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Driver Behaviour Model Based Threat Assessment for Forward Collision Warning Systems

Master's thesis in Automotive Engineering

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Department of Mechanics and Maritime Sciences
CHALMERS UNIVERSITY OF TECHNOLOGY
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Abstract

Forward Collision Warning systems warn the driver when there's a risk of a collision with a car or truck in front of the equipped vehicle. Different drivers have different driving styles, and an attempt is made to come up with a conceptual design of such a system that adapts to these differences. The aim of this thesis was to develop a threat assessment algorithm that estimates the driver's "comfort zone" by continuously analyzing vehicle signals, and uses it to decide when to issue a forward collision warning to the driver. A literature survey of relevant driver behaviour models for braking was performed for this application, and estimation schemes were designed and developed for a looming threshold based, and an evidence accumulation based model. Further, a test track study was conducted to collect driving data, and the developed estimators were tested on this data. Qualitative comparisons of the two driver behaviour models were made, and used to propose conceptual designs for threat assessment algorithms. Due to the design of the test track study which used professional test drivers, and involved repetitive tasks, the data collected was not suitable to draw conclusions on the performance of the developed estimators. A comparison of the obtained estimates of driver model parameters, and parameter values reported in literature showed potential but this needs to be verified with a larger naturatlistic driving dataset.

Keywords: forward collision warning, driver behaviour models, braking behaviour, driver adaptation, evidence accumulation

Acknowledgements

A dream grounded in reality. That's how I looked at this thesis while finalizing the proposal. Forward Collision Warning systems had been in markets for years, and so had driver behaviour models. I'd even found early attempts in literature that combined the two. So how difficult could it be to develop in six months, a "conceptual design" of a driver based FCW system that can be out on production trucks in a couple of years?
Quite a bit. The numerous challenges that I faced - technically and mentally could've easily broken the thesis and me along with it. Luckily, I had the support of incredible colleagues and friends at the Volvo Group and at Chalmers. I'd like to take the opportunity to acknowledge some of them here.
Mathias Theander, Markus Gerdin, and my supervisor, Laurent Decoster at Volvo helped me understand how a production Forward Collision Warning system works, and the challenges involved. Emma Johansson, Fabio Forcolin, Martin Sanfridson, and Giulio Bianchi Piccinini patiently listened to my proposed driver parameter estimation schemes and gave valuable feedback. My examiner, Leo Laine was instrumental in reducing the gargantuan scope of my naive original thesis proposal, which proved to be crucial for my sanity. The support of my manager at Volvo, Christer Åkerblom and the head of the Vehicle Dynamics Group, Bengt Jacobson was crucial to deal with all the complex administrative issues that kept cropping up during the course of this thesis.

Abhishek Karunagaran, Gothenburg, June 2018

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1
Introduction

Traffic crashes and accidents can leave deep psychological scars on survivors, families of victims, witnesses and society in general, in addition to severe property damage. In 2015, road injuries were responsible for the deaths of 1.3 million people according to the World Health Organization (WHO) [2], making it the 10th leading cause of death globally. This implies the occurrence of a much larger number of traffic crashes and accidents that didn't lead to fatalities.
Volvo Group's Accident Research Team concluded that Active Safety systems designed to prevent accidents have a great potential to improve Traffic Safety [3]. Systems such as the Forward Collision Warning (FCW) and Advanced Emergency Braking System (AEBS) that warn drivers of impending frontal collisions, and take preventive action respectively were highlighted.
Considering that these systems interact with the driver, it is essential that they don't become a nuisance by interfering with normal driving tasks. However, warnings and interventions should still be provided when needed. A FCW system should hence consider the driver's preferences and driving style to suitably adjust the timing of warnings, while ensuring compliance with safety and legal requirements.

1.1 Background

Accident Causation and Active Safety

An important step towards understanding the motivation behind this thesis is to grasp why accidents occur, and the role that active safety functions play in mitigating or preventing them.
To this end, Ljung Aust and Engström developed a conceptual framework to help standardize the criteria and metrics used for requirement specification and evaluation of active safety systems [4]. This framework will be used to explain accident causation and the role of active safety. "*Situational control*" is the central concept of this framework, where drivers choose a "*goal state*" which balances goal fulfillment against the feeling of discomfort, and continuously adapt to disturbances due to a changing environment. This is based partly on Summala's zero discomfort model in which drivers "strive to maintain a state of zero discomfort"[4, 5].
The goal state consists of the driver's goal, described by the states/parameters values of the driver, the vehicle, and the environment (DVE). The region of states/parameters in the DVE space that correspond to a controlled operation is called the "*safety zone*". Drivers attempt to select a goal state within this zone, keeping a safety

margin to its boundaries. This sub-region of the safety zone accounting for the safety margin is called the "*comfort zone*". The boundaries of the comfort zone are based on expectations of discomfort by the driver, which comes from a subjective understanding of the vehicle and environmental conditions. The estimation of the safety zone and comfort zone boundaries depends on the driver's ability, experience, expectancy and level of alertness [4]. **Hence, the zone boundaries will vary for different drivers and different situations (varying with traffic conditions and driver alertness).**
When the DVE states exceed the comfort zone, drivers feel discomfort and take corrective action to return to the comfort zone. An incorrect estimation of the safety zone boundaries, or failure to maintain situational control could lead to an accident. This could happen due to several factors such as erroneous perception (e.g. due to poor visibility), distraction, misallocated attention, incorrect prediction of other road users' movements, overestimation of driver/vehicle capabilities, and sudden unexpected events [4].
With this understanding of why accidents occur, the role of active safety functions can be better explained. Active safety functions support the driver in maintaining situational control by addressing the accident causing factors listed above. Estimation of zone boundaries can be improved through functions such as distance alert, FCW, blind spot detection, etc. while functions like AEBS, Lane Keeping Assist can help keep or bring back the DVE states into the safety zone [4].

Forward Collision Warning Systems

The ISO standard 15623:2013, "Intelligent transport systems – Forward vehicle collision warning systems – Performance requirements and test procedures" defines a forward vehicle collision warning system (referred to in this thesis as FCW) as a "system capable of warning the driver of a potential collision with another forward vehicle in the forward path of the subject vehicle" [6]. It further specifies that the purpose of this system is to warn the driver in time to help prevent/mitigate a frontal collision (frontal from the perspective of the subject vehicle). The warning should be provided early enough to help avoid most common frontal collisions by the application of brakes alone, *but the warning should also not be perceived as being false or a nuisance* [6].
Hence, in Ljung Aust and Engström's conceptual framework, the purpose of FCW is to warn the driver as the DVE states exceed the boundary of the comfort zone. The warning helps the driver better perceive the safety zone boundaries and in the case of misallocated attention, direct the attention of the driver to the threat in front [4],[7].

Driver Behaviour Models

Michon classified driver behaviour models based on whether they were concerned with the motivations of the driver or their behavioural characteristics (input-output), and whether they're dynamic or not [8]. This thesis primarily deals with driver behavioural model that mathematically describe the relation between driver inputs

and outputs. Several such models have been proposed to represent driver behavior under routine and near-crash situations, with some treating driving as a 'tracking' task and thereby taking a control theory approach, while others take an approach based more on human psychology [9].

Driver Adaptive FCW

Over the previous subsections it's been established that the boundaries of the driver's comfort zone and safety zone vary across drivers, and that FCW warns the driver when DVE states go outside the comfort zone. Hence, it can be inferred that a FCW system should adapt it's timing of warnings for different drivers to improve driver acceptance.
Jamson et al. performed a simulator study where drivers were asked to compare two FCW systems - one with fixed timing of warnings, and the other which adapted the timing based on each driver's reaction time. They concluded that while both systems reduced the risk of crashes by a similar amount, aggressive drivers preferred the adaptive system [10].
Wang et al. developed an FCW algorithm that adapts to different drivers and variations in the behaviour of a driver over time. The algorithm is based on a hypothesis that drivers attempt to control the vehicle such that the time headway is a desired value and the inverse time-to-collision is zero. A risk perception quantity was defined based on this hypothesis, and the FCW algorithm issued a warning when the quantity crossed a threshold. The parameters of the risk perception model are estimated using recursive least squares, and the threshold is determined using decision tree learning. The algorithm was evaluated on driving data collected using an experimental passenger car and the algorithm was found to have a lower rate of false alarms than a non-adaptive traditional algorithm with fixed threshold values [11].

1.2 Research Objectives

Motivated by the conceptual need for driver adaptation and the potential shown by adaptive FCW algorithms in literature, the aim of this thesis was to set the foundation for developing a production FCW system that can continuously analyze sensor signals, and:

- estimate the driver's comfort zone boundary in the DVE space during routine driving,
- check for short-term deviations from routine behaviour (e.g. due to fatigue, a change in driver, etc.),
- calculate if required evasive action leads to DVE states going out of comfort zone, and
- give different levels of warning, if needed, based on the situation's criticality.

Research Questions

Such a foundation was to be developed by answering the following research questions:

A **How can driver status (e.g. Reaction time) and threat status be observed by the adaptive FCW system?**
   1. What models should be used in driver observation status for estimating comfort zone boundaries?
   2. How can a conceptual design be made for the adaptive FCW?

1.3 Limitations

The following limitations were placed on the scope of the thesis:
- Presence of only a single leading vehicle.
- Target vehicle present in the path of the ego vehicle.
- Roads have limited curvature density.
- Driver considered to brake only in response to target vehicle's motion (i.e. no engine braking).
- Driver decelerates the truck by pressing the brake pedal.
- Driver does not steer to avoid collision.

1.4 Approach

The following approach was used to attempt to answer the posed research questions:
1. **Identify driver behaviour models** from literature that can be applied for the FCW use case. This formed the first step in answering research question A.1.
2. **Find/Collect driving data** for testing estimation and threat assessment algorithms. After an attempt to get access to a large driving database failed, data collected on a test track was used.
3. **Develop algorithms for estimating parameters of driver models** and evaluate performance on driving data. The aim of this step was to answer research question A and A.1.
4. **Design a threat assessment framework** that adapts to the varying comfort zone of different drivers. This partially answered research question A.2 and set the framework for answering research question A.

1.5 Thesis Structure

The thesis has been structured along the same lines as the approach outlined in Section 1.4. Chapter 2 contains a brief literature survey of driver behaviour models and a more detailed description of the two models selected for designing parameter estimation algorithms. Chapter 3 describes the methodology used while collecting driving data on the test track. The parameter estimation algorithms are described in Chapter 4 along with the results obtained by running the algorithms on the collected driving data. Chapter 5 describes threat assessment frameworks designed based on the parameter estimation algorithms. Conclusions and envisioned future work are presented in Chapter 6.

2

Driver Behaviour Models for Braking

2.1 Literature Survey

The transition of driving states from routine to conflict and near-crash situations is of great importance while designing a FCW threat assessment algorithm. Markkula et al. performed a comprehensive literature review of driver behaviour models depicting near-collision behaviour [9]. While routine driving behaviour varies significantly from near-collision behaviour, routine driver behaviour models have been applied to understand near-collision behaviour. Such models were included in this literature review in addition to models designed for more critical situations, and was hence used as a starting point for this literature survey [9]. Due to the scope of this thesis which dealt primarily with longitudinal dynamics, the main focus of this survey was on models depicting braking behaviour.
Markkula et al. divided the braking models into two categories - models where the driver starts to brake "at the instant a collision course is established", and models that display *satisficing* behaviour, where the driver starts to brake later based on the driver's safety margins [9]. The following two subsections describe models from each of these categories.

Non-Satisficing Models

In the category of non-satisficing models, the Gazis, Herman, and Rothery (GHR) model is well known [9]. The model was developed to represent car-following behaviour where the acceleration of the following vehicle depends on the following vehicle's velocity, space headway, and relative velocity [12]. The model is non-linear and a lot of research has been done on finding the right parameters for the model, and on modifying the model to improve realism, or in some cases, even to simplify it [12],[13],[14]. One such simplified model is the Helly model, which is linear [15].
Another model class which has been widely used for studying forward collision warning systems is the delayed constant deceleration models, described by Markkula et al. as, "Starting at a (reaction) time T after a stimulus S, the driver applies a constant deceleration D." This approximates the behaviour of the GHR model in situations where the lead vehicle decelerates. In the review, the stimuli cited included "sudden appearance of an unexpected obstacle", "first glance back towards the road after a lead vehicle has begun deceleration", and "the establishment of an initial collision

course"[9]. Considering these stimuli, the resulting models would be non-satisficing since they don't account for the driver's safety margins while representing the start of braking.

Models that simulate Human Satisficing Behaviour

Lee established that the Time to Collision (TTC) can be estimated using a visual variable related to the optic flow field of the driver, and proposed that drivers start to brake once this visual variable crosses a threshold [16]. Kiefer et al. proposed that the driver starts to brake once the inverse time to collision (invTTC) exceeds a speed dependent threshold, based on a driving database containing "3536 last-second braking judgement trials" [17].
A popular satisficing model is the Gipps model where the driver controls the speed of the vehicle such that, if the leading vehicle suddenly brakes with a certain deceleration (a parameter of the model), a collision can be avoided without exceeding the driver's preferred deceleration limit, provided the driver's reaction time is within a certain limit [18]. Markkula et al. performed simulations with the Gipps model and showed that the invTTC values when the driver starts to brake follows a similar trend to the speed dependent thresholds of Kiefer et al. [9].
Markkula proposed a modeling framework that could represent both routine and near-crash driving behaviour. The framework was not limited to braking, and key features of this framework include:

- representing the driving task as a series of discrete adjustments rather than a continuous closed loop control task
- the timing of these adjustments are based on the accumulation of evidence (e.g. invTTC)
- the amplitude of the adjustments depend on the value of the evidence and the predicted effect of adjustments on the evidence [19].

Markkula showed that an accumulator that used a visual estimate of the inverse time to collision was able to closely predict the time when drivers start to brake in the driving database of Kiefer et al. for cases where the lead vehicle was moving. However, for cases where the lead vehicle was stationary, the model's prediction were much earlier than what was observed in the data [19]. Svärd et al. manually parameterized a driver braking model based on Markkula's framework, and simulated it on Euro NCAP scenarios [20]. The resulting behaviour in near-crashes and crashes showed similar trends observed by Markkula et al. in the SHRP2 naturalistic driving database [20, 21]. The framework was later extended to human sensorimotor control in general [22].

2.2 Model Selection

Having gained knowledge of most of the popular driver behaviour models for braking, the next step was to select which models to use for developing FCW threat assessment algorithms.
With guidance from the objectives outlined in Section 1.2, the following factors were considered while selecting models:

- ability to accurately represent and predict driver braking behaviour,
- compatibility with theories from human psychology,
- ease of estimating parameters on production ECUs,
- sensitivity to different driving scenarios, and
- robustness to possible limitations of production sensors.

It was promising to note that a lot of models could in theory be used to observe driver status. Unfortunately, the time constraints of a master's thesis meant that only two models could be investigated.

The first model investigated was a delayed constant deceleration model. The simplicity of the model combined with its prior applications in evaluating FCW systems made it a very attractive option [9]. To better account for satisficing behaviour, the stimulus for this model was defined to be the crossing of a driver specific invTTC threshold rather than a lesser kinematics dependent stimulus like the appearance of a target.

While the delayed constant deceleration model is simple, in routine driving the deceleration could significantly vary over the duration of the braking event as the kinematics of the situation vary. For example, consider the situation where the leading vehicle starts to accelerate shortly after the driver of the following vehicle starts to brake. Further, there is some evidence to suggest that a mechanism like evidence accumulation can better explain when drivers start to brake, particularly in cases where the driver's eyes are not on the threat [23]. For these reasons, the second model investigated was based on the computational framework of Markkula et al. [22]. The following subsections describe the details of the selected models.

2.2.1 Delayed Constant Deceleration Model

As seen in Figure 2.1, once the invTTC crosses a threshold, $iTTC_{th}$, the driver starts to apply a constant acceleration, a_c, after a time delay of t_D. Each driver is assumed to have a driver specific range of $iTTC_{th}$ and a_c, which corresponds to the comfort zone of the driver. The time delay, t_D is driver independent and is based on considerations of human physiology and possible limitations of a production truck's sensors.

The inverse time to collision is defined as:

$$invTTC = \frac{v_{ego} - v_{target}}{x_{target} - x_{ego}}. \tag{2.1}$$

where v_{ego}, x_{ego} are the following vehicle's velocity and longitudinal position respectively, v_{target}, x_{target} are the leading vehicle's velocity and longitudinal position. For the sake of brevity, the leading vehicle will be called the target, and the following vehicle, the ego vehicle.

2.2.2 Evidence Accumulator Model

This model is a watered down implementation of the framework designed by Markkula et al. with the major simplification being the use of sustained closed loop driver intervention instead of a series of discrete open loop interventions. This was done

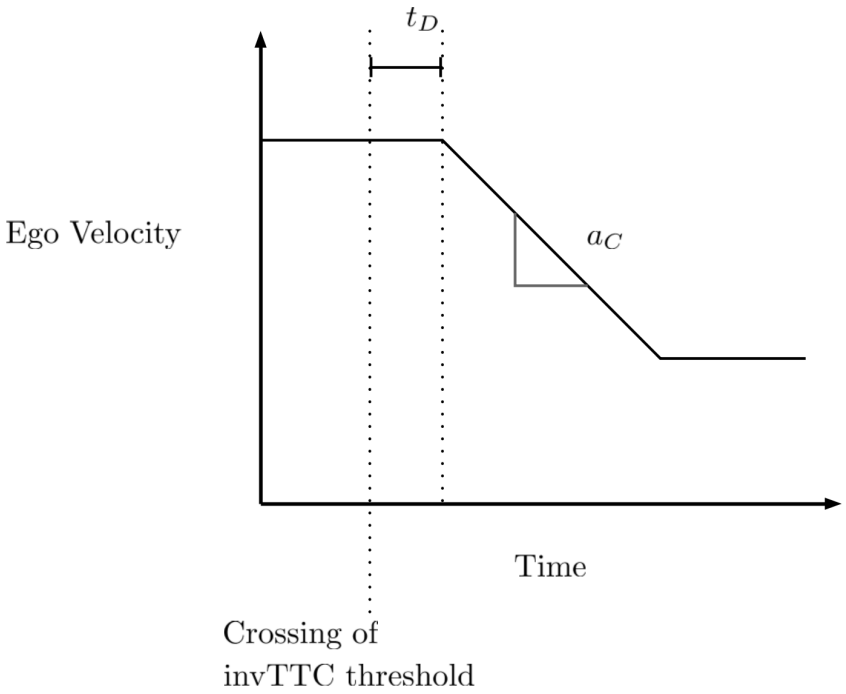

Figure 2.1: Graphical representation of Delayed Constant Deceleration model.

since it simplified the design of the estimation algorithm, and in many cases intermittent control could be represented using sustained control [22]. Further details about the start of braking, and acceleration during braking are mentioned below.

Start of braking event

The concept of evidence accumulation is inspired by concepts from psychology where an action is triggered once the accumulation of neuron firing rates crosses a threshold [24]. The accumulator is mathematically described as:

$$\frac{dA}{dt} = k_A \gamma(\epsilon(t)), \tag{2.2}$$

where, A is the activity, a dimensionless term inspired by neuronal activity, but can be both positive and negative, k_A is the accumulator gain, $\epsilon(t)$ is the evidence being accumulated, which in this model is the invTTC, and γ is a gating function that allows the accumulation of evidence only if $\epsilon(t)$ is above a lower limit. The invTTC has the same definition as in Equation 2.1 and the gating function was defined as:

$$\gamma(\epsilon) = sgn(\epsilon) max(0, \epsilon - \epsilon_0), \tag{2.3}$$

where ϵ_0 is the threshold that ϵ has to cross to be accumulated. The driver is considered to start braking, a time delay, t_A after A crosses the accumulator threshold, which is set to 1.
Of all the parameters, k_A is the only one that's driver specific, with t_A being dependent on human physiology and potential sensor limitations similar to t_D in Section 2.2.1, and ϵ_0 being dependent on sensor specifications.

Acceleration during braking event

Once the accumulator triggers the start of intervention, the driver's desired acceleration was defined using the Helly model [25].
In the original Helly model, the driver's acceleration is described as:

$$a_{ego} = C_1(v_{ego}(t-\tau_r) - v_{target}(t-\tau_r)) + C_2(x_{target}(t-\tau_r) - x_{ego}(t-\tau_r) - D(t)), \quad (2.4)$$

$$D(t) = \beta_1 + \beta_2 v_{ego}(t-\tau_r) + \beta_3 a_{ego}(t-\tau_r), \quad (2.5)$$

where a_{ego}, v_{ego}, x_{ego} are the ego vehicle's acceleration, velocity and longitudinal position respectively, a_{target}, v_{target}, x_{target} are the target vehicle's acceleration, velocity and longitudinal position, $D(t)$ is the driver's desired space headway, τ_r is the driver's reaction time, and C_1, C_2, β_1, β_2, β_3 are gain factors [25].
The acceleration term in the definition of desired headway was dropped since researchers have shown that the desired acceleration can be reasonably estimated without this term [26]. In order to design estimators that can run on embedded hardware, the relations were discretized using a step size, T_s of 400ms (selected as twice the sampling rate of the sensors' outputs). Hence,

$$D[k] = \beta_1 + \beta_2(v_{ego}[k]), \quad (2.6)$$

where k is the index, and the desired acceleration, a_d was defined as:

$$a_d[k] = \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 & \alpha_4 \end{bmatrix} \begin{bmatrix} v_{ego}[k] - v_{target}[k] \\ v_{ego}[k] \\ \Delta x[k] \\ 1 \end{bmatrix}, \quad (2.7)$$

where

$$\alpha_1 = C_1, \quad (2.8)$$

$$\alpha_2 = -\beta_2 C_2, \quad (2.9)$$

$$\alpha_3 = C_2, \quad (2.10)$$

and

$$\alpha_4 = -\beta_1 C_2, \quad (2.11)$$

The gains, α_1, α_2, α_3, and α_4 are driver specific parameters. It should be noted that the longitudinal positions of the target and ego vehicle were defined based on a fixed global coordinate system. The origin of this coordinate system was not specified since the model is concerned only with the space headway, which is the distance of the front of the target vehicle from the front of the ego vehicle.

3

Test Track Study

A test track study was conducted in March 2018 for the purpose of collecting data to help in the development of driver model parameter estimation algorithms. The study was conducted at the AstaZero test site in Sandhult, Sweden with three professional Volvo test drivers. The following sections describe the details of how the study was conducted including details about the test site, vehicle, and equipment used, participating drivers, and the test scenarios.

3.1 Test Site

The tests were performed in the "Multilane Road" environment at AstaZero, a layout of which can be seen in Figure 3.1. The sides of the curved acceleration road are adjacent to raised mounds which prevents the driver from seeing any object placed on the four lane road until reaching near the end of the acceleration road. The multi-lane road has four lanes, but in the two test scenarios, the target vehicle was placed only on the second lane from the right (while approaching from the acceleration road).

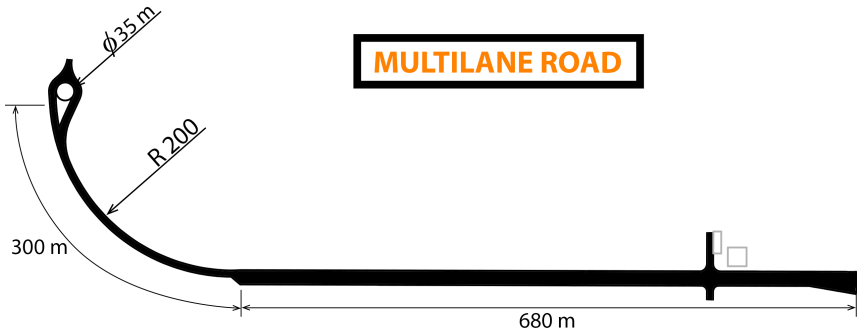

Figure 3.1: Dimensions and layout of multi-lane environment at AstaZero [1]. Image reproduced with permission from AstaZero.

3.2 Vehicle and Equipment

The ego vehicle was a rigid 4x2 Volvo FH tractor with a fully loaded load cage resulting in a Gross Combination Weight of 18000 kg. The truck was a test vehicle fitted with medium and long range radars, and a camera. The sensor package also included a sensor fusion algorithm that combined measurements from the radar and camera to provide estimates of the target vehicle's states. In this thesis, only the longitudinal position and velocity estimates of the target were used. The truck also had a logger that could log CAN signals and signals from the sensor package. The start and stop of logging were controlled manually using an on-board computer.
The target vehicle used was a regular Volvo V70.

3.3 Participating Drivers

Three drivers participated in the study, all of whom were professional test drivers employed by Volvo and regularly tested active safety functions at AstaZero. The data was anonymized at the time of collection, with the labels, 'Driver 1', 'Driver 2' and 'Driver 3' being assigned to them. All three drivers were male, had a Swedish CE driver's license, and were of ages 28, 41 and 40 years respectively. Drivers 2 and 3 had more than five years of experience testing different truck functions for Volvo, while Driver 1 had little more than a year's experience driving trucks. All three drove an average of approximately 5 hours a day.

3.4 Test Scenarios

Two test scenarios were specifically designed by the author for this study. In this report, scenario is defined as the setup including location, speed, and path of the ego and target vehicle, and other instructions given to the driver. A run is defined as an instance of a scenario. Both scenarios were meant to mirror situations encountered in real-life city traffic. Drivers were briefed regarding the design and purpose of the scenarios, and were instructed to keep their eyes on the target while driving, and to start braking and control the deceleration as they would in real city traffic. The author was present in the truck, controlling the start and stop of logging.

3.4.1 Scenario 1

In scenario 1, the target vehicle was placed around 100m from the start of the multi-lane road, and remained stationary throughout the scenario. The ego truck started from the acceleration road, and approached the multi-lane road at 50 km/hr with cruise control activated. The driver braked softly and came to a stop behind the target. This is similar to the real-life situation where a car is waiting for the traffic light to turn green, and the ego truck needs to stop and wait behind the car.
The drivers took turns performing runs of the scenarios. First, Driver 1 performed 5 runs, and then the drivers were switched. Due to a miscommunication, Driver 2 thought that the task was for the driver to start braking once the AEBS system had

started to brake automatically. Hence, the first four test runs were excluded from subsequent analysis, and Driver 2 eventually completed five runs as per specifications, and drivers were switched again, and Driver 3 drove five times uneventfully. A summary of which runs were included in the final analysis can be found in Table 3.1.

3.4.2 Scenario 2

Scenario 2 mirrors the situation where the ego truck approaches a traffic light that's just turned green, and the car in front is about to start accelerating, but the faster ego truck needs to brake to maintain a comfortable headway to the car in front. Similar to scenario 1, the ego truck approaches from the acceleration road at 50 km/hr with cruise control activated, but in this scenario, the target vehicle starts to slowly accelerate to 20 km/hr when the ego truck is around 100m behind, and then maintains that speed. Again, the driver of the ego truck brakes softly to reach around the same speed as the target vehicle, and then starts following it.
The three drivers each performed five runs of the scenario without any issues. However, in subsequent analysis it was found that the logging of Driver 1's run 1 had been stopped prematurely, and that the log of Driver 1's run 3 was corrupted. Hence, these two runs were excluded from further analysis.

Table 3.1: Summary of runs included in analysis.

	Driver 1	Driver 2	Driver 3
Scenario 1	1, 2, 3, 4, 5	5, 6, 7, 8, 9	1, 2, 3, 4, 5
Scenario 2	2, 4, 5	1, 2, 3, 4, 5	1, 2, 3, 4, 5

4

Driver Model Parameter Estimation

4.1 Recursive Least Squares

Considering that the selected models were linear with respect to the parameters to be estimated, the linear least squares estimation scheme would seem like a good choice. However, storing a large number of measurements and then calculating the psuedo inverse would require storage and computational resources that may not be feasible on a production ECU. Hence, the recursive least squares (RLS) scheme was chosen to estimate the parameters of both the selected driver models.
The RLS with forgetting factor scheme as seen in Vahidi et al. was used [27]. If the model whose parameters need to be estimated can be described as follows:

$$\mathbf{y} = \phi^{\mathbf{T}}\theta, \tag{4.1}$$

where $\mathbf{y}$ is the vector of measurements, ϕ is the vector of states, and θ is the vector of parameters to be estimated, then the recursive scheme is:

$$\hat{\theta}[k] = \hat{\theta}[k-1] + \mathbf{l}[k](\mathbf{y}[k] - \phi^{\mathbf{T}}[k]\hat{\theta}[k-1]), \tag{4.2}$$

$$\mathbf{l}[k] = \mathbf{P}[k-1]\phi[k](\lambda + \phi^{\mathbf{T}}[k]\mathbf{P}[k-1]\phi[k])^{-1}, \tag{4.3}$$

$$\mathbf{P}[k] = (\mathbf{I} - \mathbf{l}[k]\phi^{\mathbf{T}}[k])\mathbf{P}[k-1]\frac{1}{\lambda}, \tag{4.4}$$

where $\mathbf{P}$ is the covariance matrix and λ is the forgetting factor [27].

4.2 Simulation Environment

The simulations were performed using a Simulink model that takes signal data from the log files recorded at the test track, passes it through a sensor data fusion algorithm, thereby giving estimates of the ego vehicle and leading vehicle's states, which could be used by the online estimator as inputs. The log files consist of logged vehicle CAN signals and signals from the truck's on-board sensors and fusion algorithms. The sensor data fusion module in the Simulink model was developed by Volvo and can be uploaded to a truck's ECU. Hence, the inputs to the estimation algorithms are representative of what could be seen on a production truck.
The designed estimation functions are called every 0.04s, while the sensor data fusion module in the Simulink model is called every 0.02s.

Manual Recording of Measurements

During the analysis of the logs from Scenario 1 where the target was stationary, it was found that the fusion algorithm of the sensor package was unable to detect the target with sufficient confidence in time to accumulate enough evidence, and in some runs, even to estimate the invTTC threshold in the delayed constant deceleration model. The radar was able to detect the target in enough time, but the radar measurements were not logged in a manner that they could be accessed separately in the Simulink model. However, the radar measurements could be viewed manually in the sensor provider's review software. Range and range rate measurements were noted down manually at a frequency of 1Hz from this software. This data was given as an input to the estimation algorithm until the time that the sensor's fusion algorithm detected the target with sufficient confidence. 1 Hz was considered to be enough since in this scenario the target remains stationary, and during the period when the fused target measurements are not available, the ego truck hadn't started braking significantly, and after that the fused measurements are available at 50 Hz. There were some runs in scenario 2 where the same issue was observed, however it wasn't as severe as seen in scenario 1, so a decision was made not to take manual measurements, and use this as an opportunity to analyze the effect of sensor limitations on the estimation of driver model parameters.

4.3 Delayed Constant Deceleration Model

As described in Section 2.2.1, the delayed constant deceleration model has two driver specific parameters that need to be estimated, $iTTC_{th}$ and a_c.

4.3.1 Inverse Time to Collision Threshold

Estimation Scheme

Once the estimator receives target measurements, i.e. once a target is detected with sufficient confidence, invTTC is calculated at each time step, and the value of invTTC delayed by t_D is stored at each time step. The delayed invTTC at the time when a non-zero brake pedal position is first detected, becomes the estimate of $iTTC_{th}$. A simple quality check was implemented to ensure that the $iTTC_{th}$ was not zero, which could happen if the sensors drop the target.
Ideally, t_D should account for the driver's perceptual and motor delays, which can be taken as 0.15s [24],[22]. To account for possible delays due to the sensors themselves, t_D was taken to be 0.2s.

Results and Analysis

Figure 4.1 shows how $iTTC_{th}$ varied across different drivers and scenarios. A significant difference can be observed across the three drivers. Further, this difference follows a similar trend in both scenarios. Due to several factors such as varying experience, miscommunication, comfort levels, etc. which could be working together to lead to this difference, no attempt is made to explain it.

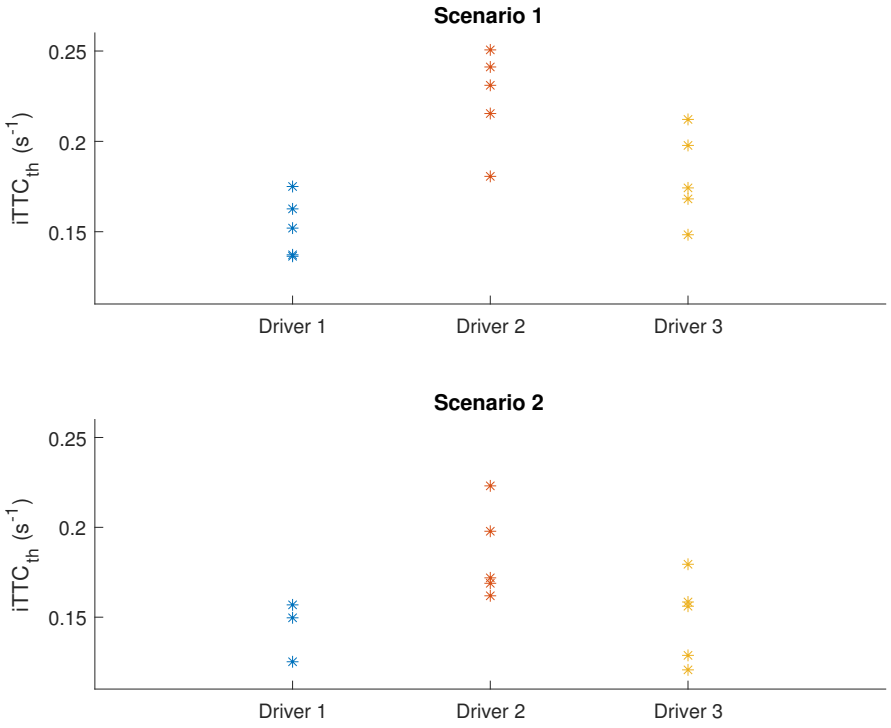

Figure 4.1: Scatter plot of invTTC thresholds across different drivers and scenarios.

It is important to compare the obtained estimates with the invTTC thresholds observed in other driving studies in literature. In the study by Kiefer et al. drivers were "asked drivers to maintain their speed and brake at the last second possible in order to avoid colliding with the target using "normal" braking intensity or pressure"[28]. 54 drivers performed a test case similar to scenario 1 where the ego vehicle was initially travelling at 30 mph towards a stationary target. The mean invTTC at the start of braking (across all drivers) for this case was found to be 0.25 [28]. While this is higher than most of the $iTTC_{th}$ values seen in scenario 1, it should be noted that in scenario 1 drivers were instructed to brake whenever they wanted to, as compared to the Kiefer et al. study where they were instructed to brake at the last possible second. This could explain why the $iTTC_{th}$ values were lower.
36 drivers performed the case similar to scenario 2, where the ego vehicle was initially travelling at 30 mph while the target travels at a constant speed of 10 mph. Again, drivers were asked to brake at the last possible second. In this case, the mean invTTC values at the start of braking was 0.26 which is again higher that the $iTTC_{th}$ values in scenario 2 [28].
A cause for concern is the level of variation in the $iTTC_{th}$ values of each driver. Unfortunately, due to the nature of the instructions given to the drivers, only guesses can be made as to why this was seen. Figure 4.2 shows how the $iTTC_{th}$ values varied over the consecutive runs. It should be noted that certain runs were excluded from the analysis as explained in Section 3.4.
While one would expect drivers to have higher $iTTC_{th}$ values in subsequent runs as

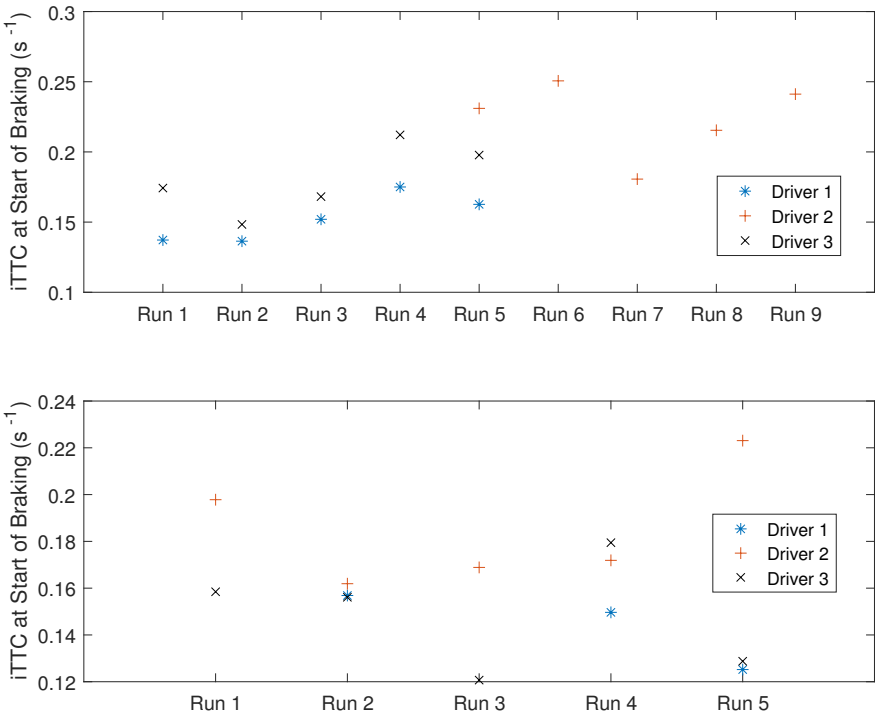

Figure 4.2: Variation of invTTC thresholds over consecutive runs.

they get used to the repetitive nature of the task, such a trend cannot be clearly seen for all drivers in both the scenarios.

4.3.2 Constant Acceleration

Detection of Start and End of Near-Constant Acceleration Phase

It is not necessary nor feasible to run the constant acceleration estimation algorithm all the time on a production ECU. Rather, the estimator should ideally run only during the part of the braking event where the acceleration is nearly constant. This leads to the need for detecting when this constant acceleration phase starts and ends.

The conditions selected for the start of the phase were:

- Position of Brake Pedal $>$ 5%, and
- invTTC $>$ 0 s^{-1},

while the conditions selected for the end of the phase were:

- Position of Brake Pedal $\leq$ 5% and Estimated Jerk $\geq$ -0.1 m/s^3, or
- invTTC $\leq$ 0.1 s^{-1} and Estimated Jerk $\geq$ -0.1 m/s^3, or
- Ego Velocity $\leq$ 1 m/s.

The limit for the brake pedal position was selected based on the mapping between the brake pedal position and requested acceleration, while the limits on invTTC and jerk were manually tuned. It should be noted that the jerk was estimated using an

RLS scheme similar to the one described below, but with the first order estimate of jerk as the measurement, $\mathbf{y}$.

Estimation Scheme

The RLS scheme described in Section 4.1 was used to estimate the constant acceleration. The acceleration signal from the ego vehicle's CAN signals was taken as the measurement, $\mathbf{y}$. The constant acceleration parameter, a_c was the parameter to be estimated, θ, and ϕ was hence 1. The forgetting factor was manually tuned to obtain a suitable compromise between capturing the trend of the signal while discarding sharp fluctuations, resulting in a choice of 0.99.
A rough quality check was designed through an error measure inspired by the root mean squared error (RMSE). It's not trivial to calculate the RMSE online since the estimate varies at each time step. Hence, a measure of error was defined that could be calculated online:

$$\text{Measure of Estimation Error} = \sqrt{\frac{\Sigma(\mathbf{y} - \phi^{\mathbf{T}}\hat{\theta})^2}{N}}, \tag{4.5}$$

where, N is the number of samples. The estimate was considered to be of acceptable quality if the error measure was less than half the magnitude of the estimate (similar to a signal-to-noise ratio of 2). While this check has no foundation in statistical theory, it can be used to identify situations where the variation in acceleration is so high, that a constant acceleration model can't be used to describe it.

Results and Analysis

Figure 4.3 shows the RLS estimator in action. As seen, the RLS estimator is enabled when the brake pedal is pressed and the target is detected with sufficient confidence. The standard deviation of the estimate converges but to a non-zero value. This is due to the use of a forgetting factor.
The updates from the RLS estimator can be seen in Figure 4.4. Note how the constant acceleration estimate is updated at around 545s even though the RLS estimator runs until around 548s. This is because the estimates are updated as soon as the end of the near-constant acceleration phase is detected. The acceleration update quality is a binary quantity, which in this case turns 1 since the measure of estimation error is less than half the magnitude of the constant acceleration estimate.
Figure 4.5 shows how the a_c estimates vary across drivers and scenarios. Again a significant difference can be seen in the a_c estimates of Driver 1 compared to the others in both scenarios. It's also worth noting that the estimates of Driver 2 and 3 in scenario 1 have a much larger variation than in scenario 2. The mean accelerations in the study by Kiefer et al. for the cases corresponding to scenarios 1 and 2 were 1.6 m/s^2 and 1.27 m/s^2 respectively [28]. The obtained estimates are quite close to those reported by Kiefer et al. with the significant exception of Driver 2 and 3's estimates in Scenario 1 [28].

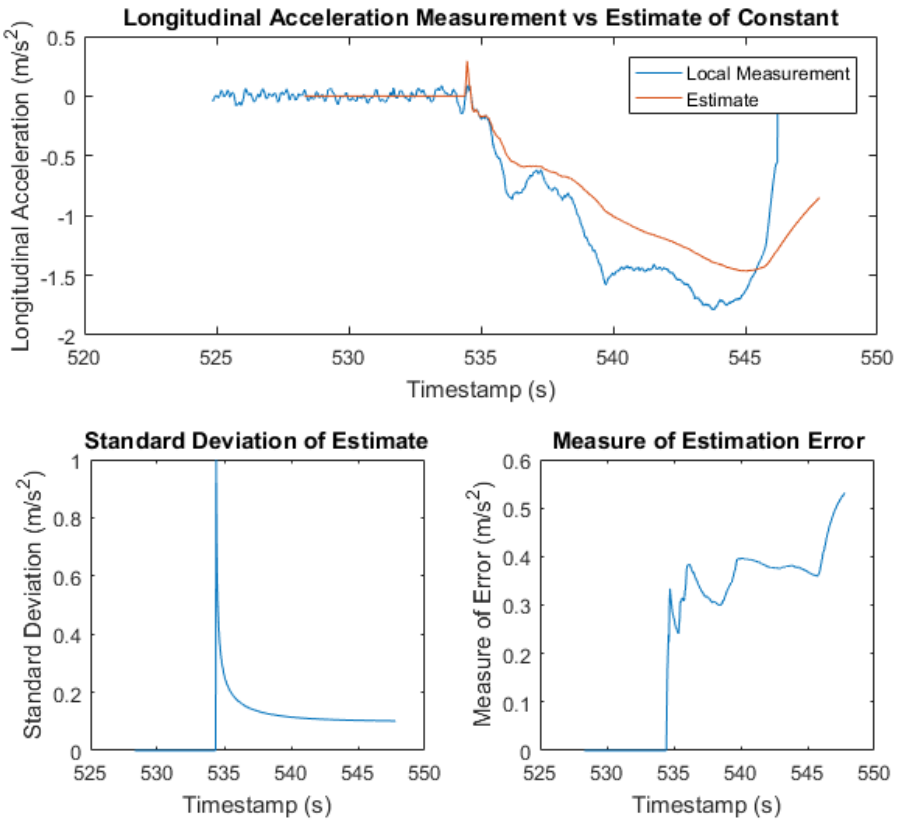

Figure 4.3: Functioning of RLS estimator for Driver 1's Run 1 in Scenario 1.

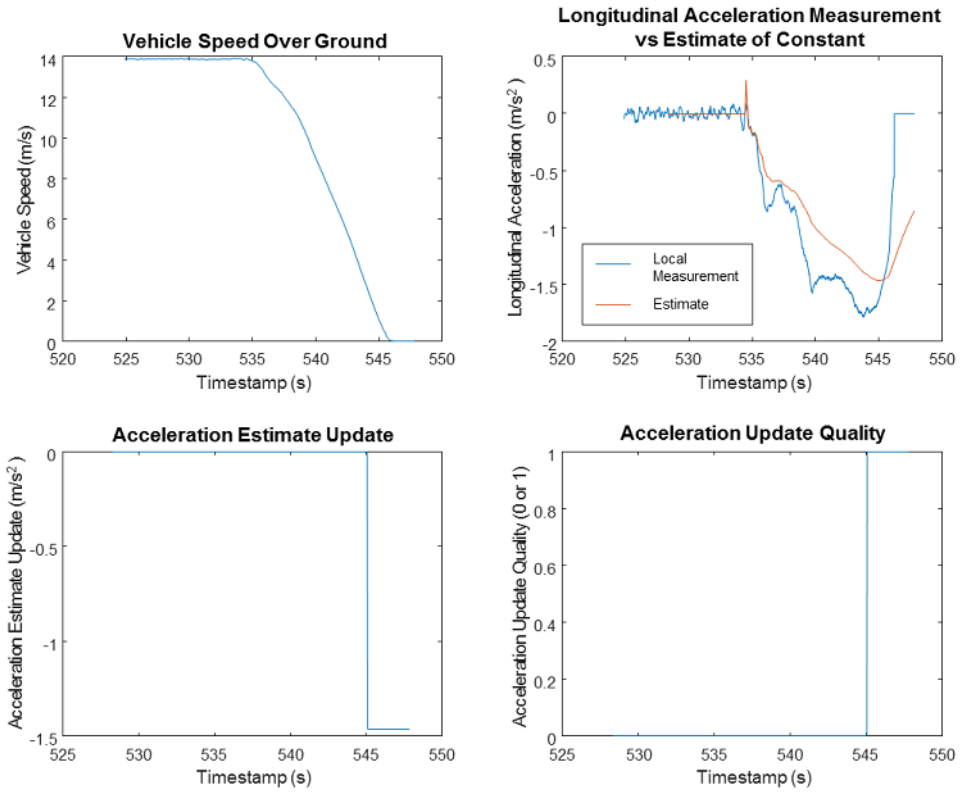

Figure 4.4: Outputs from RLS estimator for Driver 1's Run 1 in Scenario 1.

4.4 Evidence Accumulator Model

In order to implement the evidence accumulator on an ECU, equation 2.2 was discretized as:

$$A[k] = \frac{k_A T_s}{z-1}\gamma(\epsilon[k]), \tag{4.6}$$

where, A is the activity, k_A is the accumulator gain, T_s is the sampling time, $\epsilon[k]$ is the evidence being accumulated, and γ is a gating function.

4.4.1 Accumulator Gain

Estimation Scheme

Out of the terms in equation 4.6, the time integral of the gated invTTC (i.e. the term multiplied by k_A on the right hand side of the equation) is calculated at each time step. When t_A is selected as 0.2s, the value of A is 1 0.2s before a non-zero brake pedal position is detected. t_A was selected based on the same reasoning used in the selection of t_D in the delayed constant deceleration model. Hence, the estimate of k_A is the inverse of the time integral of the gated invTTC stored 0.2s before the brake pedal is pressed.

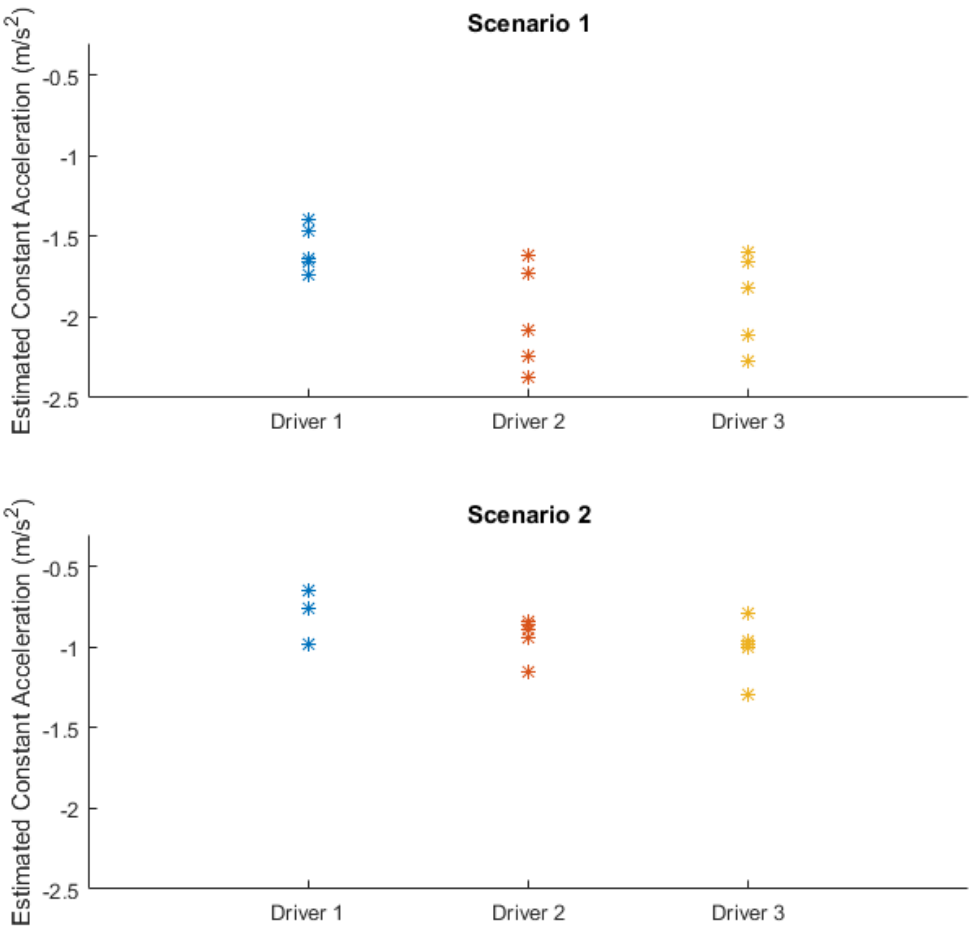

Figure 4.5: Scatter plot of constant acceleration, a_c estimates across different drivers and scenarios.

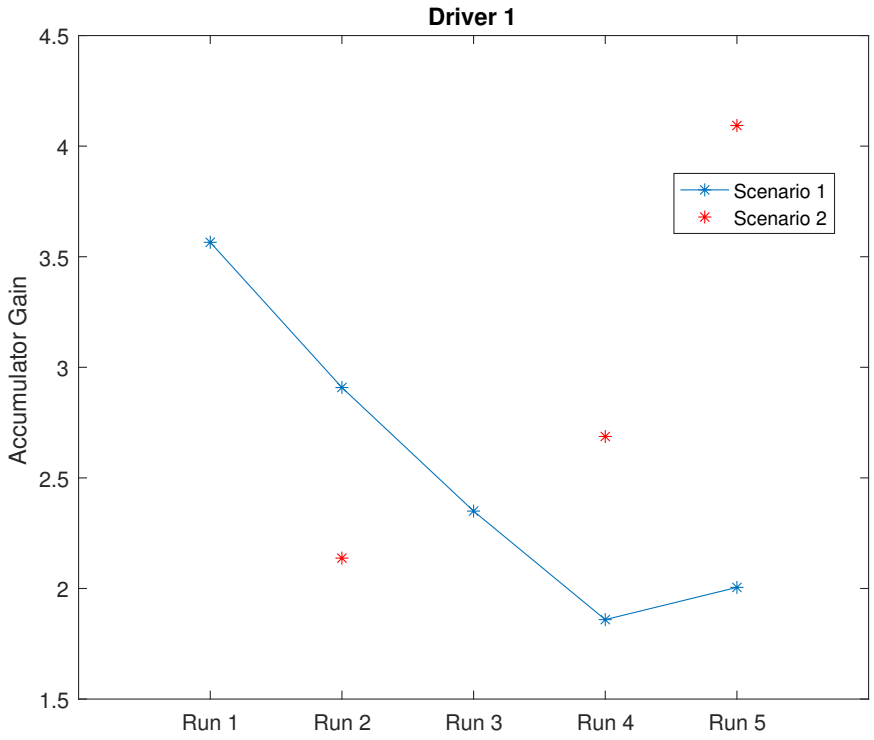

Figure 4.6: Estimates of Accumulator Gain for Driver 1 in Scenarios 1 and 2.

Results and Analysis

Figure 4.6 shows that the accumulator gain varies significantly over the consecutive test runs. In Scenario 1, the gain shows a mostly decreasing trend, which can be expected as the driver gets more comfortable with the task, but Scenario 2 appears to show the opposite trend. Upon further investigation it was found that this was because the time at which the sensor package started to detect the target with significant confidence varied significantly. Ideally these times should be the same, considering that the kinematics of the situation don't vary. This affected the precision of the estimates since the accumulator ran for different lengths of time in the three runs, 3.92 s, 3.28 s and 2.36 s respectively which explains the apparent increasing trend in k_A. This shows the extent to which sensor performance can affect the gain estimates.

Since repetition clearly had a major effect on the estimates, only the estimates from the first runs of each scenario were considered important and can be found in Table 4.1. Compared to the level of variation seen in Figure 4.6, it's promising to see how close the gain estimates for Driver 3 are in Scenarios 1 and 2.

4.4.2 Acceleration Gains

Estimation Scheme

The RLS estimation scheme from Section 4.1 was used to estimate α_1, α_2, α_3 and α_4, where:

$$\mathbf{y} = a_{ego}, \tag{4.7}$$

$$\theta = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix}, \tag{4.8}$$

$$\phi = \begin{bmatrix} v_{ego}[k] - v_{target}[k] \\ v_{ego}[k] \\ \Delta x[k] \\ 1 \end{bmatrix}, \tag{4.9}$$

and the forgetting factor, λ was chosen to be 0.99.

Results and Analysis

Figure 4.7 shows how the acceleration gains vary for Driver 1 over successive test runs. As seen in Section 4.3.1, there's no clear trend due to the nature of the test track tests.

Table 4.1 shows how that the median gains show some variation across the three drivers. Unfortunately, at the time of writing, there were no published estimates for this type of model in literature, preventing an analysis similar to the one done in Section 4.3.2.

The table contains only the accumulator gain estimates from the first runs in each scenario. This is because the accumulator gain is highly sensitive to the driver's expectancy and since subsequent runs were repetitive in nature, it's only the first runs that should be included.

For the acceleration gain estimates, the median values are listed. For each driver and scenario, a set of acceleration gains are obtained for each run. Even for the same driver and scenario, the estimates will vary across runs, especially in this analysis as seen in 4.7. Hence, the median is used as a robust estimate of the parameters over the duration of all the runs.

Table 4.1: Overview of estimates for Evidence Accumulator Model

	Driver 1	Driver 2	Driver 3
k_A, Scenario 1 Run 1	3.56	-	1.77
k_A, Scenario 2 Run 1	-	1.45	1.82
Median α_1 (s^{-1})	-0.33	-0.02	-0.02
Median α_2 (s^{-1})	-0.02	-0.27	-0.11
Median α_3 (s^{-2})	-0.04	-0.07	-0.05
Median α_4 (s^{-2})	-1.77	-1.54	-1.63

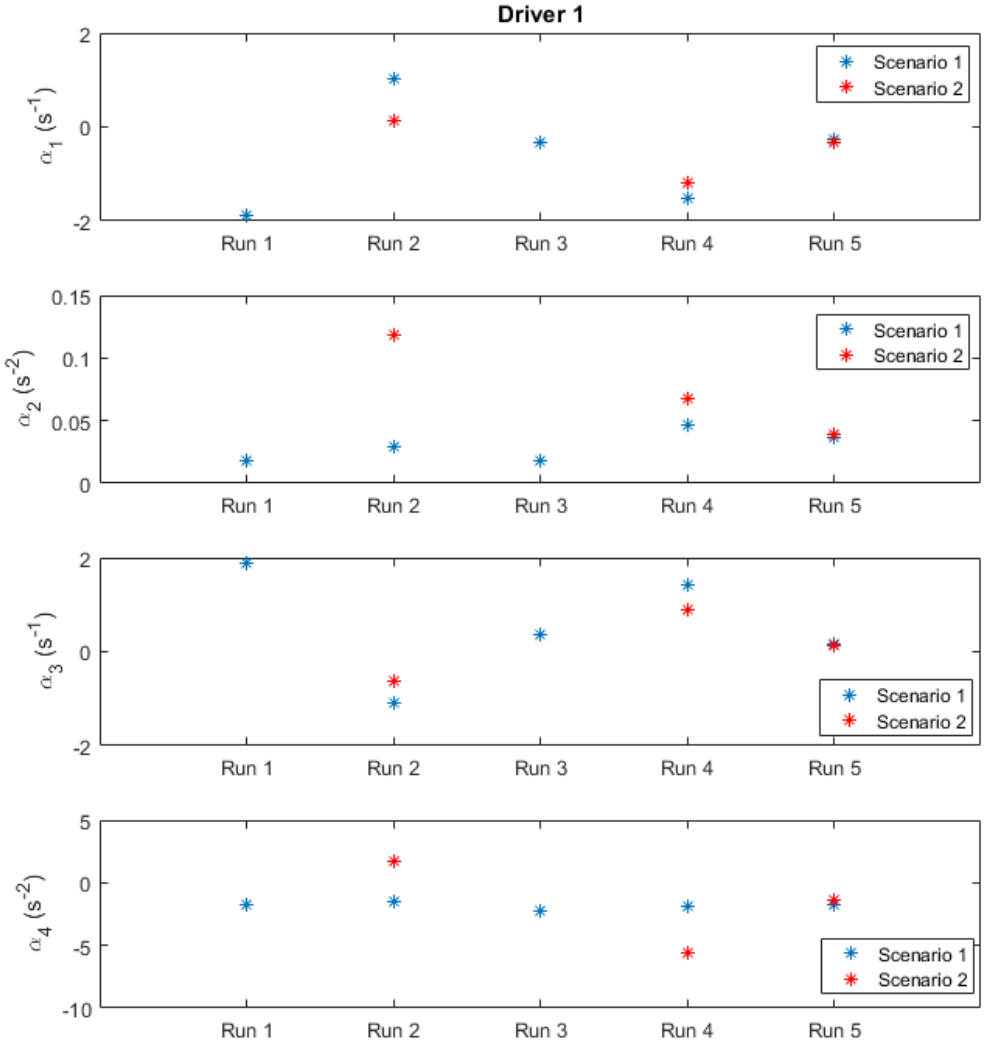

Figure 4.7: Variation of Acceleration Gains for Driver 1 across different test runs.

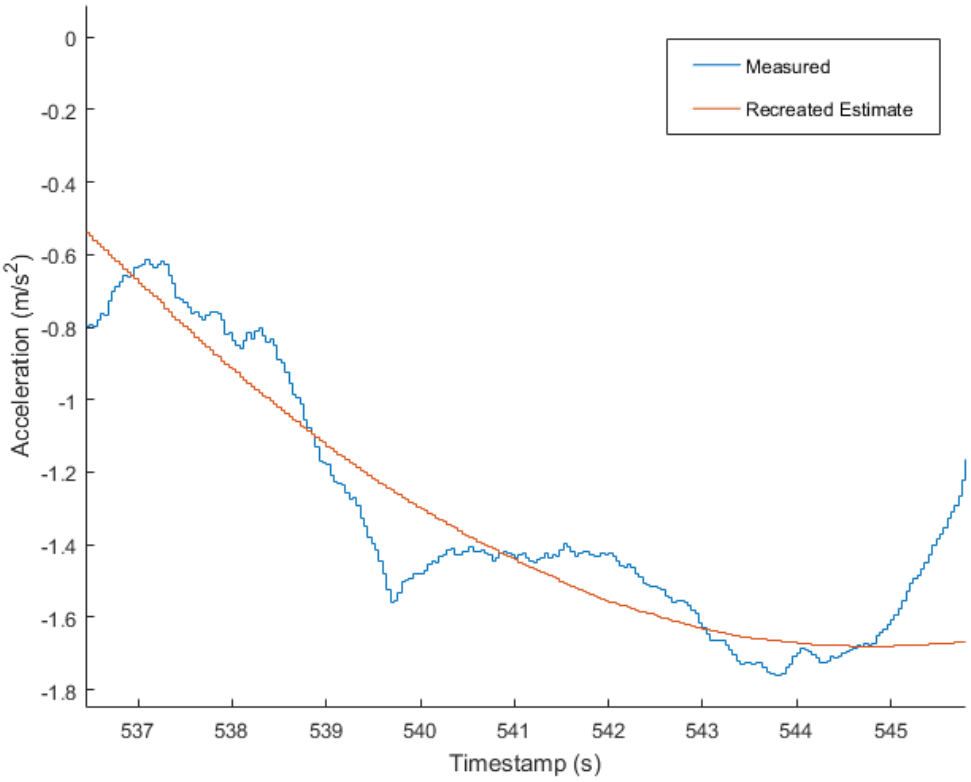

Figure 4.8: Verification of Acceleration Gain estimates for Driver 1 Scenario 1 Run 1.

Using the acceleration gain estimates and the inputs to the Helly model, the model's output could be compared with the acceleration measurement that was fed into the estimator. As seen in Figure 4.8 the estimates manage to capture the general trend of the signal which is what is needed for threat assessment in FCW.

5

Threat Assessment Design for Forward Collision Warning

Chapter 4 described methods to get an estimate of driver model parameters during each braking event under routine driving. This chapter discusses how these estimates could be used for threat assessment, and also a method of detecting when such an assessment method should not be used.

5.1 Logical Architecture of Comfort Zone Boundary Estimator

In order to observe the driver's current status, the estimates of driver model parameters obtained at the end of each braking event need to be analyzed with respect to the range of parameter estimates observed over a long period of time. This should be done to check whether there are any short term deviations in driver behaviour due to factors such as fatigue, intoxication, varying road conditions, etc. Further, this could also help identify if there has been a change of drivers, so that the warnings are appropriately adjusted. Figure 5.1 offers a visual representation of such a setup.

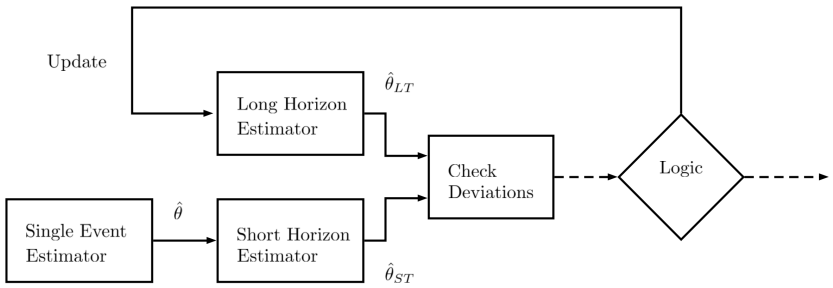

Figure 5.1: Logical Architecture of Comfort Zone Boundary Estimator.

The single event estimator would contain the estimation schemes described in Chapter 4, giving a set of estimates, $\hat{\theta}$ at the end of each braking event. The short horizon estimator estimates the statistical properties, $\hat{\theta}_{\mathbf{ST}}$ of the vector of estimate sets obtained over multiple braking events over a short time interval of around 15-20 minutes. These statistical properties could include sample mean, median, and variance, estimated through a recursive online scheme. This recursive estimator should be reset every 15-20 minutes. This interval was selected since it has been observed that

fatigue can have an impact on driving behaviour within 20-25 minutes of driving [29].
The estimates from the short horizon estimator should be compared with the usual range of estimates observed over several driving sessions, $\hat{\theta}_{\mathbf{LT}}$. If there are significant deviations, it could imply a temporary shift in driver behaviour or a change of driver or driving conditions. In such cases, the FCW timings should not be based on $\hat{\theta}_{\mathbf{ST}}$ and should instead be based on the traditional purely kinematics approach. The knowledge of these deviations could also be of use in other active safety functions such as Driver Alert Support, Lane Departure Warning, etc.
If the deviations are not too high, $\hat{\theta}_{\mathbf{ST}}$ is fed as an input to the long horizon estimator. This estimator works just like the short horizon estimator, except that it works on much longer time intervals.

5.2 Proposed Threat Assessment Algorithms

5.2.1 Delayed Constant Deceleration Model

Using the delayed constant deceleration model, a range of the driver's invTTC threshold and constant acceleration estimates can be obtained. Using the invTTC threshold, for the current kinematic situation a range of times when the driver would usually brake can be obtained. If this range has been crossed, and the driver hasn't braked then it's a deviation from normal behaviour and a less intrusive warning (e.g. visual) can be provided. Simultaneously, the acceleration needed to avoid the crash can be calculated and if this exceeds the range of the driver's usual applied acceleration, then the second level of warning (auditory) should be given. Figure 5.2 shows how this algorithm would look like.

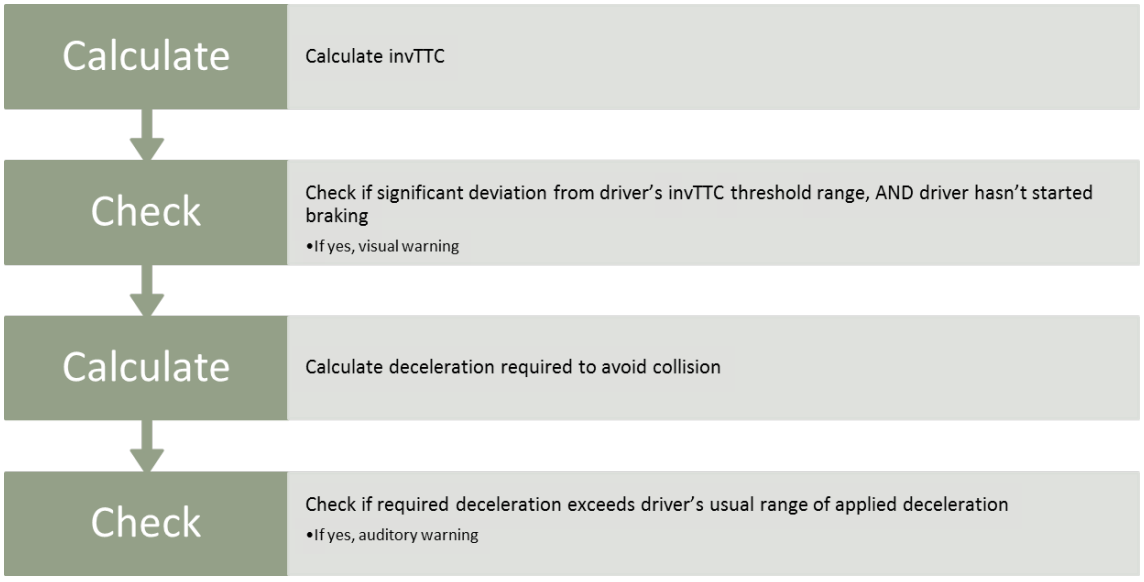

Figure 5.2: Threat Assessment algorithm based on Delayed Constant Deceleration Model.

5.2.2 Evidence Accumulator Model

A similar algorithm was proposed for the evidence accumulator model as seen in Figure 5.3. The main difference from the previous algorithm is in the conditions for the second level of warning. The evidence accumulator model can actually predict the acceleration the driver would usually apply based on the current kinematics. Assuming that this acceleration is applied, an enhanced time to collision (ETTC) can be calculated, and the auditory warning would be provided if this crosses a certain threshold.

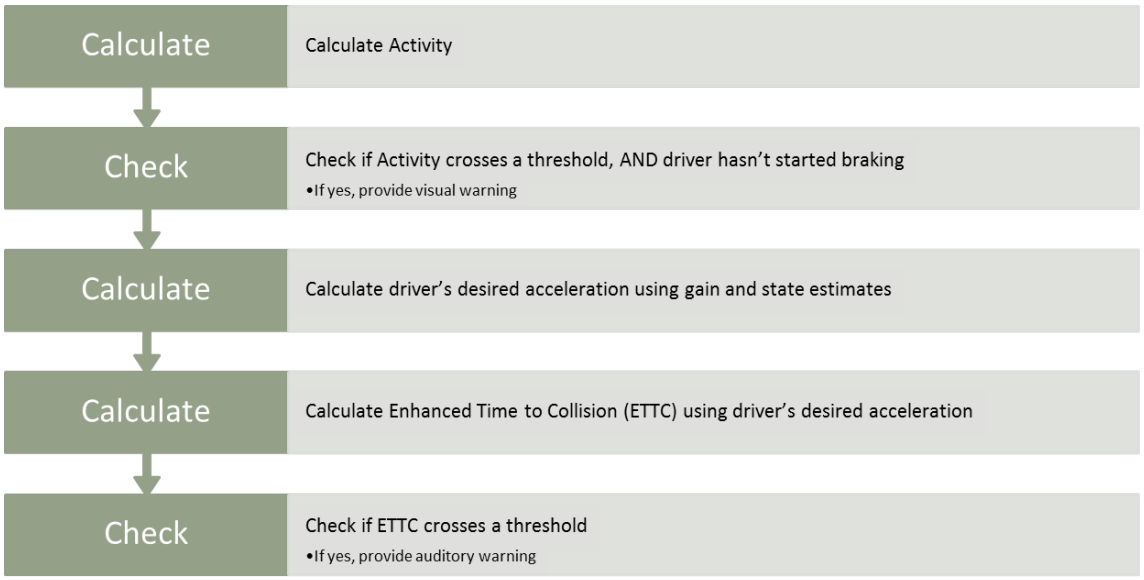

Figure 5.3: Threat Assessment algorithm based on Evidence Accumulator Model.

6
Conclusions and Future Work

A literature survey of driver behaviour models for braking was conducted to find models that could be used to estimate the comfort zone boundaries of a driver. Several models were identified that could theoretically be used, and two models - delayed constant deceleration and evidence accumulator were selected for further investigation. Estimation schemes were designed for these two models, and proof of concept functions were developed.
In order to test the performance of developed estimators, a test track study was conducted with three professional test drivers. Several test runs were performed for two scenarios which were designed to emulate real-world traffic situations. CAN and sensor signals were logged during the test runs and imported into a simulation environment where the developed estimators were simulated.
Analysis of the simulation results showed that the test data collected was not particularly suitable for drawing detailed conclusions due to large unexplained variations in driver behaviour, and the effect of performing a repetitive task. However, qualitative conclusions could be drawn, and for some models, a clear difference could be seen between the driving styles of the three drivers. Further, the effect of practical issues such as sensor limitations could also be seen in the results.
An analysis involving much larger naturalistic driving databases is needed to definitively conclude if the developed estimators can be used for estimating comfort zone boundaries, and decide which one is better.Based on the developed estimators, conceptual designs for threat assessment algorithms were made.
A brief look at the ISO standard for collision warning systems (ISO 15623:2013) showed that existing standards are not a hurdle for introducing such functions into the market, although the functions need to satisfy the requirements that current FCW systems already fulfill [6]. Hence, if driver adaptation for the FCW system is found to significantly improve driver acceptance, it could be introduced to a production FCW system.
However, several steps need to be performed in order to develop such a system. First, the estimators developed in this thesis should be tested on a large naturalistic driving database so that a clear conclusion can be drawn on their performance. If the performance is found to be promising, the next logical step would be to develop prototype threat assessment functions based on these designs and test them on data from naturalistic driving databases or field tests. These prototypes would then act as a foundation for the development of a production ready FCW function.

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