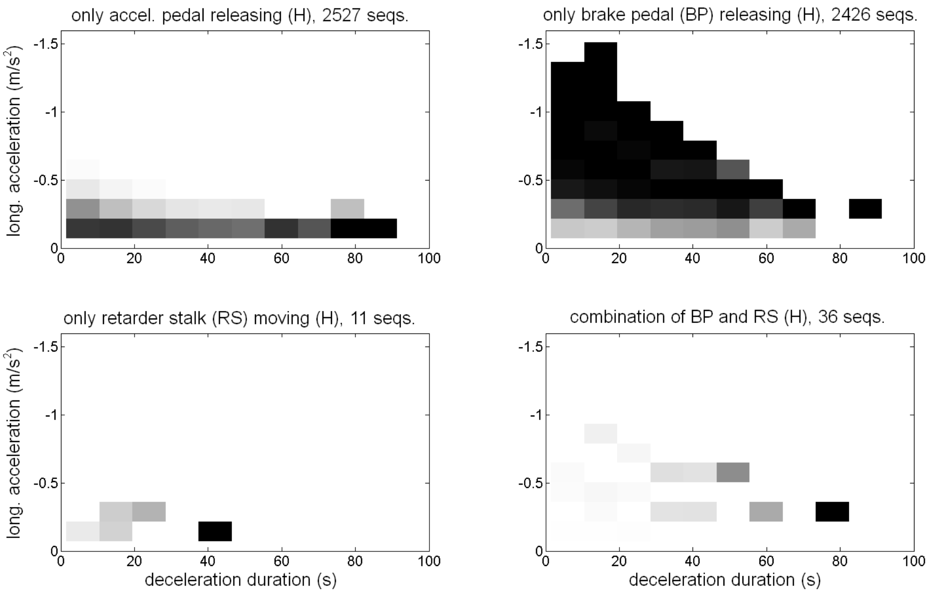

Figure 3.4: *500 deceleration sequences are extracted for each of the ten randomly selected drivers in the Netherlands.Their collective deceleration initiation behavior is categorized into four groups.*

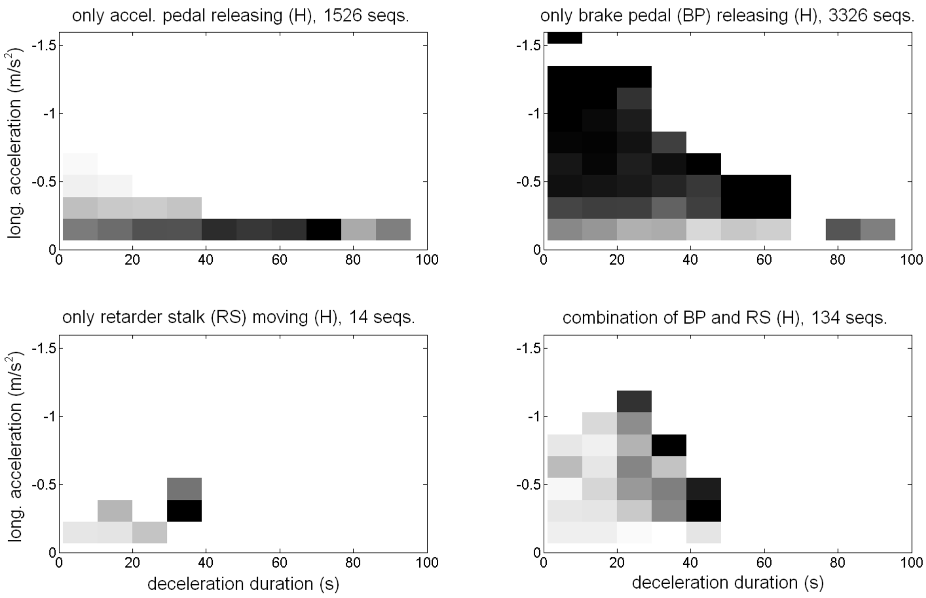

Figure 3.5: *The same amount of deceleration sequences are extracted for each of the ten randomly selected drivers in the UK.*

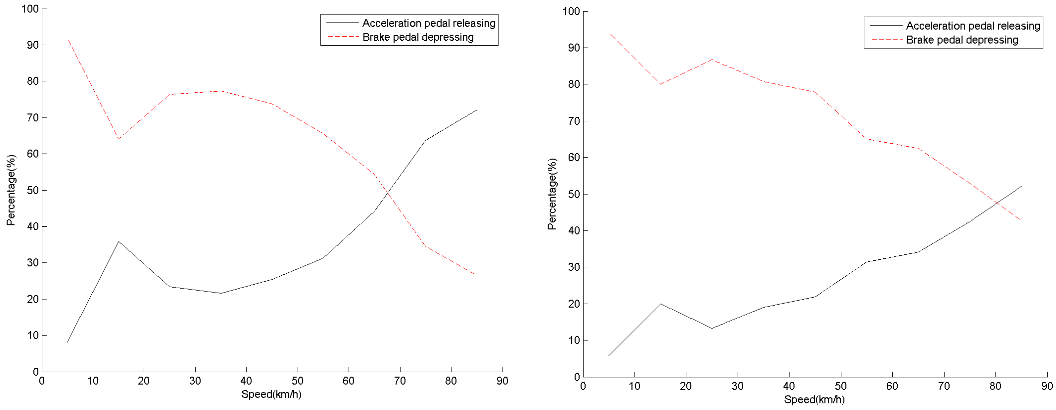

Figure 3.6: *General statistics of usage tendency of brake pedal and accelerator pedal at different speed. The left figure is for Dutch drivers and the right one is for UK drivers.*

3.2.3 Discussion

For every Dutch driver and UK driver, the tendency of switching from the accelerator pedal releasing to the brake pedal depressing resembles the statistical pattern illustrated in Figs. 3.4 and 3.5, i.e. around -0.2 m/s^2. A driver would just release the accelerator pedal to decelerate gently or depress brake pedal if harder deceleration is required. Retarder usage in deceleration was not found to be common in either country. For drivers in both countries, most of the deceleration sequence time length is shorter than 60 s. However, the figures also suggest some possible differences between UK and Dutch drivers. The frequency of the accelerator pedal releasing for Dutch drivers, as shown in Figure 3.4, is close to the frequency of the brake pedal depressing; in the contrast, it was found one third of the total registered decelerations for UK drivers in Figure 3.5. In Figure 3.6, statistical counting of the tendency of pedal usage in deceleration maneuver at different speed are presented.

Figure 3.6 signify a clear speed dependency in pedals usage during deceleration. When the vehicle is at a high speed, releasing accelerator pedal is preferred to initiate deceleration. One possible explanation can be: drivers tend to maintain high speed as much as he or she can because to regain the same status is economically expensive. However, it is not that expensive to brake at a low speed and speed up again. Furthermore, UK drivers have more severe (hard and short duration) braking than Dutch drivers. One possible explanation could be: the transportation missions of the fleet in the UK were national, while the missions for Dutch fleet was pan-European. Therefore these UK drivers might have more decelerations on arterial roads than the Dutch drivers, while incidents that demand immediate responses (e.g. short, hard decelerations) were more likely to happen on an arterial road than those on a freeway. Like Dutch drivers,

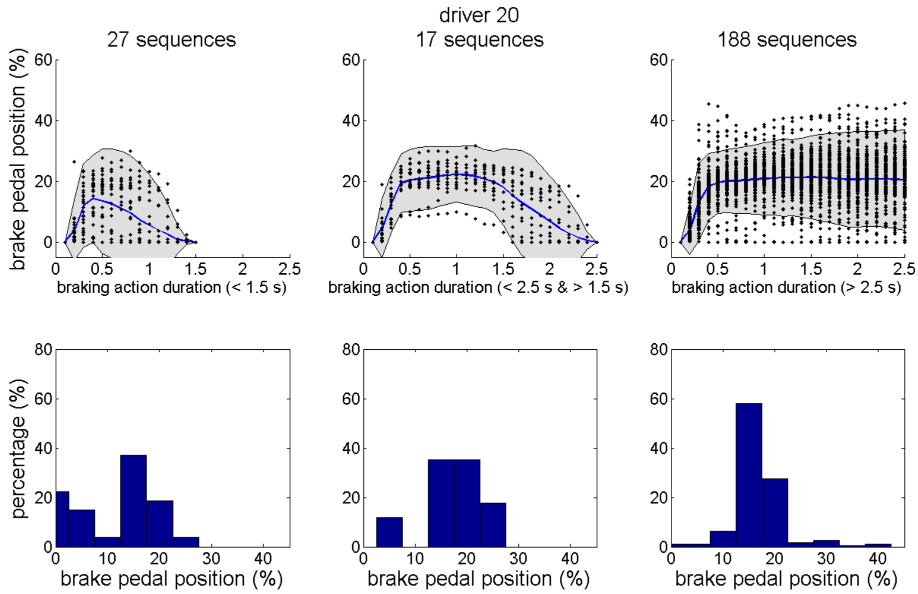

Figure 3.7: *The upper three subplots show deceleration sequences from driver 20 which, from the left to right, were: less than 1.5 s long, longer than 1.5 s and shorter than 2.5 s long, and longer than 2.5 s long. Each point is a discrete-time sampled (in a frequency of 10 Hz) brake pedal position. The thick line in the middle of the gray area represents the mean value of all measured trajectories of the brake pedal, while the gray area covers 95% of the observed trajectories. Each of the lower three histograms (corresponding to their upper subplots) look into the distribution of brake pedal position at the instant of 0.5 s after the initiation of the braking maneuver.*

drivers from UK tend to depress the brake pedal to decelerate the truck as soon as the needed average deceleration exceeds 0.2 m/s^2. Interestingly, it appears that for some drivers in the UK (e.g. driver 108 and 922), who have more registered retarder stalk usage, are more in favor of releasing accelerator pedal to decelerate. While those Dutch drivers (e.g. driver 28 and 804) who also used retarder stalk did not possess such kind of preference.

3.3 Hypothesis testing

Give a very large amout of on road data, many hypotheses can be tested. One such hypothesis, proposed by Markkula [19], was that a driver will most often apply the same depressing force at the initiation of braking, and may then adjust the force according to the situation. In this section, a series of statistics were generated to study the typical brake magnitude for each driver, and then to validate such a hypothesis.

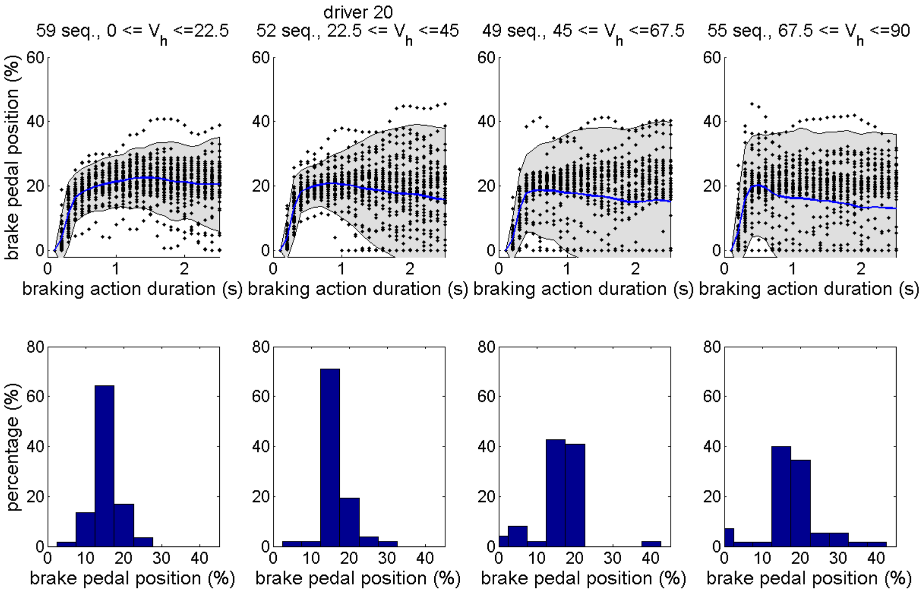

Figure 3.8: *Speed binning search of brake pedal position in time series for all decelerations of driver 20 regardless of length. The histogram in the lower row shows the same kind of statistics as done in previous figure for position distribution at the instant of 0.5 s after the brake initiation.*

3.3.1 Typical brake magnitude

The study of the typical brake magnitude is straightforward, as the brake pedal position (the position in relation to its full depression, in percentage) signal measurement is available in the euroFOT database and self-sufficient for generating the statistics. The only work is to edit all deceleration sequences so that each of which starts from the brake initiation and lasts a fixed 2.5 s, as shown in Figure 3.7 for driver 20. It is especially clear for the middle and right upper subplots in Figure 3.7, the brake pedal position often reaches a stable level around 17% after 0.5 s of the brake initiation. The following Figure 3.8 demonstrates an alternative approach to check the position for the same driver, which is the speed binned plot of to check if driver behaves differently at different speed.

It seems that the vehicle speed does not affect the way the driver depresses the brake pedal. The same statistical analyses were performed for the other nineteen randomly selected drivers, Figure 3.9 shows the brake pedal position distribution at the instant of 0.5 s after the braking maneuver is initiated. Most of the histograms have a single peak and it locates roughly in an interval [15,20].

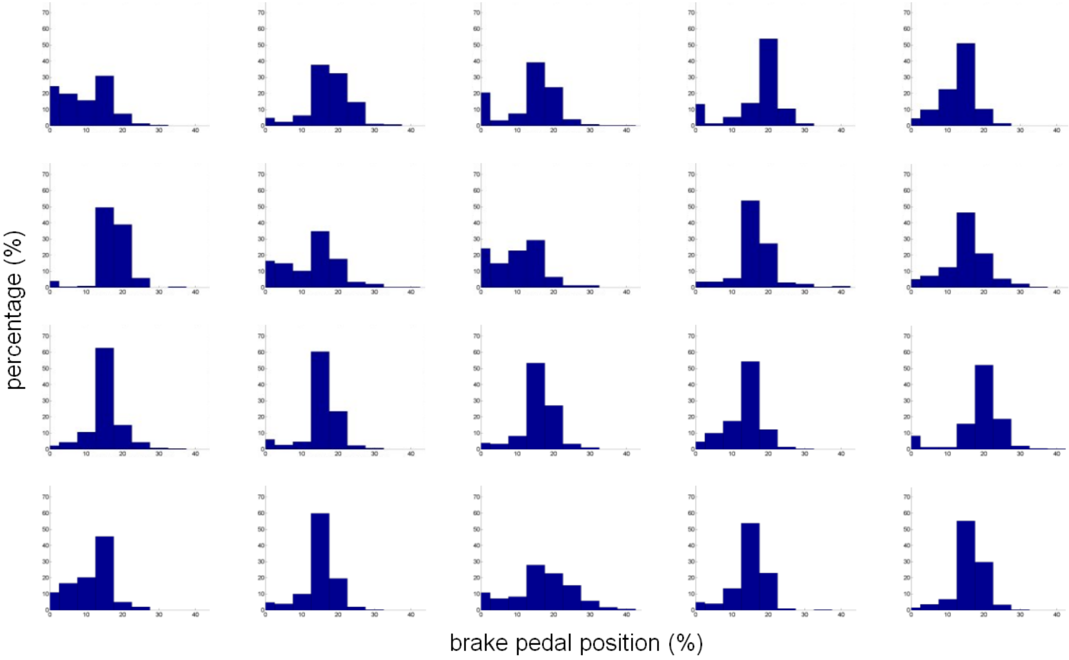

Figure 3.9: *Each subplot shows the histogram of brake pedal position at 0.5 s after the brake initiation for all brake sequences of a driver (often significantly fewer than 500). the first two rows are Dutch drivers (from left to right: 217 sequences for driver 2, 255 for driver 6, 306 for driver 8, 150 for driver 10, 270 for driver 12, 209 for driver 14, 330 for driver 16, 237 for driver 18, 232 for driver 20, 265 for driver 22), the lower two rows are UK drivers (from left to right: 236 for driver 60, 268 for driver 62, 370 for driver 64, 380 for driver 66, 392 for driver 68, 375 for driver 70, 322 for driver 88, 414 for driver 90, 336 for driver 92, 347 for driver 94).*

All the above observations not only strongly supported the hypothesis in the beginning of the section, but also provides valuable insight of driver's deceleration behavior for active safety system development. As a complement, the longitudinal acceleration has also been investigated with the same approach to see the relationship with brake pedal position for all drivers. As an example, Figure 3.10 visualizes the deceleration value in time series for the same divided groups of the same driver as in Figure 3.8. At the first glance, Figure 3.10 appears to fail to deliver the expected result. As noticed in the upper right subplot of Figure 3.7, the brake pedal position basically remains at a fixed level from 0.5 s to 2.5 s while the acceleration is decreasing instead of remaining at a constant level. That shows the brake pedal position and the acceleration are not linearly related. However, the nonlinear relationship somehow reveals the degree of complexity of a truck deceleration system. As noticed in all lower subplots of Figure 3.10, the sharp peaks suggest that at the instant of 0.5 s the effect of depressing

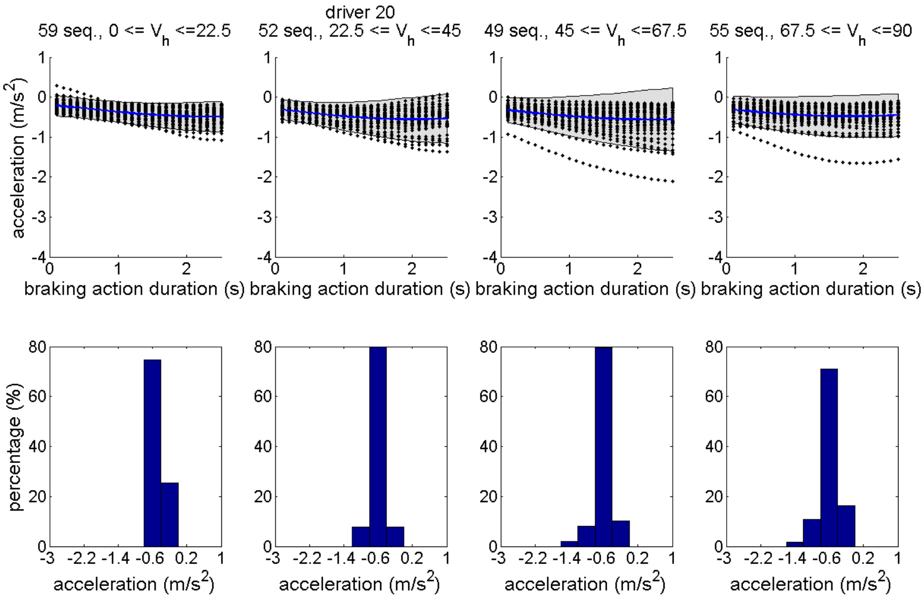

Figure 3.10: *Visualizing the acceleration value during the first 2.5 s of all decelerations achieved by depressing brake pedal for driver 20. Same approach as done in Figure 3.7 was employed. From the upper row, a slight acceleration decreasing is noticeable. The thick line in the middle is the average deceleration in time series. The histogram in the lower row shows the distribution of the truck acceleration at the instant of 0.5 s after the brake initiation.*

brake pedal are highly consistent.

3.3.2 Discussion

The focus of the typical brake magnitude study was on the brake pedal position and deceleration in the first 2.5 s, especially at the 0.5 s after initiating the braking maneuver. The average brake pedal position trajectories of drivers are roughly resembling to each other, that the brake pedal position increases to a stable level approximately at 0.5 s after the brake initiation, then remains at that position in the following 2 s. Figure 3.11 shows the general effect on deceleration by depressing the brake pedal for all drivers. With so many data points collected, the pattern is still quite clear, i.e. the brake pedals becomes effective after it exceeds the position around 17%. However, after that 17% the same brake pedal positions seems to be leading to rather different decelerations. One reason might be that a braking effect generated by depressing the brake pedal to a position is different than that generated by releasing it back to the same position. Despite that, drivers are still quite consistent in bringing the pedal to the level around 17% in half seconds, and then remain at that level for about another two seconds.

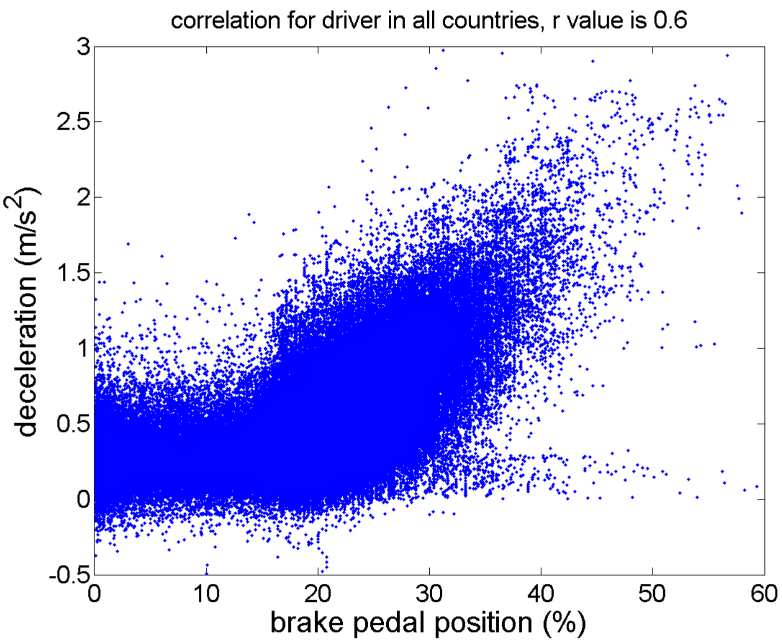

Figure 3.11: *A statistical assembling of all the different brake pedal positions and their respective decelerations from all drivers. Generally, brake pedal does not have an effect on deceleration until it reaches the level around 17%.*

In the light of the above observations, a brake system equipped in a truck is a highly sophisticated control system: through the system a low level deceleration process may involve other systems such as retarder, brake balance depending on the specific external and internal situation, so that driver on the highest level can have a simple, comfortable control over the whole truck.

Chapter 4

Model testing

In this chapter, first all the deceleration sequences are classified into scenarios according to lead vehicle status then some of the models discussed in the related work section are fitted to the extracted data.

The statistical data analysis in the previous chapter suggests that making the simplification of only looking at brake pedal usage still lets us cover a reasonable proportion of the deceleration sequences, especially those with highest deceleration magnitudes which are the most relevant to active safety systems. Therefore the study of deceleration initiation in model testing is based on brake pedal depressing. In the model testing phase it is of importance to find out:

- Whether or not the existing models are applicable to the study of truck driver behavior.
- If the logged brake initiation timing can be described by the models.

4.1 Scenario classification

The iTTC model proposed by Kiefer et al. [1] handles a deceleration scenario based on lead vehicle status at the instant when the host vehicle starts braking, i.e. lead vehicle being stationary (LVS), lead vehicle being moving at a constant speed (LVM), or lead vehicle being decelerating (LVD). For consistency in testing the iTTC model as well as the others, such a way of deceleration scenario classification is used to further organize all deceleration sequences.

However, the boundaries between scenarios in reality are not as clear as in theory. To mark a deceleration as a LVS scenario, instead of 0 km/h, 5 km/h was chosen to be the upper bound of lead vehicle being stationary. Our motivation here, is not only to make the algorithm robust against possible noise, but also to increase the amount of sequences in which the deceleration behaviors are similar, assuming when the lead vehicle is making such a slow movement in real traffic, the response of the host vehicle should not be much different from that if the lead vehicle were standing still. Such a kind of ambiguity manifests itself especially when trying to distinguish LVD from LVM. Due to the difficulty of judging whether a lead vehicle is decelerating or moving at a constant speed at the instant of brake initiation, the concept of a time window (a duration right before initiating the brake, e.g. three-second duration prior to the brake initiation) was introduced to calculate the speed difference for the estimation of the lead vehicle's status.

As no clear empirical evidence could be found on how much time would be sufficient for a driver to recognize the status of a lead vehicle, the following equation with time window T_w as a variable was used in each repetition of the sequence extraction in hope of revealing some sharp changes in the result of classification. Sequences were classified as LVM if the average deceleration in the time window was below a threshold $\max(d_{\text{LV}})$. In practice, sequences were classified as LVM if the observed reduction V_{change} of lead vehicle speed during the time window was smaller than:

$$V_{\text{change,max}} = T_w \times \max(d_{\text{LV}}) \tag{4.1}$$

If $V_{\text{change}} > V_{\text{change,max}}$, the sequence was classified as LVD.
If $V_{\text{change}} < V_{\text{change,max}}$, the sequence was classified as LVM.

Three rounds of sequence extraction were carried out using a different time window (2 s, 3 s, or 4 s) each time. Together with the discretized $\max(d_{\text{LV}})$ within the range of [0, 2.5] m/s^2, a threshold $V_{\text{change,max}}$ was defined for each repetition of the extraction under a round, as shown in Figure 4.1. The aim of this experiment is to find any obvious turning point in the LVM or LVD subplots, and then the turning point will be regarded as the appropriate threshold for scenario classification. However, it is hard to find such a point in Figure 4.1. To separate LVM from LVD anyway, the observation of the frequency distribution plot in the previous chapter was adopted: a brake pedal was typically used when a decelerations larger than 0.2 m/s^2 is needed. Checking the Figure 4.1, there is no harm to appoint 0.2 m/s^2 as the turning point. And for the benefit of model testing, let the time window be 3 s, therefore half of the situations that lead vehicle speed is bigger than 5 km/h will be considered as LVM and the other half be LVD.

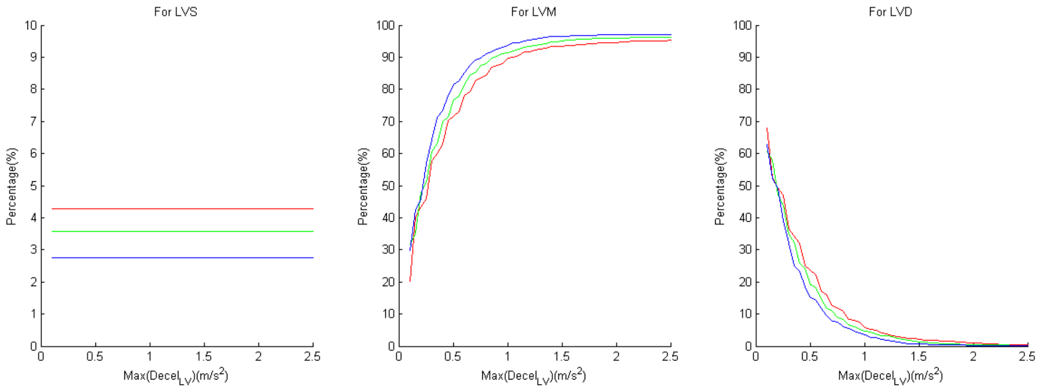

Figure 4.1: *In each round of sequence extraction, a different time window T_w (2 s, 3 s, 4 s) is used. Together with the discretized maximum deceleration of the lead vehicle* $\max(d_{\mathrm{LV}})$*, every maximum change of the lead vehicle speed $V_{\mathrm{change,max}}$ is used as a threshold in a repetition of classification. Each point in an interpolated graph (a horizontal line or a curve) in a subplot represents the classification result of a single repetition in one meta round. The upper graph, in the rightmost and the leftmost subplots, is using time window 2 s, the middle graph using 3 s, the lower graph using 4 s; whereas the upper one in the middle subplot using 4 s, the middle one using 3 s, the lower one using 2 s.*

4.2 Model testing

Both Newtonian models and optical variable models discussed in the literature review were tested. In addition, considering their different personalities, accident records, etc., drivers react differently even in identical situations. Therefore a driver-specific study of the models was conducted, and then an inspection was carried out to check whether or not the descriptions of drivers' behaviors are in any way similar in a model. Finally, efforts were taken to find a model competent in describing truck driver behavior.

4.2.1 Reaction to brake light

The most intuitive deceleration initiation will be reacting on the brake light of lead vehicle, which is a clear indication that the lead vehicle is decelerating or not. When the host vehicle driver perceived the brake-light-goes-on signal, he/she is supposed to prioritize the deceleration task among all the others. As many researchers (e.g. [1, 3, 10]) pointed out, most of the time the distance to the lead vehicle is kept depending on the host vehicle speed. That is to say, a brake-light-goes-on signal, which implies the safe distance is about to be shortened by lead vehicle decelerating, should stimulate a response from the host vehicle, i.e. to decelerate to update the safe distance at the expected new speed of the host vehicle. However, an open question is if drivers always

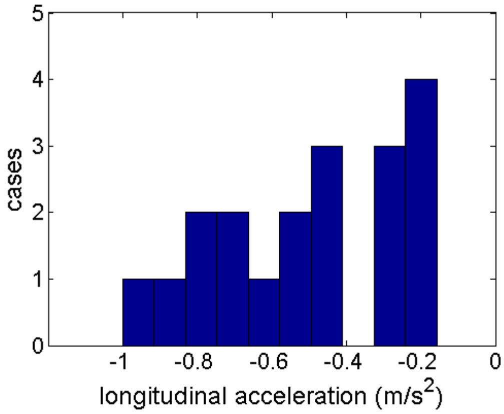

Figure 4.2: *Distribution of longitudinal acceleration of lead vehicle at the instant when its brake light goes on, based on fifteen qualified cases inspected frame by frame from different trips of different drivers.*

react immediately when the brake light goes on.

A statistical extraction of the reaction time appeared to be the most straightforward way to answer the question. But since there were no sensors recording the brake light status of the lead vehicle, an indication of brake light going on was desired. Drawing on the experiences gained in data extraction, we simplify the issue by associating the longitudinal acceleration with the brake light status. Whenever the lead vehicle decelerates more than a certain threshold, we assume the driver of the lead vehicle is depressing the brake pedal, thereby the brake light goes on. The desired threshold, i.e. a proper value of longitudinal acceleration indicating that the light must goes on, was determined through a frame-by-frame video inspection. However, the low resolution of the video data has limited the inspection strictly to the short distance situation in which any update from the brake light pixel can be perceived. Hence a rough estimation was computed based on fifteen cases of lead vehicle decelerations when the brake light goes on as indicated in Figure 4.2. To increase the estimation accuracy of a lead vehicle's acceleration value when its brake light goes on, many cases such as slowing down right after it cut in front were discarded, because in situations like that the response of a host vehicle driver is assumed to be different from that to the situations of following a decelerating lead vehicle (denoted as *qualified* in the caption of Figure 4.2).

Unfortunately the collected value did not converge well to have good estimation. In the end, the average value of all fifteen recorded acceleration -0.50 m/s^2 was used, i.e. whenever the lead vehicle decelerate more than 0.50 m/s^2, the brake light of lead

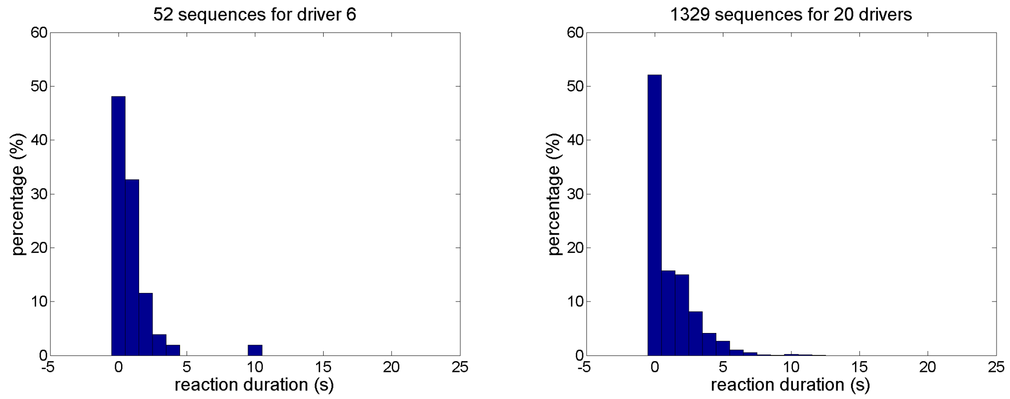

Figure 4.3: *Statistics of reaction time to brake light of the lead vehicle going on. The left plot is for driver 6 and the right plot is for all drivers.*

vehicle goes on. The average acceleration value is currently acceptable from the view of the statistics of brake pedal usage in the previous 2D density plot Figs. 3.4 or 3.5. With the estimated threshold, the time from the brake light going on (as approximated by lead vehicle deceleration exceeding 0.50 m/s^2) till the brake pedal of the host vehicle being depressed was collected in the form of a histogram as shown in Figure 4.3. The same threshold was applied for all other drivers as well, the right plot in Figure 4.3 summarized the reaction time span for all drivers. As shown in the right sub-figure, in nearly half of the cases it takes more than half second to get response from a driver. In line with many other models of driver braking, it seems that in many situations where the driver doesn't have to brake immediately, he or she will not [7]. However, it should be noted that this is not a final proof, as the result was delivered by using a threshold that was generated with only fifteen cases.

4.2.2 iTTC model by Kiefer et al.

As mentioned earlier in the literature research, experiments carried out by Kiefer et al. were based on passenger cars. Kiefer then generated a set of best-fitting functions with logistic regression for the empirical data. These functions drew the boundaries in the inverse TTC estimation space to distinguish whether or not a braking onset scenario was a normal or hard braking onset scenario. What interests us was the quantitatively proven relationship between iTTC threshold and host vehicle speed shown in Figure 2.1. The model can also be interpreted as: upper half of the iTTC-speed space separated by the line holds hard braking onset (as Kiefer et al. instructed the drivers to brake at the latest possible time in one part of the experiment), whereas the other half contains normal brake onset (as Kiefer et al. instructed the drivers to brake 'as they normally would do' in another part of the experiments). Its validity in the context of

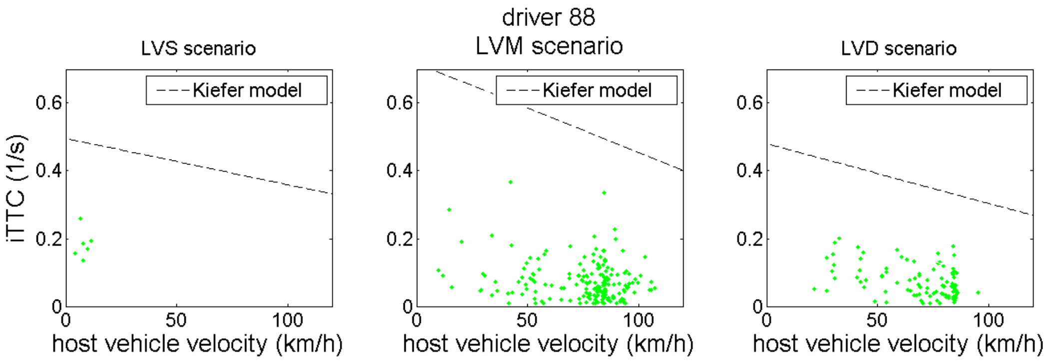

Figure 4.4: *Results of comparing deceleration initiation data for driver 88 with the iTTC model of Kiefer et al. Data points represent the actual brake onset data from 500 deceleration initiations. The Kiefer et al. model suggests that 95% of normal, non-critical brake onsets should be below the dashed line.*

truck driver behavior was checked, such as in Figure 4.4 for driver 88. Obviously most of the data points fall far under the dashed threshold line, i.e. in such an iTTC-speed space almost all the extracted decelerations are very *normal* decelerations according to Kiefer's passenger car model.

Testing of the model has been performed for other drivers as well. Figure 4.5 shows the performance of the model given data points from all drivers. The fact that all data points converge far under the dashed line may be understood as saying that the truck drivers brake earlier in a rear-end situation than what passenger car drivers do. A slight adjustment of this iTTC model was carried out to properly respond to the extracted data. In order to translate the model vertically downward until 95% of the data points are covered, the constant component of each equation of the iTTC model (-9.073 in LVS, -6.092 in LVM, -6.092 in LVM-B) has been simultaneously increased while leaving the other two (the iTTC and speed components) as they were. The dash-dotted line in figure 4.6 represents such an adjusted version of the model.

Since such a kind of covering capabilities will be used as a performance indicator in some of the following model testing tasks, it is addressed as *coverage* henceforth; the rate of the covered points will be regarded as *coverage rate*.

4.2.3 Gipps model

According to the Gipps [2] model (Equation 2.3), the speed V_{free} represents the strategy of how a driver travels freely, i.e. when there is no predecessor, driver would first increase acceleration to approach to the desired speed then decrease the acceleration

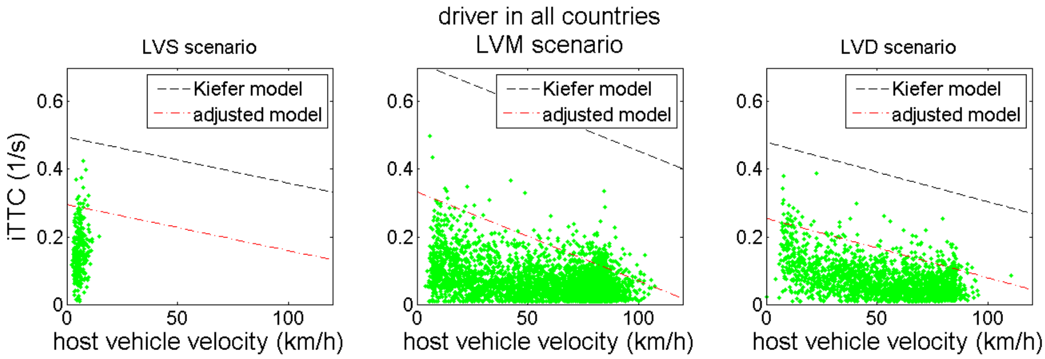

Figure 4.5: *All the data points are covered by the dashed line. The dash-dotted line in each subplot is the adjusted version of the Kiefer et al. model and covers 95% of the data points. The points covered by the adjusted version of the model is recognized as normal, non-critical brake onsets.*

back to zero when the vehicle speed is close to the desired speed. The speed V_{constr} describes his driving behavior in response to a predecessor. When these two terms are equal to each other, it is the time a driver starts to react to lead vehicle which, among many possibilities, can lead to the deceleration initiation.

An intuitive way to validate such possibility is to check the time it takes from the beginning of a deceleration sequence to the instant of the brake initiation during the course of the deceleration, and then compare it with the time at which V_{free} and V_{constr} intersect. As a preparation, all the parameters mentioned in the Gipps model were estimated by averaging (or maximizing, to obtain estimates close to the real values of the parameters) all the observed values in the collected deceleration sequences for each driver. These estimated parameters are:

- The maximum acceleration the host vehicle driver wishes to undertake.
- The speed at which the host vehicle driver wishes to travel.
- The most severe braking the host vehicle driver wishes to engage (< 0).
- The estimated most severe braking the lead vehicle driver wishes to engage.
- The estimated safe distance the host vehicle driver will never intrude.

Unfortunately, after experiments on all drivers from both country, the correlation between the actual brake initiation and the reaction to lead vehicle calculated via model (2.3) for every driver has been found to be very low. Figure 4.6 shows a general correlation between the two times for all drivers. One of the reasons for the low correlation may be due to the optimistic estimation of parameters for Gipps model which makes

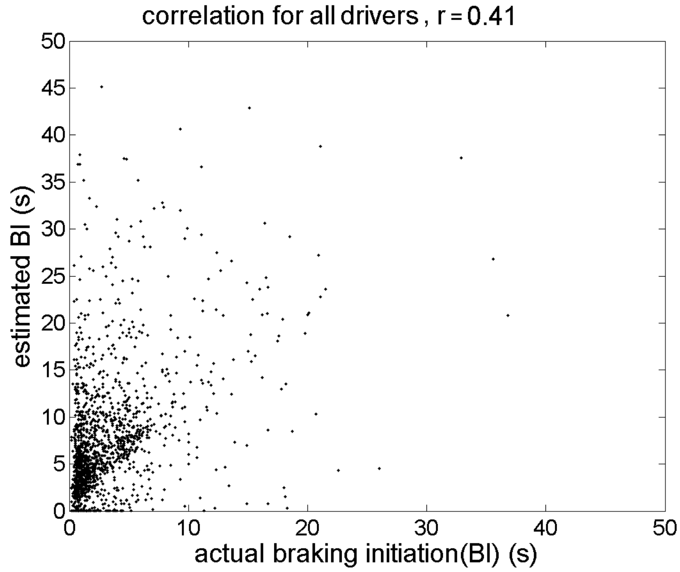

Figure 4.6: *The X axis represents the time it takes to actually initiate the braking counted from the start of a sequence. The Y axis denotes the estimated reaction time in the same sequence, i.e. when* V_{constr} *equals* V_{free} *a driver may initiate braking to react to the lead vehicle.*

the V_{constr} too large, so that the estimated reaction time from the start of a sequence is much delayed compared to the actual brake initiation time. Also during the experiment, often the V_{constr} was already smaller than V_{free} at the beginning of a deceleration sequence, i.e. before the beginning of an extracted deceleration the driver should already have reacted to the lead vehicle in the view of Gipps model.

4.2.4 A new optical model assuming constant deceleration

As a test of the validity of the optical variable state space model proposed by Flach et al. [3] in the context of truck applications, the extracted data were used as input for such model. In the actual experiment, the size of the obstacle in Equation (2.5) can be the width of the lead vehicle, width of brake light, or so. As long as it was an unchanging value during the course of deceleration, the effect of any chosen size can be canceled by normalizing optical variables (e.g. θ, $\dot{\theta}$) with the width. To simplify the model, the width was set to a constant value - 1.8 m - a typical passenger car width.

Figure 4.7 shows all trajectories made by $(\theta, \dot{\theta})$ during the course of deceleration for one example driver, the asterisk represents the deceleration initiation moment. Although the shape shares no similarity with the linear relationship proposed by Flach et al. depicted in Figure 2.3, blurry regularities can be observed from those trajectories

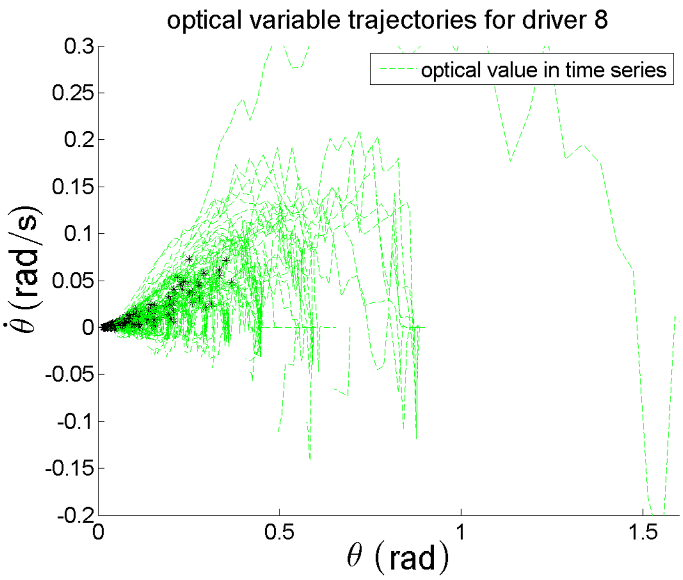

Figure 4.7: *Each dashed $(\theta, \dot{\theta})$ trajectory represents a deceleration sequence of driver 8. the asterisk denotes the $(\theta, \dot{\theta})$ at the instant of brake initiation. Such a kind of curvy trajectories have been found common for all other drivers.*

altogether in the plot for driver 8, which implies the deceleration behavior can be somehow related to optical variable. To understand above trajectories, a more specific kinematic formula which can be specified by the optical variable is desired. Markkula [19] advised to use the following inequality which describes the distance at which the driver should start braking with deceleration d in order to avoid forward collision.

$$D_{\mathrm{B}} \geq ((V_{\mathrm{H}} - V_{\mathrm{L}})^2/2d) + D_{\min} \tag{4.2}$$

where V_{H} stands for the host vehicle speed; V_{L} stands for the lead vehicle speed; d stands for the deceleration; $D_{\min}$ indicates the marginal distance the host vehicle shall keep from the lead vehicle. Since in reality the safety distance to the lead vehicle a driver tries to maintain is depending on the traveling speed [1, 3], the safety distance in above inequality has been updated as $\max(D_{\min}, V_{\mathrm{L}} \times T_{\min})$, where $V_{\mathrm{L}} \times T_{\min}$ represents the marginal distance when the lead vehicle is moving. We use the inequality as the basis to quantify the relationship of the two optical variables in Equations (2.5), and get:

$$\dot{\theta} \leq \sqrt{\frac{2d\theta^3}{W}(1 - \frac{\theta}{W}\max(D_{\min}, V_{\mathrm{L}}\, T_{\min}))} \tag{4.3}$$

A preliminary model parameters setting was suggested from real world experience as: the time headway $T_{\min}$ is set to 1 s, safety margin $D_{\min}$ is set to 2.25 m and width of

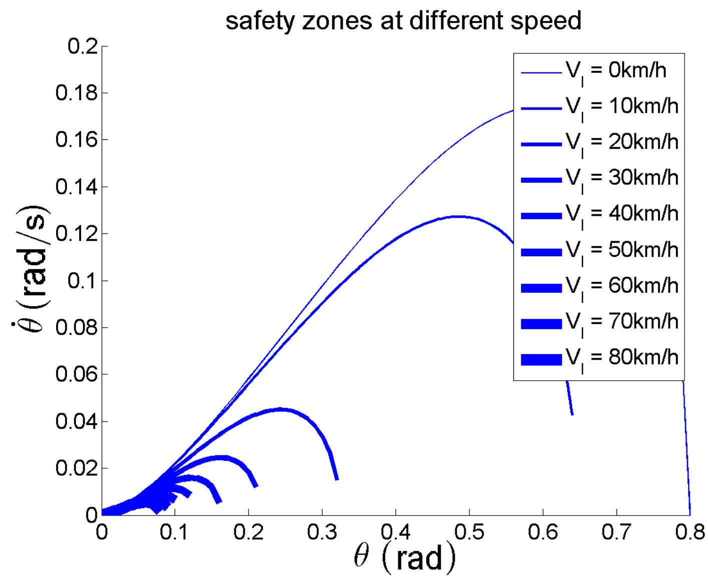

Figure 4.8: *A new optical models developed based on* (4.3). *Assuming a driver is able to estimate speed of lead vehicle directly, each of the lines represents the boundary of a model given a specific lead vehicle speed. The area contained between a curve and the x axis will be viewed as a safety zone from now on. As long as an asterisk point* $(\theta, \dot{\theta})$ *with a specific lead vehicle speed falls within the safety zone specified by such speed, the brake initiation is to be regarded as a safe brake initiation, i.e. given a valid* θ *(within the safety zone), collision can be avoided as long as the driver keep the* $\dot{\theta}$ *within the zone as well.*

the lead vehicle W is set to 1.8 m. While the maximum constant deceleration d shall be different from driver to driver because their maximum decelerations in the first 2.5 s have been shown to be different in the study of driver's typical brake magnitude. With the kinematic inequality (4.3), a model can be visualized by further specifying the V_{L}, Figure 4.8 is a model for driver 8. Importantly, when the speed is getting higher, the area covered by the curve shrinks dramatically as demonstrated in Figure 4.8. That is, a driver has more time to initiate braking in response to the change of lead vehicle status when the speed is low; but when the speed gets higher, the driver must react immediately to prevent a rapid growing in visual expansion rate.

On the other hand, even though Equation (4.3) suggests that lead vehicle speed alone should be enough, in reality, drivers may not be good at estimating lead vehicle speed. Estimating based on the own speed could be one simple hypothesis on what drivers do, e.g. $V_{\mathrm{L}} = k \times V_{\mathrm{H}}$, where k can be assumed to be a constant factor. Exploration has been carried out to compare the performance of these two models derived from their different ways of estimating lead vehicle speed. Take the experiment on driver 22 as an example, when k = 0.6, the average coverage rate for direct V_{L} access model is 0.905.

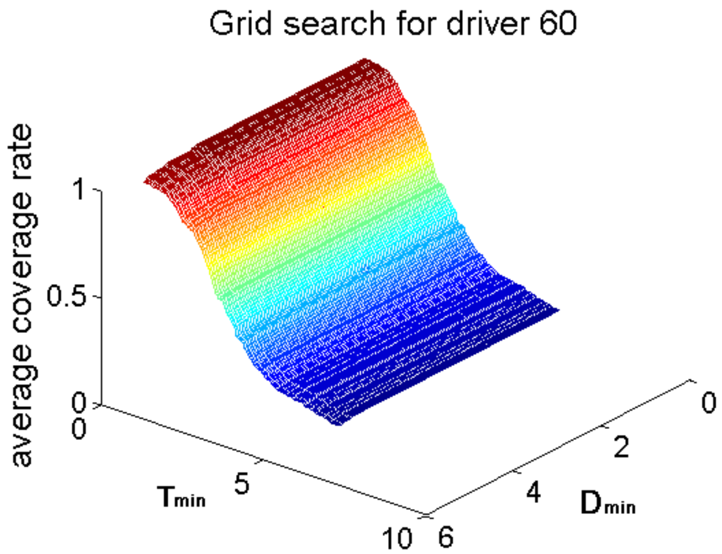

Figure 4.9: *A grid search to find the best combination of D_{min} and T_{min} in terms of maximizing average coverage rate for driver 60.*

Whereas for $V_{\mathrm{L}} = k \times V_{\mathrm{H}}$ model, the average coverage rate is 0.950. More exploration has shown that the model based on $V_{\mathrm{L}} = k \times V_{\mathrm{H}}$ is able to cover more optical data points (asterisked points as shown in Figure 4.7), given any reasonable k factor.

From a series of experiments on coefficient setting, it appeared that time headway T_{min} decides the effective interval of the safety zone. The smaller T_{min} is, the wider the safety zone will be extended. For higher, more realistic values of T_{min} such as 1.5 s, capability of both models was impaired. Take driver 22 for example, the average coverage rate based on host vehicle information is approximately 0.921, while that based on lead vehicle information is approximately 0.675. Grid search has been applied for D_{min} and T_{min} to get the best coverage rate of the model. Take driver 60 as one example, according to Figure 4.9, when T_{min} is smaller than 0.5 s the coverage rate will reach optimal. But in reality it is not a valid setup when time headway is close to zero. D_{min}, on the other hand, does not appear influential after same kind of exploration. T_{min} = 1 s, D_{min} = 2.25 m seems the most reasonable and capable of covering speed binned optical points of $(\theta, \dot{\theta})$ at deceleration initiation moment. To better demonstrate the idea, a separated plot of speed binned model of all recorded $(\theta, \dot{\theta})$ of all drivers has shown in Figure 4.10, with nine different host vehicle speed levels.

Since the optical model was developed based on the kinematic inequality (4.2), supposedly, a Newtonian model based on the same inequality should be able to deliver identical results with the same parameter setup as the optical model does. Surpris-

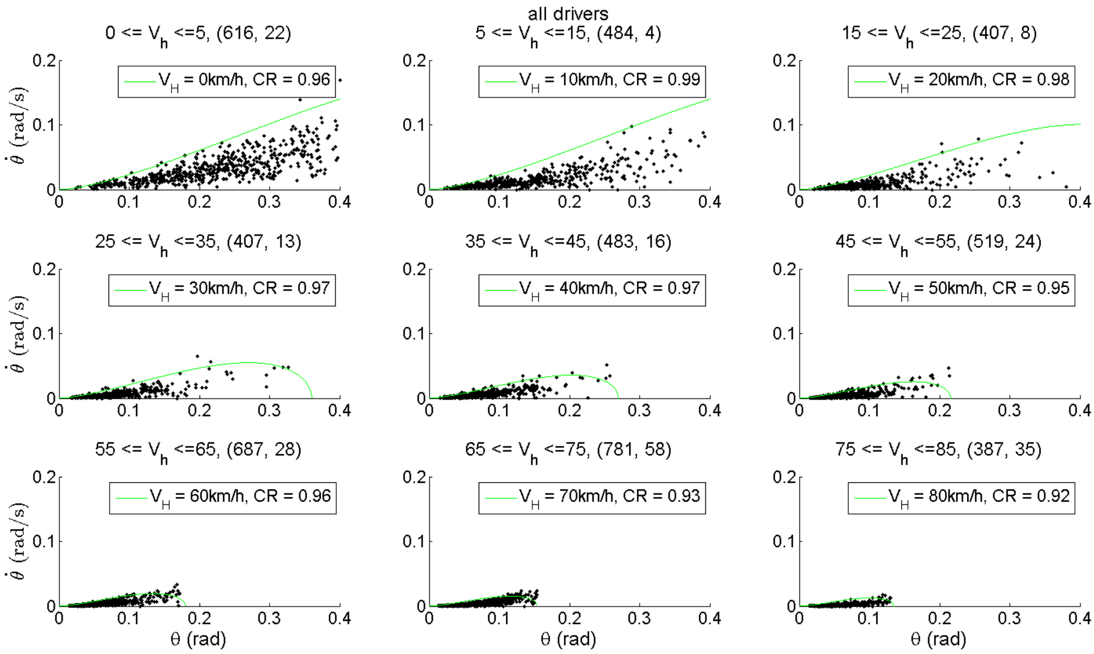

Figure 4.10: *Speed binning plot (based on host vehicle speed) of the optical model for all drivers. The constant deceleration (d) has been set to the observed maximum deceleration of all drivers, whereas T_{min} = 1 s, D_{min} = 2.25 m, k = 0.6. The title of each subplot states the speed interval for containing the appropriate data points, also indicates the amount of (covered data points, uncovered data points).*

ingly, this Newtonian failed to provide the same coverage rates as the optical model. The failure may be interpreted by increasingly under-estimating V_{L} with a constant k factor in the constant deceleration model. The quadratic curve in Figure 4.11 illustrates the performance of the model for driver 22.

4.2.5 Summary

For future research about the reaction-to-brake-light model as well as having a more plausible estimation of a lead vehicle's average acceleration when its brake light goes on, it needs to be argued that different lead vehicle decelerating situations (e.g. following a decelerating lead vehicle v.s. quick response to a decelerating one who just cut in front) will indeed cause different kinds of the host vehicle driver responses; and more inspections will be necessitated as well. The testing of reaction-to-brake-light model and iTTC model were restrained by the limited range of measured data (the lack of hard or normal brake measurement in iTTC model and the brake light measurement for the reaction-to-brake-light model). The adjusted Gipps model appeared incapable of producing convincing estimation.

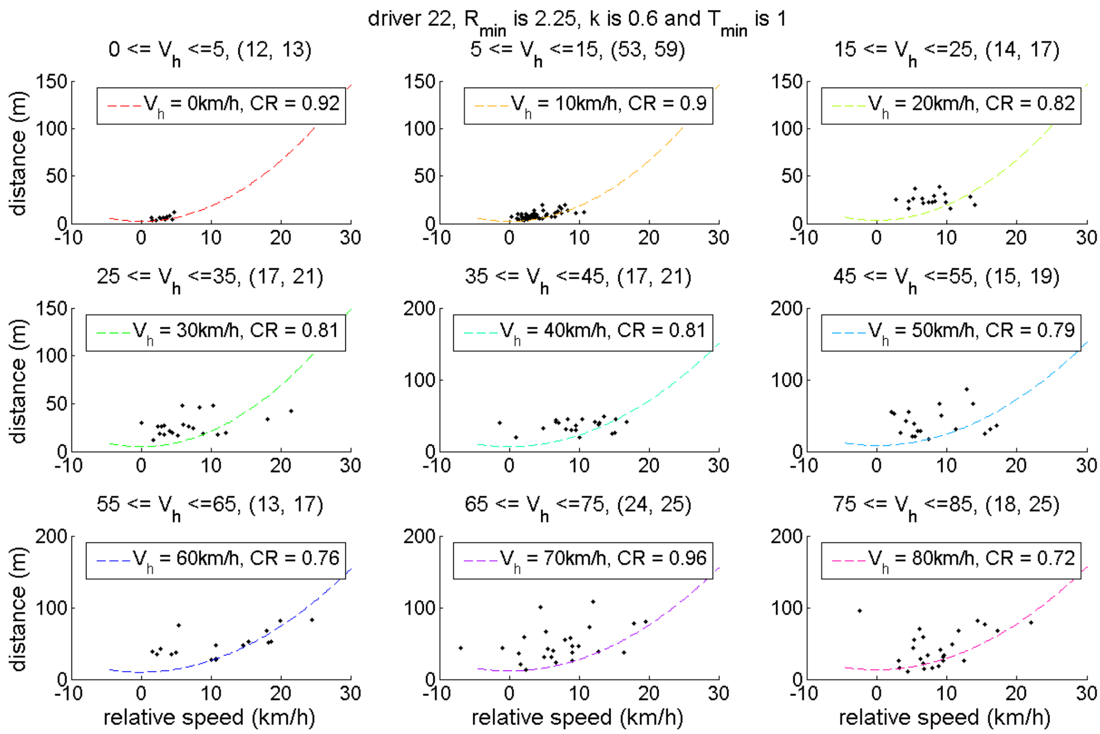

Figure 4.11: *Speed binning plot of the constant deceleration model (Equation 4.2) for driver 22. The parameter setup is the same as used in optical model. The data points in each subplot are the actual instance of Newtonian variables at the instant of brake initiation: speed of the host vehicle and distance margin to the lead vehicle that a driver should take actions upon. Note that in this model a data point is considered to be covered when it is above the quadratic curve. The title of each subplot states the speed interval for covering the appropriate data points, also indicates the amount of (covered data points, un-covered data points).*

Among all the models tested above, the new optical model was able to adjust itself with the change of the host and lead vehicle speed, managed to cover more data points with the aid of the host vehicle speed information and succeeded in covering the speed binned data with a fairly tightly fitting zone. However, it is unfair to conclude that optical model is generally superior than all the others without declaring a specific application scope. In addition, the gap between the data point and the curve implied possible directions for future work, such as introducing deceleration of the host vehicle as another variable of the model. In the constant deceleration model (Equation 4.2), the relatively impaired performance when the host vehicle speed got higher can be inferred as: the insufficiency of using fixed k factor as the basis on estimating of lead vehicle status. If the k factor were set to be a variable, however, the relationship between the host vehicle speed and the lead vehicle speed would become non-linear. Such a non-linear relationship suggests that a driver may assess the lead vehicle speed using some other factors than just the host vehicle speed, such as the optical variables θ and $\dot{\theta}$, which may explain why the optical model outperforms the constant deceleration model with fixed k. To conclude at the current stage, it is suspected that the inconsistent performance of these two models was caused by the lack of perceptual features in Newtonian variables from constant deceleration model has been fully offset in optical model. However, such interpretation should be further studied.

Chapter 5

Conclusion

This report has presented analysis work on extracting and analyzing data from the euroFOT database with the purpose of studying the deceleration initiation behavior of truck drivers. The second part of the report has focused on testing some existing models of such behavior, and development of a new optical model and their performance given the extracted data as input.

5.1 Data extraction and analysis

When the vehicle coasted without intervention from a driver, the logged acceleration was discovered to be approximately -0.05 m/s^2. It may be caused by mechanical friction, air drag, etc. This value was adopted as the threshold for deceleration sequence extraction.

Statistically, it was a common deceleration initiation behavior for drivers from both UK and the Netherlands that most of the decelerations were short, light-footed decelerations. A driver from either country would release the accelerator pedal when a mild deceleration was needed; if a deceleration harder than 0.2 m/s^2 was required she or he would depress the brake pedal. Changing the retarder settings (using the retarder stalk) during deceleration to achieve desired deceleration was rare. The choice of alternative ways of deceleration (accelerator pedal releasing and brake pedal depressing) was speed dependent, i.e. drivers tended to depress the brake pedal more often when the host vehicle speed was low. When the speed got higher, they tended to more often release the accelerator pedal to decelerate the truck. However, there were some differences between nationalities. Statistically, UK drivers were more in favor of releasing accelerator pedal than depressing brake pedal to decelerate the truck. While Dutch drivers did not show much preference. Furthermore, UK drivers appeared to have more severe (short but hard) braking.

The most important observation in the study of typical brake magnitude is that drivers were rather consistent in the brake pedal positions after 0.5 s of the brake initiation. When the brake pedal position was approximately less than 17%, the effects on deceleration were generally not noticeable. From the driver's perspective, it normally takes 0.5 s to reach the position 17% of brake pedal. Drivers then typically remain at this position, or slightly increase brake pressure in the following 2 s (Figure 3.8).

5.2 Model testing based on brake pedal depressing

The reaction-to-brake-light model, at a very initial stage of such experimental study, showed that in about half of the observed cases, the drivers did not respond immediately to the brake light of the lead vehicle. However, this claim needs to be further tested with more elaborate experimental designs and more intensive data collection. The iTTC model by Kiefer et al. is not suitable to describe truck driver behavior because it is a regression model developed based on a set of delicately designed experiments for passenger car drivers. Nonetheless, an adjusted version of the model has been carried out so that 95% of the data points fall inside the model's prescribed area of normal braking. The Gipps model seems unable to produce good prediction, which may be the result of optimistic parameter estimation or incomplete deceleration sequences (from the view of Gipps model).

The new optical model derived from a constant deceleration model (Equation 4.2) produced high coverage rate of the real data. The promising performance of the new optical model suggests a model involving more factors such as optical variables is likely to produce results with higher coverage rate, whereas the linear dependence on the host vehicle speed and the lack of other inputs for estimation may be the reason of the low coverage rate in constant deceleration model. Given a real data set, the optical model is more capable of describing the driver behavior in brake initiation.

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