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Effectiveness of Evasive Manoeuvre Assist Function for Different Driver Skills

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Cover: Volvo XC 90 car model performing lane change manoeuvre in CarMaker.

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Abstract

The thesis work aims to develop a driver model suitable for test of vehicle dynamics functions where an overlay torque through Electric Power Assisted Steering (EPAS) is applied on the steering wheel. The scope of the thesis work has been to develop a driver model which can mimic the steering behaviour of skilled drivers as well as unskilled drivers. By using different parameter sets for the driver model, it is possible to differentiate between skilled and unskilled drivers steering through the path and thereby assess the benefit of a vehicle dynamic function. The driver model presented in the thesis consist of Preview Controller, Neuromuscular System (NMS) and Arm Dynamics. The Preview Controller is designed based on the concept of Linear Quadratic Regulator (LQR) and a second order filter is considered as NMS model and Arm Dynamics. In order to identify driver model parameters, a handling test with a real world car and drivers with a variety of driving experience was performed. By post processing the measured data with numeric optimization, driver model parameters for each driver category were found.

The driver model, including a family of different parameter sets, has been used to investigate the effectiveness of an Evasive Manoeuvre steering Assist function (EMA). By performing computer simulations with the driver model and a vehicle model, tests have been made with and without the function, and in turn a benefit measure comprising of a margin to avoid colliding with a threat has been found. The hypothesis was that the function benefit of the EMA function for unskilled drivers should be higher than for the skilled ones. The result obtained from the thesis work shows that EMA function helps the unskilled drivers.

Keywords: Linear Quadratic Regulator, Neuromuscular System, Evasive Manoeuvre steering Assist, Driver Model

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Contents

List of Figures	x
------------------------	----------

List of Tables	xiii
-----------------------	-------------

1 Introduction	1
1.1 Background	1
1.1.1 EMA	1
1.2 Problem Formulation	2
1.3 Literature Review	4
2 Methods	7
2.1 Driver Model	7
2.2 The vehicle model in the preview controller	8
2.3 Design of the preview controller	10
2.3.1 Simplified bicycle model with feedforward controller	11
2.3.2 Simplified Bicycle Model with LQR	12
2.3.3 Results and Discussion	15
2.4 Verifying Driver Model with 6 DOF Vehicle Model	16
2.5 Design of Neuro-muscular System	21
2.5.1 Neuro-muscular System and Arm dynamics	21
3 Data Collection	25
3.1 Test	25
3.1.1 Test Setup	25
3.1.1.1 Test 1: Lane change with obstacle	26
3.1.1.2 Test 2: Follow a lane change path	26
3.2 Analysis of test data	27
3.2.1 Test 1	27
3.2.1.1 Case 1: At velocity of 50 kph	27
3.2.1.2 Case 2: At velocity of 80 kph	29
3.3 Test 2	29

4	Tuning Parameters	35
4.1	Tuning the Vehicle Model	35
4.2	Tuning the Driver Model	36
4.2.1	Defining Reference Path	37
4.2.2	Methods	38
4.3	Results and Analysis	42
4.3.1	Simulation result and analysis	42
4.3.2	Evaluation of the result	44
5	Results and Discussion	47
5.1	Evaluation criterion of the effectiveness of EMA	47
5.2	Testing Results	48
6	Conclusion and scope for future work	53
6.1	Conclusion	53
6.2	Future Work	54
6.2.1	Parameters of NMS model	54
6.2.2	Testing methods	54
6.2.3	Simulation and testing environment should be same	55
6.2.4	Updating the reference path (driver brain path)	55
6.2.5	Curved Road	55
	Bibliography	57
	Appendix A Comparison of the driver model output and the measured result for the speed of 50 kph without EMA	I
	Appendix B Comparison of the driver model output with and without EMA for the speed of 50 kph	V
	Appendix C Comparison of the driver model output and the measured result for the speed of 80 kph without EMA	IX
	Appendix D Comparison of the driver model output with and without EMA for the speed of 80 kph	XIII

List of Figures

1.1	Metric Measurement	2
1.2	Conceptual working of EMA	3
1.3	Problem	3
1.4	Block diagram of working of EMA function	4
1.5	NMS model developed by Pick et al	6
1.6	NMS model developed by Katzourakis et al	6
2.1	Block diagram of the driver model	7
2.2	Bicycle Model	9
2.3	Sketch of mechanism of feedforward controller	11
2.4	Showing global position of the vehicle and road path preview information, where y_{pN} is the road path lateral displacement and ψ_{pN} is the road heading angle	14
2.5	Performance of different Models/Controllers	15
2.6	Schematic representation of Dymola connected to preview controller	17
2.7	Vehicle states obtained from numerical optimization; blue path for 50 kph, black for 70 kph, red for 80 kph, magenta for 90 kph, cyan for 100 kph and green for 110 kph	17
2.8	Optimal Path obtained by numerical optimization; blue path for 50 kph, black for 70 kph, red for 80 kph, magenta for 90 kph, cyan for 100 kph and green for 110 kph	18
2.9	(a) Path travelled by a vehicle at velocity 50 kph, (b) lateral acceleration of the vehicle travelling at 50 kph	18
2.10	(a) Path travelled by a vehicle at velocity 80 kph, (b) lateral acceleration of the vehicle travelling at 80 kph	19
2.11	(a) Path travelled by a vehicle at velocity 50 kph with inputting braking sequence, (b) lateral acceleration of the vehicle travelling at 50 kph with inputting braking sequence	20
2.12	(a) Path travelled by a vehicle at velocity 80 kph with inputting braking sequence, (b) lateral acceleration of the vehicle travelling at 80 kph with inputting braking sequence	20
2.13	Driver Model with NMS Dynamics	21
2.14	The simplification of the NMS model	22
2.15	Schematic block diagram of the simplified design	22

3.1	Test Setup	26
3.2	Reference path for test 2	27
3.3	Path travelled by all the test drivers at speed of 50 kph	28
3.4	Steering Wheel Angle of all the test drivers at a velocity of 50 kph . .	28
3.5	Path travelled by all the test drivers at speed of 80 kph	29
3.6	Steering wheel angle of all the test drivers at a velocity of 80 kph . .	29
3.7	Path travelled by all the test drivers in order to follow the reference path	30
3.8	Steering wheel angle of the test drivers in order to follow the reference path	30
3.9	Deviation of the reference path and driver's path	32
4.1	Verification of Car Model in CarMaker	36
4.2	Driver I's Performance for the Case of 50 kph	38
4.3	Driver H's performance for the case of 50 kph	38
4.4	Schematic diagram of the tuning method	39
4.5	Schematic diagram of tuning preview controller	41
4.6	Schematic diagram of tuning NMS model	41
4.7	Measured steering torque of Driver F at the speed of 50 kph	43
4.8	Bode Diagram for all the drivers at the speed of 50 kph	43
4.9	Typical steering wheel torque profile from two test drivers	44
4.10	Trajectory of Driver A for the speed of 50 kph	45
4.11	Steering wheel torque of Driver A for the speed of 50 kph	45
4.12	Trajectory of Driver B for the speed of 80 kph	46
4.13	Steering wheel torque of Driver B for the speed of 80 kph	46
5.1	Metric Measurement	47
5.2	Trajectory of Driver G after the connection with EMA	48
5.3	Braking pressures on individual wheel of Driver G for the speed of 80 kph	49
5.4	Steering wheel torque of Driver G for the speed of 80 kph	49
5.5	Trajectory of Driver G with tuned EMA	50
5.6	Braking pressures on individual wheel of Driver G with tuned EMA .	50
5.7	Steering wheel torque of Driver G with tuned EMA	50
5.8	Trajectory of Driver E with tuned EMA	51
5.9	Steering wheel torque of Driver E with tuned EMA	51
A.1	Trajectory and steering wheel torque from Driver A without EMA . .	I
A.2	Trajectory and steering wheel torque from Driver D without EMA . .	II
A.3	Trajectory and steering wheel torque from Driver E without EMA . .	II
A.4	Trajectory and steering wheel torque from Driver F without EMA . .	II
A.5	Trajectory and steering wheel torque from Driver G without EMA . .	II
A.6	Trajectory and steering wheel torque from Driver H without EMA . .	III
A.7	Trajectory and steering wheel torque from Driver I without EMA . .	III
A.8	Trajectory and steering wheel torque from Driver J without EMA . .	III
B.1	Trajectory and braking torque from Driver A with EMA	V

B.2	Trajectory and braking torque from Driver D with EMA	V
B.3	Trajectory and braking torque from Driver E with EMA	VI
B.4	Trajectory and braking torque from Driver F with EMA	VI
B.5	Trajectory and braking torque from Driver G with EMA	VI
B.6	Trajectory and braking torque from Driver H with EMA	VI
B.7	Trajectory and braking torque from Driver I with EMA	VII
B.8	Trajectory and braking torque from Driver J with EMA	VII
C.1	Trajectory and steering wheel torque from Driver A without EMA . .	IX
C.2	Trajectory and steering wheel torque from Driver B without EMA . .	IX
C.3	Trajectory and steering wheel torque from Driver C without EMA . .	X
C.4	Trajectory and steering wheel torque from Driver D without EMA . .	X
C.5	Trajectory and steering wheel torque from Driver E without EMA . .	X
C.6	Trajectory and steering wheel torque from Driver G without EMA . .	X
C.7	Trajectory and steering wheel torque from Driver H without EMA . .	XI
C.8	Trajectory and steering wheel torque from Driver I without EMA . .	XI
C.9	Trajectory and steering wheel torque from Driver J without EMA . .	XI
D.1	Trajectory, SWT and braking torque from Driver A with EMA	XIII
D.2	Trajectory, SWT and braking torque from Driver B with EMA	XIV
D.3	Trajectory, SWT and braking torque from Driver C with EMA	XIV
D.4	Trajectory, SWT and braking torque from Driver D with EMA	XV
D.5	Trajectory, SWT and braking torque from Driver E with EMA	XV
D.6	Trajectory, SWT and braking torque from Driver G with EMA	XVI
D.7	Trajectory, SWT and braking torque from Driver H with EMA	XVI
D.8	Trajectory, SWT and braking torque from Driver I with EMA	XVI
D.9	Trajectory, SWT and braking torque from Driver J with EMA	XVII

List of Tables

- 2.1 Comparison of two models 16
- 3.1 Parameter table for all test drivers for test 1 at speed of 50 kph . . . 28
- 3.2 Parameter table for all test drivers for test 1 at speed of 80 kph . . . 30
- 3.3 Parameter table for all test drivers for test 2 at speed of 70 kph . . . 31
- 3.4 Deviation table for all test drivers for test 2 at speed of 70 kph . . . 32
- 4.1 Values of the parameters for the speed of 50 kph 42
- 4.2 Values of the parameters for the speed of 80 kph 42

List of Abbreviation

EU	European Union
ESC	Electronic Stability Control
EMA	Evasive Manoeuvre Assist
CG	Center of Gravity
VCC	Volvo Car Corporation
NMS	Neuromusclar System

Chapter 1

Introduction

1.1 Background

Road transportation is responsible for a large number of human injuries and fatalities due to accidents. Among European Union countries, approximately 12000 people were killed in a car or a taxi every 30 days in 2013, according to statistics from the European Commission [1]. Those data reveal the reason why safe-driving becomes an increasingly more important concept nowadays. Nevertheless, it is gratifying to see that the number of fatalities is reduced, with the improvement of technologies and the introduction of hi-tech programs and functions. Among those technologies, both passive and active safety systems play important roles. A passive safety system indicates those technologies, which aims to protect the occupants and mitigate the injury during and/or after an accident, especially a crash. Three-point seat belt implemented in the 1950s was one of the examples. On the other hand, active safety system refers to technologies that prevent an accident from occurring, like Electronic Stability Program (ESP) also known as ESC. Another example for active safety system is EMA.

1.1.1 EMA

An EMA function, abbreviation for *Evasive Manoeuvre Assist* function, aims to help to avoid a collision, when an evasive manoeuvre is performed by the driver. In an emergency, an evasive action is sometimes more effective than just braking to prevent an accident. The function generally works in cooperation with ESP, and will be triggered, once the rate of change of the steering wheel angle exceeds a certain value, or in other words, the driver steers the vehicle evasively. This enables the vehicle to start turning earlier, while still remaining stable. A survey conducted by *Bosch GmbH* in Germany implies that *Evasive Steering Support* is one of the most interesting driver assistant systems and 8.4% of respondents think that such a function is more important than other driver assistant systems [2].

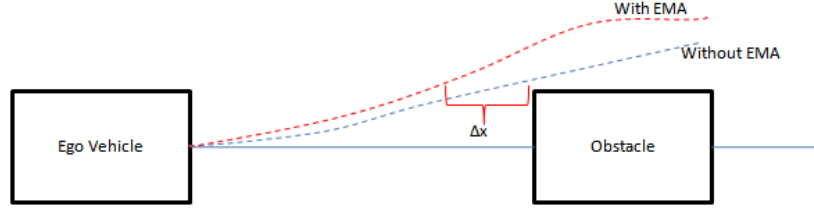


Figure 1.1: Metric Measurement

The idea of a EMA function is to increase the lateral movement of the vehicle to avoid an obstacle for those drivers who under steer or over steer the vehicle, as shown in Figure 1.1. The input to the EMA function consist of the steering wheel angle δ_{SWA} , longitudinal velocity V_x , lateral acceleration A_x , angular velocity $\dot{\delta}_{SWA}$ and side slip at rear axle α_r from a vehicle state estimator. Other fixed parameters of the vehicle, for example mass, steering gear ratio, wheelbase, center of gravity position are initialized in the function itself. The function is triggered when some necessary conditions are met. In order to trigger the function the steering angle, longitudinal velocity, side slip angle should be greater than a threshold value. The necessary condition to trigger the function can be summarized as follows [7]:

1. Driver initiates manoeuvre, detected by steering wheel activity (i.e. Steering wheel angular velocity is more than a threshold value)
2. Environment sensors detect a threat
3. Longitudinal velocity of the ego vehicle should be above a threshold value

It is also necessary to determine when to disable the function. The function is disabled when one of the above condition is not true or if one of the following condition is met:

1. If the lateral acceleration is more than a threshold value
2. If the side slip at the rear axle is more than a threshold value

The above mentioned conditions are necessary to disable the function if the driver achieves high lateral acceleration or the vehicle starts to skid. Figure 1.2 shows the conceptual working of the EMA functions and control events[7].

1.2 Problem Formulation

Collision avoidance functions using active vehicle chassis control are becoming increasingly more important and popular. *Volvo Car Corporation* (VCC) has launched related research and development many years ago in this area. On the other hand, it is also necessary to include the driver model at the development stage of the active safety function, in order to study the interaction between the driver and the vehicle, such that benefit gained by active safety function can be maximized.

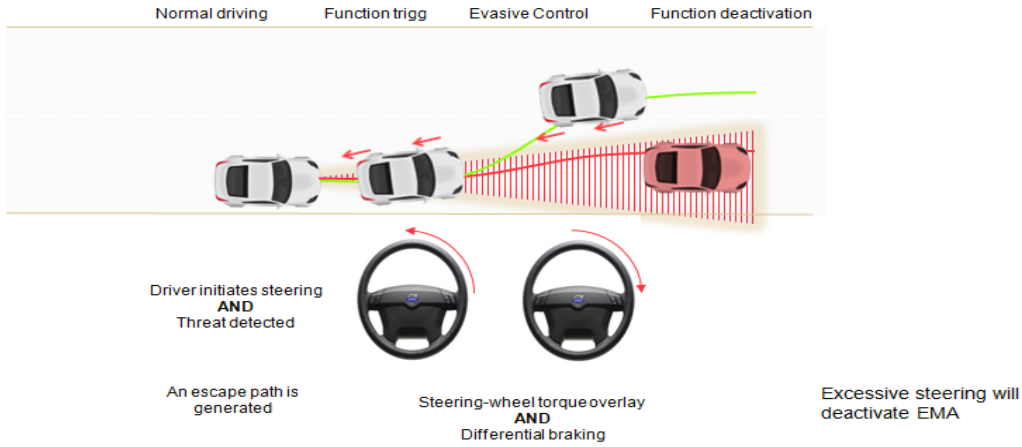


Figure 1.2: Conceptual working of EMA

The EMA active safety function works by applying not only a brake force on individual wheel, but also an extra torque on the steering wheel, in order to give more yaw angle to the vehicle, when it turns. The ultimate goal is to maximize the lateral displacement within a reasonable region and thus help the driver to avoid a collision. One should also make sure that the function is able to ensure the stability of the vehicle, so EMA function works in conjunction with ESP.

To understand the working principle of the EMA function, an example is showed in Figure 1.3. The blue box and red box in the figure represents the ego car and the obstacle respectively. In order to avoid the collision with the obstacle, the ego vehicle must be controlled within the time interval of Δt and the final lateral displacement of the ego vehicle should exceed the sum of half of the width of the obstacle and half of the width of the ego vehicle. Additionally, the vehicle should be within the boundaries of the road [9]. In short, $Y1$ should mathematically satisfy Equation 1.1.

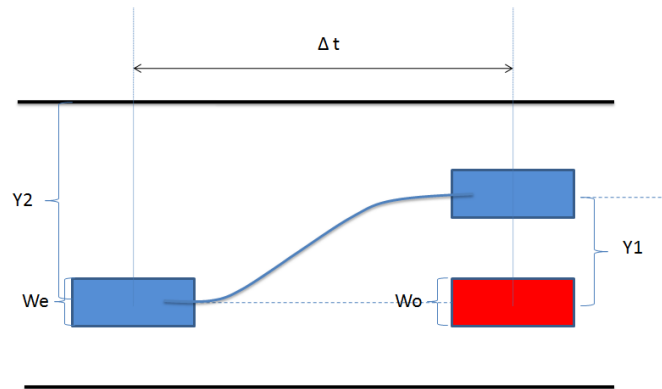


Figure 1.3: Problem

$$\frac{1}{2} (W_e + W_o) \leq Y1 \leq Y2 \quad (1.1)$$

However, without any tests or experiments, no one can guarantee that a newly-

developed function will completely meet the developers' expectation and then be put into use in reality. On the other hand, such functions without any tests will make drivers, passengers and pedestrians exposed to huge risk and danger. Therefore, testing beforehand is necessary.

The schematic representation of driver, EMA and vehicle is shown in Figure 1.4. The driver controls the vehicle with the use of the steering wheel (i.e. SWT is the input to the vehicle). As a driver is not able to brake each wheels separately, the EMA function helps the driver avoid the threat by controlling the brakes individually and apply an extra steering wheel torque to the input SWT.

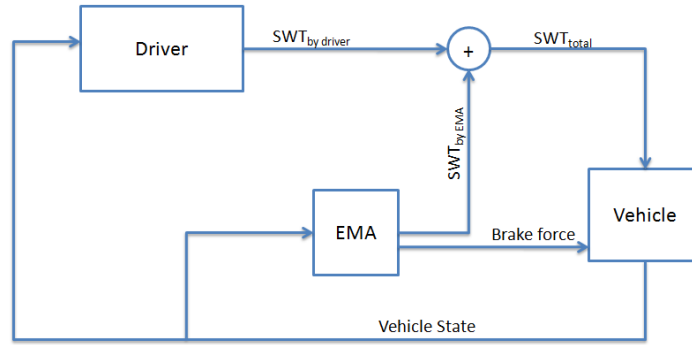


Figure 1.4: Block diagram of working of EMA function

The gain from the EMA function depends on the skill of the driver. Theoretically, the gain from the EMA function is less for skilled drivers whereas the gain will be more for unskilled drivers. Based on this hypothesis, one can formulate two research questions:

1. How to design the EMA function when the drivers have a different driving skill?
2. How much can the function help the drivers?

Therefore, involving drivers with different driving skills is of great importance. The thesis work aims to develop a driver model in order to evaluate the effectiveness of the EMA function based on the variety of driver skills. The driver model should be able to perform as a skilled driver and also like an unskilled driver by setting different values of the parameters in the driver model.

1.3 Literature Review

EMA function is supposed to be triggered in the scenario of the near-collision avoidance, when the driver performs an evasive maneuver. In other words, if the vehicle changes the lane evasively, this function should be activated automatically. Therefore, in order to test the effectiveness of the EMA for the near-collision avoidance, the driver model that would be built under this thesis work should be suitable for

this scenario.

Since decades ago, lots of scholars have been devoted themselves to investigate how to make a proper mathematical model of the driver to study the interaction between the driver and the vehicle. Different models have been thus developed and implemented in the automotive industry. The recent researches show one thing in common though: The driver model for studying the steering of the vehicle consists of two parts, the preview controller and the Neuromuscular system (NMS) [5, 10, 11, 12].

The preview controller is built based on the control theory and provides the driver with a method how to estimate the steering wheel angle based on the escape path that the driver has seen [5, 10, 11, 12, 13, 14, 15].

G. Markkula et al has done some work on the comparison of driver models with different control theories (different preview controllers) [13, 14]. To study the comparison and the list of all the available preview controllers are a good start to investigate which controller is more suitable for the evasive maneuver and the collision avoidance case.

They suggest that the two models proposed by MacAdam [15] and Sharp [16] respectively, are good enough to study the collision avoidance, but the former one shows "poor fit of stabilization steering" [14]. The reason, to some extent, lies in the fact that in Sharp's model both lateral error and yaw error are considered, whereas in MacAdam's model only lateral error is taken into account.

Additionally, two more models are compared in Ref [14], which work in the way of estimating the steering angle with respect of the heading angle of the vehicle. But the result shows "poor fit of avoidance steering".

Two research teams (Katzourakis and Pick) referenced the model by Sharp, when they were developing the driver model for investigating the steering behavior (see [10] and [5] for their current research results, respectively.). The theory behind the preview controller in both driver models are:

1. Previews several points ahead of the vehicle
2. Estimates the predicted path
3. Estimates the yaw angle error and the lateral displacement error by comparing the predicted path and the desired path and
4. Estimates the steering wheel angle by penalizing the errors of both lateral displacement and yaw angle

The difference of skilled and unskilled driver models lies mainly in Step 4, i.e. the algorithm used to penalize the errors and estimate the steering wheel angle is different. The difference is, Pick et al use a linear quadratic regulator (LQR), while

Katzourakis et al use a P-controller.

Apart from the preview controller, they study also the neuromuscular dynamics in the driver-vehicle system ([5, 10, 17]). Both of block diagrams of the neuromuscular system, along with the preview controller, can be seen in the figures ([5], [10]) below:

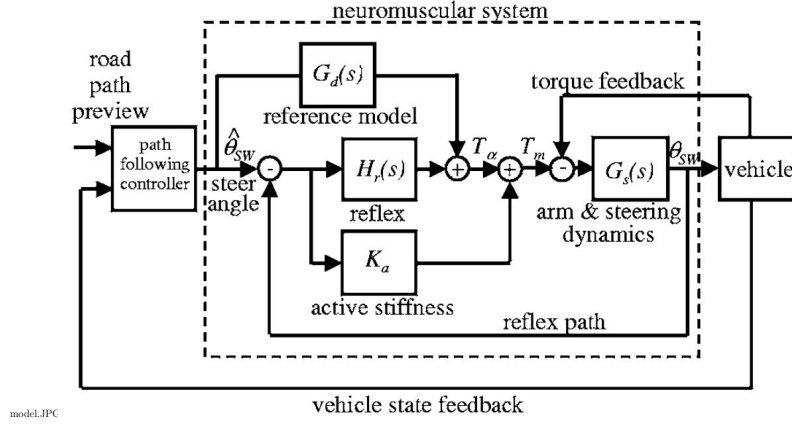


Figure 1.5: NMS model developed by Pick et al

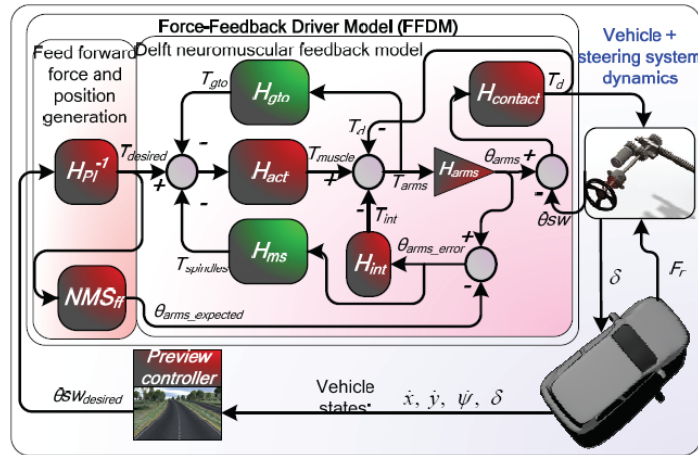


Figure 1.6: NMS model developed by Katzourakis et al

The NMS model by Katzourakis (Figure 1.6) has more details, but mostly are the same. The system identification has not been done by Katyourakis. By comparison, the work by Pick [5] shows the influence of parameters in NMS model on the whole driver model. Additionally, Pick and Cole have conducted an experiment to verify the model by asking 8 driver to preform a double lane change in a simulator [18].

Chapter 2

Methods

In order to develop a reasonable mathematical model of the driver for the evasive manoeuvre, different models are studied first. As mentioned in Chapter 1 the driver model consists mainly of two parts, i.e. *Preview Controller* and *Neuro-muscular System* (NMS). The preview controller shows the activity of the driver's brain (what the driver is thinking when driver is confronted with a specific situation), whereas the NMS model represents the muscle activation and the arm dynamics of the driver (how the driver's arms, along with the neurons inside, convert the biological signal from the brain into physical motion).

In this chapter, the designing process of the preview controller and the NMS model will be discussed. First, the mathematical model which is able to describe the lateral motion of the vehicle will be built. Then, the results of different driver models will be demonstrated and discussed.

2.1 Driver Model

The block diagram in Figure 2.1 shows different parts of a driver model.

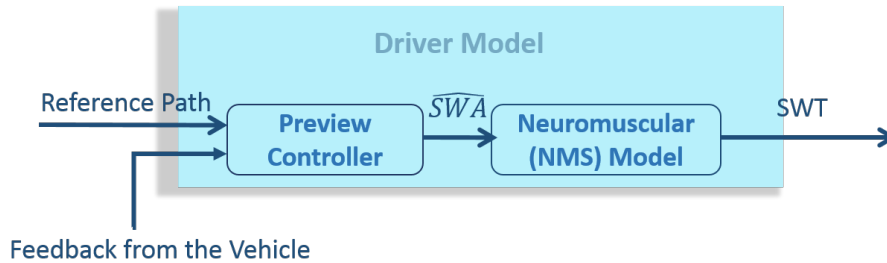


Figure 2.1: Block diagram of the driver model

The input to the Preview Controller is the reference path and the feedback from the vehicle. The feedback is mainly the states of the vehicle. The controller will then send the optimal steering wheel angle to the NMS model. From the NMS model, a steering torque will be applied to the vehicle. This has great similarities with how

humans plan and act while driving.

The **Reference Path** implies the escape path that the driver generates in their mind, when an object appears suddenly in front of the vehicle. The driver will try to follow this path, in order to avoid a collision.

The **Feedback from the Vehicle** provides the controller with the current states of the vehicle (e.g. lateral displacement y and yaw angle Ψ). Based on these parameters the controller is able to change its output and make the vehicle follow the path as good as possible.

The **Steering Wheel Angle** (\widehat{SWA}) connects the controller and the NMS model, and represents the command from the driver's brain. This command is sent to the driver's arms to steer the vehicle as expected. (This parameter is referred as $\widehat{\theta}_{SW}$ in Dr. Cole's paper [5] and can be seen in Figure 2.14 and Figure 2.13)

The **Steering Wheel Torque (SWT)** is the final output of the driver model. Theoretically, the output could be either the steering wheel angle or the steering wheel torque. But in fact, the steering wheel torque is used as output, because it is easier to connect to EMA.

2.2 The vehicle model in the preview controller

When driving a vehicle, the driver usually controls the vehicle based on a simply model in their subconscious. On one hand, this model should be accurate enough, in order to let the driver have a reasonable idea about the vehicle behaviour. On the other hand, this model should be very simply, because the driver cannot have a complicated vehicle model in their mind, especially for the those, who have no idea of the details of the vehicle. Therefore, The model should be able to describe how the vehicle moves and should not be very complicated from the driver's point of view. In this study, this model is reflected by the vehicle model in the preview control.

In academia, the bicycle model is commonly used to study the double lane change or evasive maneuver of the vehicle, for example in the study of Dr. Cole et al [5]. Hence the bicycle model is used as the vehicle model in the preview controller.

The **Bicycle model**, also known as the one-track model, is one of the most effective and simplest tools to study the dynamics of the vehicle's lateral motion.

The model in Figure 2.2 [3] shows the bicycle model in the x-y plane. The vehicle is assumed to be symmetrical around the x-axis of the vehicle. Therefore, the left and right wheels on each axle can be lumped together and finally becomes the 2-wheel bicycle model. Additionally, some other assumptions are also made [3].

1. The speed in the x-direction is constant;
2. CG is located in the x-y plane;
3. The pitch and roll motion of the vehicle are neglected, and thus no load transfer in the longitudinal direction, as well as in the lateral direction;
4. External forces, such as aerodynamic drag are not considered.

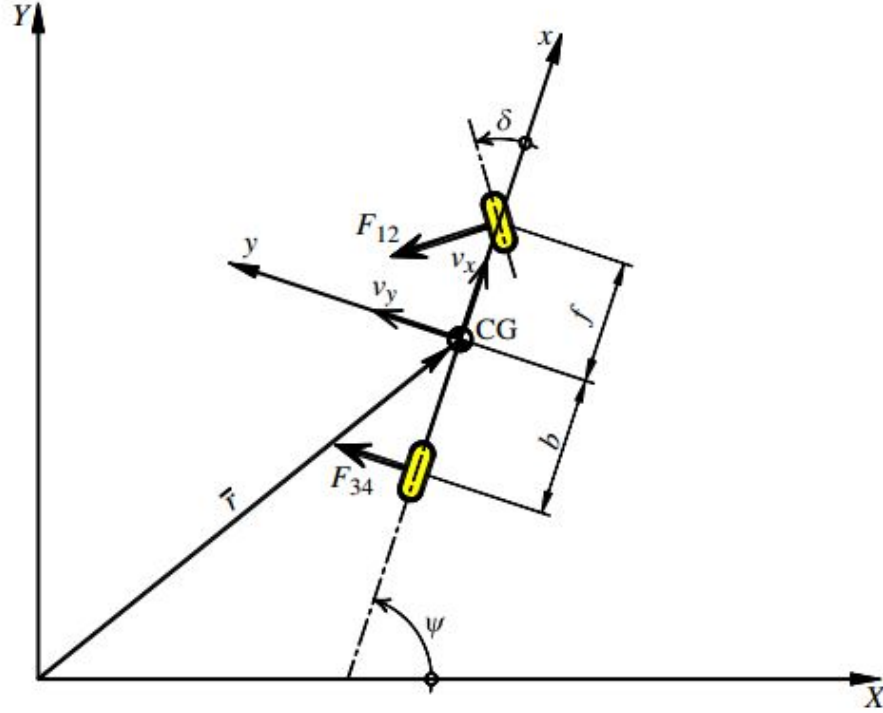


Figure 2.2: Bicycle Model

Considering all the assumptions mentioned above, the state space equation, which describes the motion of the bicycle model, could be formulated as [5]:

$$\begin{pmatrix} \dot{y} \\ \dot{v}_y \\ \dot{\Psi} \\ \dot{\omega} \end{pmatrix} = \begin{pmatrix} 0 & 1 & v_x & 0 \\ 0 & \frac{C_{12}+C_{34}}{mv_x} & 0 & \frac{fC_{12}-bC_{34}}{mv_x} - v_x \\ 0 & 0 & 0 & 1 \\ 0 & \frac{fC_{12}-bC_{34}}{I_z v_x} & 0 & \frac{f^2 C_{12}-b^2 C_{34}}{I_z v_x} \end{pmatrix} \cdot \begin{pmatrix} y \\ v_y \\ \Psi \\ \omega \end{pmatrix} + \begin{pmatrix} 0 \\ -\frac{C_{12}}{m} \\ 0 \\ -\frac{fC_{12}}{I_z} \end{pmatrix} \cdot \delta \quad (2.1)$$

where f denotes the distance from the front axle to the center of gravity (CG) and b is the distance from the rear axle to CG. Additionally, C_{12} and C_{34} is the cornering stiffness of the front and rear tyres respectively, and I_z is the rotational inertia about z axis.

However, the traditional bicycle model formulated in Equation 2.15 is not the most proper model to mimic the driver's thought, as it is still too complex. It contains a large number of parameters, e.g. the cornering stiffness of the tires, the inertia of

the vehicle, etc., which makes it impossible for the driver in reality to take so many factors into consideration. Therefore, simplifying the traditional bicycle model is very necessary.

If the vehicle has a constant speed ($\dot{v}_y = 0$ and $\dot{\omega} = 0$), the steering sensitivity, which is defined as $\frac{\dot{\Psi}}{\delta}$, can be formulated in Equation 2.2:

$$\frac{\dot{\Psi}}{\delta} = \frac{v_x \cdot L \cdot C_{12} \cdot C_{34}}{L^2 \cdot C_{12} \cdot C_{34} + m v_x^2 (b C_{34} - f C_{12})} \quad (2.2)$$

where L is the total length of the vehicle, $L = b + f$.

If the vehicle is in a circular motion with large radius ($v_y \ll v_x$), it follows: $\dot{\Psi} = \frac{v_x}{R}$ and $a_y = \frac{v_x^2}{R}$, with R is the radius. By considering this, Equation 2.2 will become:

$$\delta = \frac{L}{R} + \frac{m(b C_{34} - f C_{12})}{R \cdot C_{12} \cdot C_{34}} \cdot a_y \quad (2.3)$$

If one more assumption is taken into account, a_y is considerably small and thus neglectable, Equation 2.15 will become simply:

$$\delta = \frac{L}{R} \quad (2.4)$$

It shows the relation between the ackermann angle and the steering angle [3] and gets rid of some factors, i.e. the cornering stiffness of the tires, the inertia of the vehicle, as well as the position of CG. This is favorable to mimic driver's thought, because most of the driver don not even know the definitions of all these parameters.

Combining Equation $\dot{\Psi} = \frac{v_x}{R}$ with the Equation 2.4, the relation between the steering angle and the kinematic property of the vehicle will be formulated as below,

$$\dot{\Psi} = \frac{v_x}{L} \cdot \delta \quad (2.5)$$

This equation will be used as the basic vehicle model in the preview controller. In order to distinguish this mathematical model from the complete bicycle model, it will be called the simplified bicycle model in the subsequent part of the report. However, this model is only valid under some specific circumstances that satisfy the assumptions mentioned above. For example, if the vehicle has a large lateral displacement or yaw angle within a small time interval, this model is not valid any more.

2.3 Design of the preview controller

The simplified bicycle model is a reflection of the physical model of the vehicle in driver's mind. After knowing how the vehicle moves, the driver is then able to

control the vehicle based on this model. The driving strategy or in other words, how the driver thinks he/she follows the reference path, will be discussed in this section.

2.3.1 Simplified bicycle model with feedforward controller

Figure 2.3 below illustrates the mechanism of how the simplified bicycle model, along with the feedforward controller works.

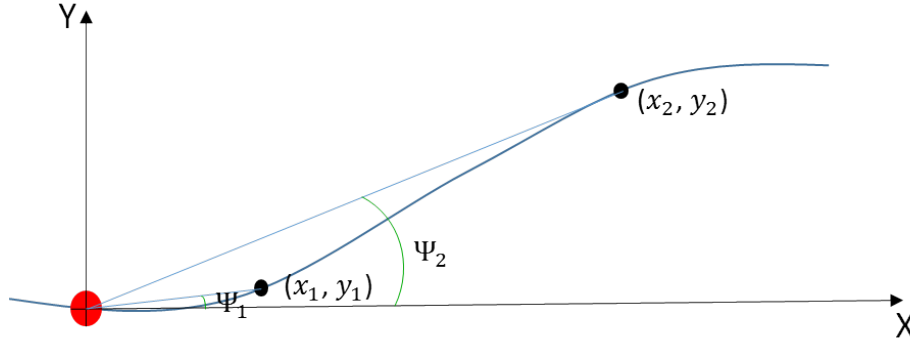


Figure 2.3: Sketch of mechanism of feedforward controller

The red point represents the vehicle. The thick dark blue curve is the reference path that the driver/vehicle tries to follow. The “driver’s brain” will work by following the steps shown below and then estimate how much he/she should turn:

1. detects several points ahead of vehicle, e.g. P_1 and P_2 in Figure 2.3
2. estimates the coordinates of the points, e.g. x_1, x_2, y_1, y_2
3. estimates how large angles the vehicle should turn in order to reach individual points, e.g. Ψ_1 and Ψ_2
4. estimate how large angle the driver should steer based on the formula 2.6, in order to follow the path

$$\Psi = \sum_{i=1}^n K_i \cdot \Psi_i \quad (2.6)$$

where K_i is the weighting on the individual heading angles Ψ_i and reflects a different drivers’ steering strategy. The weighting of K_i should be finely tuned, in order to make the vehicle to follow the path.

Considering that the longitudinal displacement is much larger than the lateral displacement for evasive manoeuvre, so $\Psi_i \approx \tan^{-1} \frac{y_i}{x_i}$. Equation 2.6 could be then reformulated as:

$$\Psi = \sum_{i=1}^n K_i \cdot \Psi_i \approx \sum_{i=1}^n K_i \cdot \tan^{-1} \frac{y_i}{x_i} \quad (2.7)$$

Since the model used here is the simplified bicycle model, equation 2.5 is introduced, in order to convert the heading angle Ψ into the steering angle δ on the front wheel. The equation is rearranged and demonstrated as follows,

$$\delta = \dot{\Psi} \cdot \frac{L}{v_x} \quad (2.8)$$

Inserting equation 2.7 into equation 2.8, then yields:

$$\delta = \dot{\Psi} \cdot \frac{L}{v_x} = \sum_{i=1}^n K_i \cdot \dot{\Psi} \approx \sum_{i=1}^n K_i \cdot \frac{d}{dt}(\tan^{-1} \frac{y_i}{x_i}) \quad (2.9)$$

A coefficient n could be introduced as well, to convert the road wheel angle into the steering wheel angle. So, the equation to estimate the steering wheel angle δ_{SW} becomes:

$$\delta_{SW} = n \cdot \dot{\Psi} \cdot \frac{L}{v_x} = n \cdot \sum_{i=1}^n K_i \cdot \dot{\Psi} \approx n \cdot \sum_{i=1}^n K_i \cdot \frac{d}{dt} \tan^{-1} \frac{y_i}{x_i} \quad (2.10)$$

2.3.2 Simplified Bicycle Model with LQR

Equation 2.5 is the fundamental equation for the simplified bicycle model, but it involves only the yaw motion of the vehicle. In fact, one more important state could be considered by the driver, i.e. the lateral displacement (y), if the driver thinks penalizing the error of lateral displacement is also important. Considering that the longitudinal velocity is larger than the lateral velocity, one more equation can be introduced to show how lateral velocity of the vehicle changes, i.e.

$$\dot{y} = v_y = v_x \cdot \tan \Psi \approx v_x \cdot \Psi \quad (2.11)$$

Combining equation 2.11 with equation 2.5, a new state space equation can be used to describe the motion of the vehicle. After introducing the ratio between the steering wheel angle on the steering wheel (δ_{SW}) and the road wheel angle (δ), the corresponding state space equation will become:

$$\begin{pmatrix} \dot{y} \\ \dot{\Psi} \end{pmatrix} = \begin{pmatrix} 0 & v_x \\ 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} y \\ \Psi \end{pmatrix} + \begin{pmatrix} 0 \\ \frac{v_x}{nL} \end{pmatrix} \cdot \delta_{SW} \quad (2.12)$$

where n is the ratio used to convert the road wheel angle to the steering wheel angle.

In spite of this, the model of the driver's brain is not complete yet, because there is no function that could reflect how a driver will perform, when the car deviates from the desired path. Therefore, the LQR is introduced, in order to help the driver to move back to the designed path, when the deviation has occurred.

LQR, is a state feedback controller, the gain for the controller is obtained by minimizing a quadratic cost function. Consider a linear system,

$$\frac{dx}{dt} = Ax + Bu$$

the quadratic cost function to be minimized can be written as

$$J = \int_0^\infty (x^T Q x + u^T R u) dt \quad (2.13)$$

where $Q \geq 0$, $R \geq 0$ and are symmetric matrices. The Q matrix penalizes the state variables and R matrix penalizes control input variables. By choosing Q and R matrices suitably the rate of convergence of the solution can be balanced with the cost of input [8].

The control law that minimizes the cost function is given by,

$$u = -Kx$$

where K is given by $R^{-1}B^T P$, P is positive definite matrix and it satisfies the *algebraic Riccati Equation*,

$$PA + A^T P - PBR^{-1}B^T P + Q = 0 \quad (2.14)$$

The equation 2.14 can be solved numerically, for example using the `lqr` command in MATLAB.

Sharp and Valtetsiotis [26] had derived a mathematical model of vehicle steering control using LQR which uses the road path preview information. Using a shift register operation, Sharp and Valtetsiotis [26] showed that road path preview can be augmented with the vehicle state space equation.

$$\begin{pmatrix} x(k+1) \\ y_p(k+1) \end{pmatrix} = \begin{pmatrix} A_d & 0 \\ 0 & D \end{pmatrix} \begin{pmatrix} x(k) \\ y_p(k) \end{pmatrix} + \begin{pmatrix} 0 \\ E \end{pmatrix} y_{p(N+1)}(k) + \begin{pmatrix} B_d \\ 0 \end{pmatrix} \theta_{sw}(k) \quad (2.15)$$

where, $y_p(k) = [y_{p0}(k) \ y_{p1}(k) \ y_{p2}(k) \ \dots \ y_{p(N-1)}(k)]^T$ is the road path preview information, as shown in Figure 2.4.

$$D = \begin{bmatrix} 0 & 1 & 0 & . & . & . & 0 \\ 0 & 0 & 1 & . & . & . & 0 \\ . & . & . & & & & . \\ . & . & . & & & & . \\ . & . & . & & & & . \\ 0 & 0 & 0 & . & . & . & 1 \\ 0 & 0 & 0 & . & . & . & 0 \end{bmatrix} \quad (2.16)$$

$$E = \begin{bmatrix} 0 \\ 0 \\ . \\ . \\ . \\ 0 \\ 1 \end{bmatrix} \quad (2.17)$$

The optimal steering angle can be calculated by solving the following quadratic function,

$$J = \sum_{k=0}^{\infty} (q_y(y(k) - y_{p0}(k))^2 + q_a(\psi(k) - \psi_{p0}(k))^2 + R_2(\theta_{sw}(k))^2) \quad (2.18)$$

where q_y and q_a are weights on states i.e. weight on lateral displacement and yaw angle respectively. R_2 is the weight on the input i.e. steering angle and it is scalar. The equation 2.18 can be written as follows in matrix form,

$$J = \sum_{k=0}^{\infty} (z^T(k)R_1z(k) + \theta_{sw}(k)R_2\theta_{sw}(k)) \quad (2.19)$$

where $z(k) = [x(k) \quad y_p(k)]^T$

$$R_1 = C^TQC \quad (2.20)$$

$$c = \begin{bmatrix} 0 & 0 & 1 & 0 & -1 & 0 & 0 & \cdot & \cdot & 0 \\ 0 & 0 & 0 & 1 & \frac{1}{v_x T} & \frac{-1}{v_x T} & 0 & \cdot & \cdot & 0 \end{bmatrix} \quad (2.21)$$

$$Q = \begin{bmatrix} q_y & 0 \\ 0 & q_a \end{bmatrix} \quad (2.22)$$

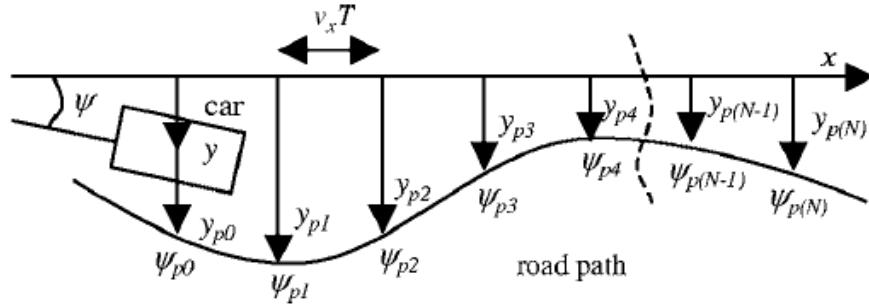


Figure 2.4: Showing global position of the vehicle and road path preview information, where y_{pN} is the road path lateral displacement and ψ_{pN} is the road heading angle

The gain \mathbf{K} of LQR controller can be calculated by minimizing the cost function J . This cost function can be solved using `lqr` command in MATLAB. The optimal steering wheel angle can be calculated by following formula,

$$\hat{\theta}_{sw}(k) = -\mathbf{K}[x(k) \quad y_p(k)]^T \quad (2.23)$$

where $\mathbf{K} = [k_1 \quad k_2 \quad k_3 \quad k_4 \quad k_{p0} \quad k_{p1} \quad \dots \quad k_{pN}]$

The \mathbf{K} matrix consist of $k_1 - k_4$ which are state gains i.e. these gains act on vehicle states and $k_{p0} - k_{pN}$ are the gains which acts on preview path information.

Different driver place different weightings on the states of the vehicle (the lateral displacement (y) and the yaw angle (Ψ)) and accordingly adjust the vehicle based on his/her judgment (weighting).

2.3.3 Results and Discussion

In order to test which controller performs better, both of the models should be requested to follow one path. The same reference path is then sent to the two preview controllers, and the output of the controllers (steering wheel angle) goes to the plant, which, at this stage, is a complete bicycle model (see Equation 2.15). The output of the plant is the four states of the vehicle, i.e. lateral displacement, yaw angle, lateral velocity, as well as yaw rate. Some of the states would be sent to the controller again as the feedback, which is used to help the controller to adjust the motion of the vehicle (the parameters sent to the controller varies according to which controller is used).

The parameters in each controller need to be tuned beforehand. For the simplified bicycle model with feedforward controller (hereinafter Model 1), the number of the parameters that should be tuned is highly dependent on how many preview points are set. In addition, other independent parameters in the controller, e.g. the length of the vehicle, preview time, the weighing on each preview points (K_i) are also need to be tuned. For the simplified bicycle model with LQR (hereinafter Model 2), there are in total 5 parameters that need to be tuned, which is much less and more predictable in comparison to the other one. Besides preview time, number of preview points and the length of the vehicle, weighting on the lateral displacement and on the yaw angle also influence a lot, due to the feature of the LQR contained in the controller. After tuning the parameters manually, Figure 2.5 shows the performance for the speed of 50 kph (above) and for the speed of 90 kph (below):

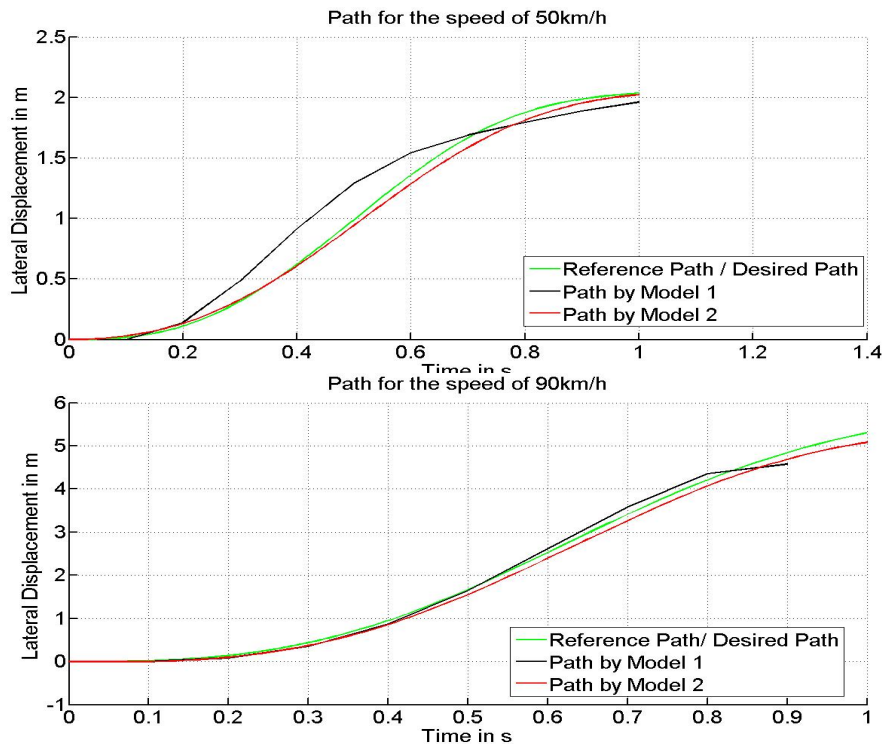


Figure 2.5: Performance of different Models/Controllers

The green line is the reference path that both controllers were requested to follow. The black trajectory is generated by the simplified bicycle model with feedforward controller, whereas the red one is by the simplified bicycle model with the LQR. For the low-speed case (speed of 50 kph), the Model 2 could generate much better trajectory than the Model 1, but for the high-speed case, the difference is not very big, which means Model 1 does not work well in the low-speed case, whereas Model 2 works well for almost all the cases.

It is also noteworthy that tuning the parameters for model 1 is very difficult and much more complicated and time-consuming than the other one, because it is very hard to decide how many preview points should be set. Additionally, deciding the weighting on each preview points is also a problem. One could maybe make model 1 also perform well for the low-speed case by fine-tuning, but it is hard to determine the values of the parameters manually. The summary of both models, as well as its pros and cons are listed in Table 2.1:

Vehicle Model	Controller	Penalty	Performance
Simplified Bicycle Model	Feedforward Controller	Heading Angle	Good at high speed
Simplified Bicycle Model	LQR	Yaw Angle/ Lateral Displacement	Relatively good in all speed range

Table 2.1: Comparison of two models

It is evident that the second model is much more suitable for the study of evasive manoeuvre. Therefore, the simplified bicycle model with LQR is chosen as the preview controller for the driver model.

2.4 Verifying Driver Model with 6 DOF Vehicle Model

The driver model was tested with a 6 DOF (Degree of Freedom) car model in the SIMULINK environment. The car model, shown in Figure 2.6, was modeled in Dymola using Modelica language. The output of the preview controller goes directly to the car model, as the input of the model is the steering wheel angle instead of steering wheel torque. The performance of the car model with the selected preview controller (LQR) was compared with the optimization result, which was obtained in [25].

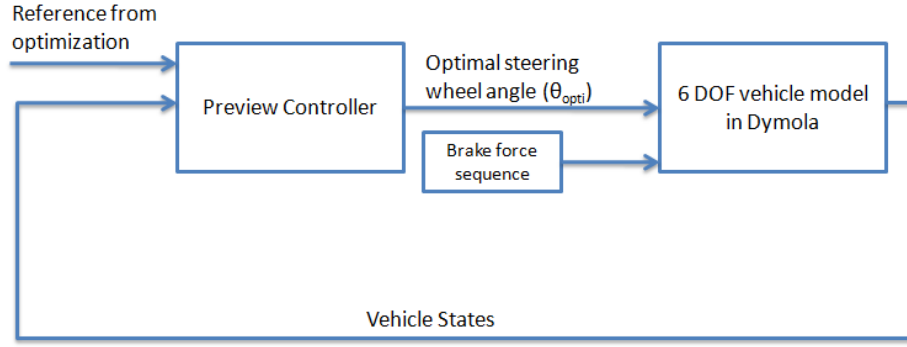


Figure 2.6: Schematic representation of Dymola connected to preview controller

Dr.Derong has carried out a numerical optimization using the same 6 DOF car model for an evasive manoeuvre situation at different velocities. The objective function used in the optimization is,

$$\text{Objective function : } J(\text{finalTime}) = \text{longitudinaldistance}(\text{finalTime})$$

Subjected to :

$$\text{lateral displacement}(\text{finalTime}) = 2m$$

$$\text{car.phi}(\text{finalTime}) \leq 0.1$$

$$\text{car.angularvelocity}(\text{finalTime}) \leq 0.05$$

$$\text{car.Velocityinydirection}(\text{finalTime}) \leq 0.1$$

The result obtained in [25] had obtained the optimal steering angle, optimal states of the vehicle to perform evasive manoeuvre at different velocities. The objective was to calculate the optimal path of the vehicle (6 DOF model) to perform evasive manoeuvre at that velocities considering above mentioned constraints. The optimal states of the vehicle are showed in Figure 2.7, and the optimal path in Figure 2.8.

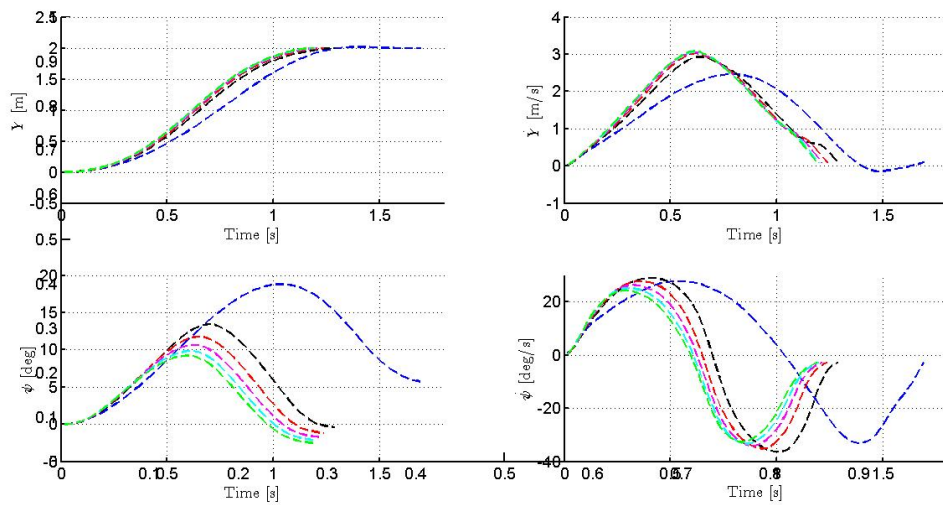


Figure 2.7: Vehicle states obtained from numerical optimization; blue path for 50 kph, black for 70 kph, red for 80 kph, magenta for 90 kph, cyan for 100 kph and green for 110 kph

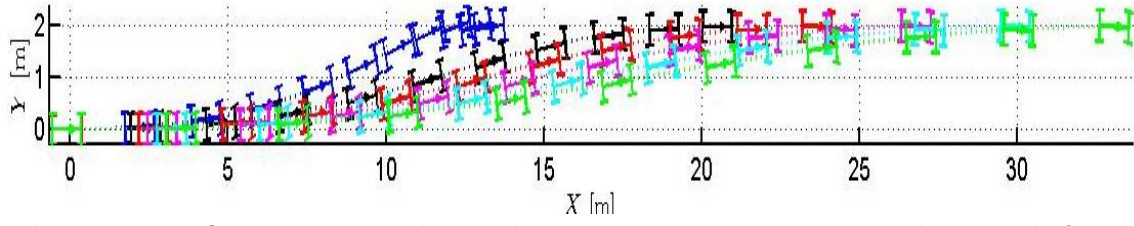


Figure 2.8: Optimal Path obtained by numerical optimization; blue path for 50 kph, black for 70 kph, red for 80 kph, magenta for 90 kph, cyan for 100 kph and green for 110 kph

The optimization results were used as reference in order to verify the performance of the driver model (at current stage, simply a preview controller). The path obtained from the optimization was inputted to the LQR controller as a reference. The parameters in the controller were tuned to follow the reference path, parameters like Q_y , Q_a and $PreviewTime$. Initially, constant velocity(V_x) was assumed throughout the manoeuvre and the driver model performance are shown in Figure 2.9 and Figure 2.10.

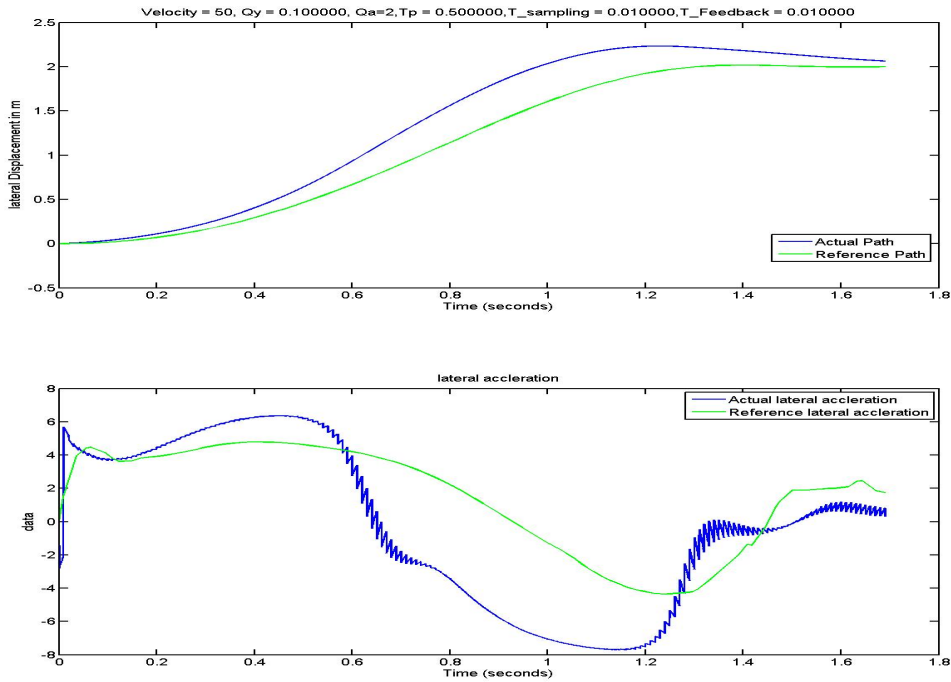


Figure 2.9: (a) Path travelled by a vehicle at velocity 50 kph, (b) lateral acceleration of the vehicle travelling at 50 kph

From Figure 2.9 and Figure 2.10, it can be concluded that at higher velocities the vehicle travelled close to the reference path, but at lower velocities there is a deviation with respect to reference path. This behavior can be explained, as the reference path was obtained by considering braking effect also, which means that the V_x was not constant. In order to have the same environment as the reference path was gen-

erated, the braking force sequence on each wheel is inputted to the Dymola model, the braking force on each wheel was obtained as result of numerical optimization. In the following figure it can be seen that the performance is better than the previous case.

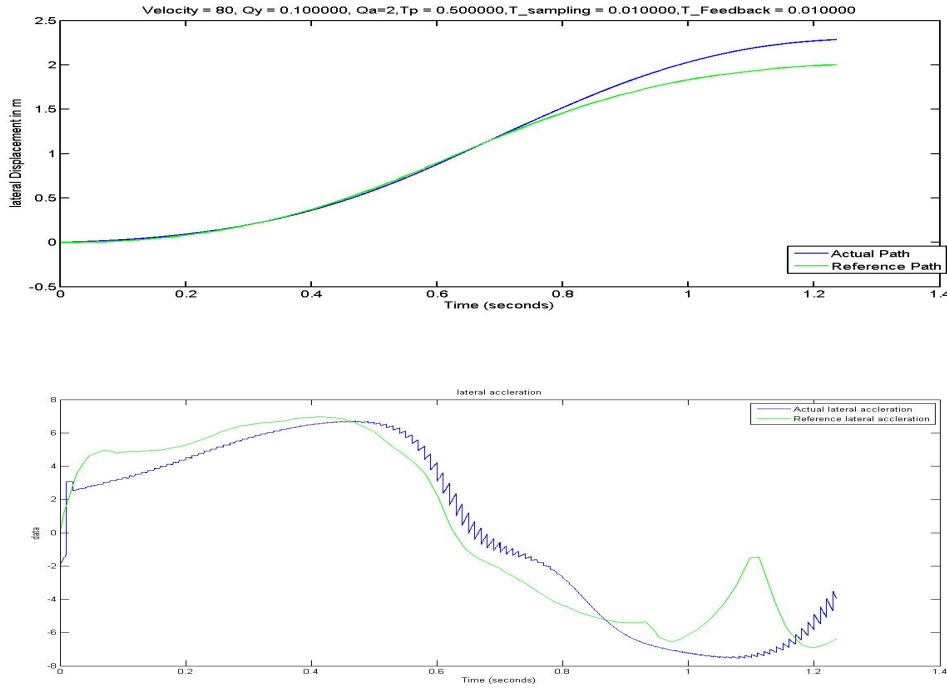


Figure 2.10: (a) Path travelled by a vehicle at velocity 80 kph, (b) lateral acceleration of the vehicle travelling at 80 kph

From Figure 2.9 and Figure 2.10, it can be concluded that at higher velocities the vehicle travelled close to the reference path, but at lower velocities there is a deviation with respect to reference path. This behavior can be explained, as the reference path was obtained by considering braking effect also, which means that the V_x was not constant. In order to have the same environment as the reference path was generated, the braking force sequence on each wheel is inputted to the Dymola model, the braking force on each wheel was obtained as result of numerical optimization. In the following figure it can be seen that the performance is better than the previous case.

From Figure 2.11 to Figure 2.12 it is clear that the driver model is good enough to follow the reference path. Based on these results it was concluded that the designed LQR controller is good enough to behave as preview controller. All these results were obtained without connecting the NMS model, it's assumed that the preview controller will not be having information of the NMS model. It is very similar to assume that the driver brain will not have the information regarding arm dynamics.

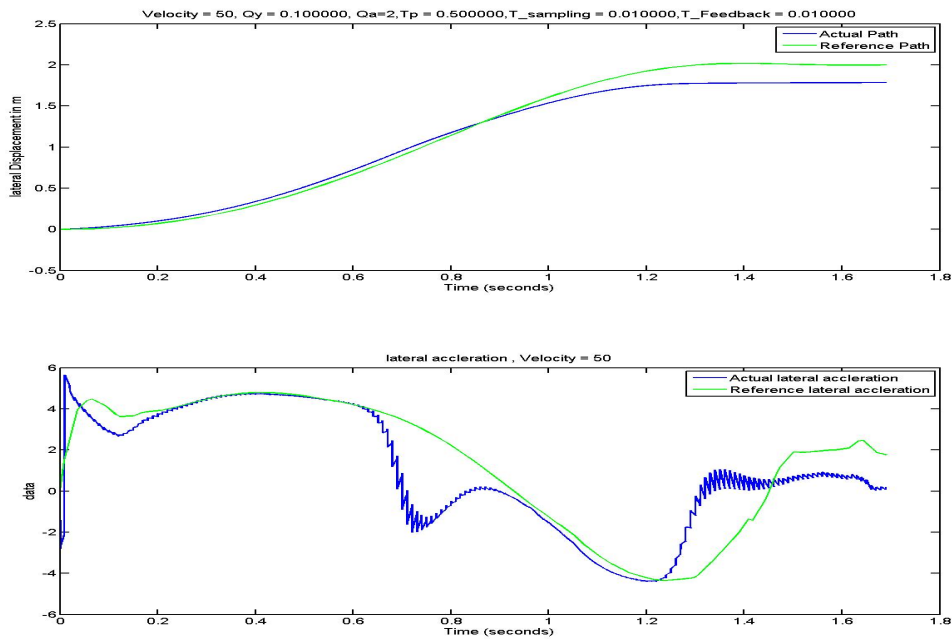


Figure 2.11: (a) Path travelled by a vehicle at velocity 50 kph with inputting braking sequence, (b) lateral acceleration of the vehicle travelling at 50 kph with inputting braking sequence

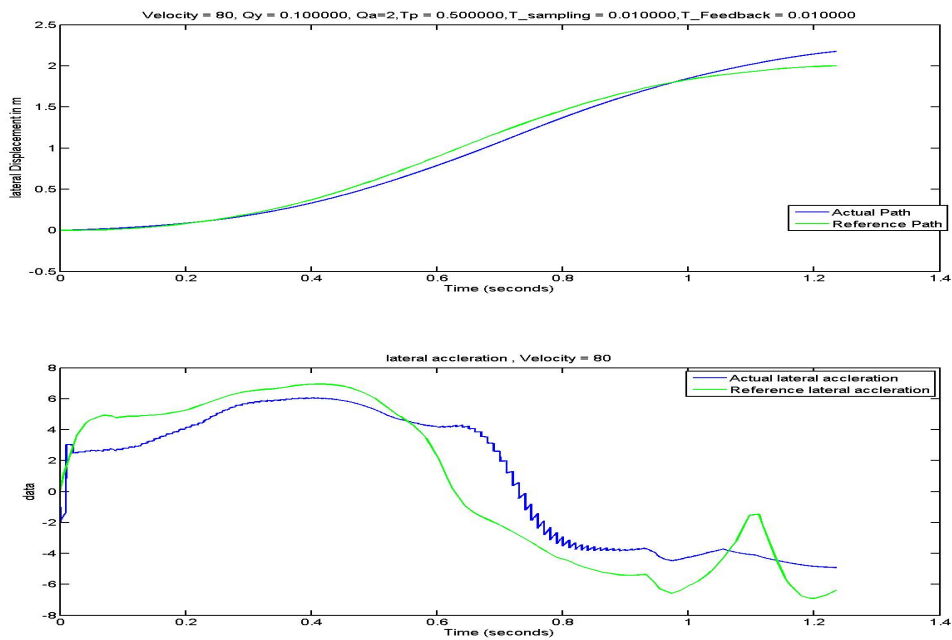


Figure 2.12: (a) Path travelled by a vehicle at velocity 80 kph with inputting braking sequence, (b) lateral acceleration of the vehicle travelling at 80 kph with inputting braking sequence

2.5 Design of Neuro-muscular System

The Neuro-muscular system (NMS) can be modeled in different ways, such as the ones showed in Figure 1.5 and Figure 1.6. Among those researches, the one from Pick and Cole shows a clearer picture and working mechanism of the NMS. They have also studied the influence of the parameters in the NMS based on the test they had done before. Thus, it is easier to understand their model and simplify it, if necessary.

In this section, the working mechanism of the NMS model will be discussed roughly. Based on the function of different blocks in the model, the unnecessary part will be neglected and the similar parts will be merged into one main block. The objective is to simplify the NMS model developed by Pick and Cole and thus be prepared for the tuning of the driver model.

2.5.1 Neuro-muscular System and Arm dynamics

The steering angle determined by the path following controller developed in the previous subsection is transmitted to the vehicle in the end as steering wheel torque (SWT) via the muscles and the arms of the driver. Therefore, the main function of NMS model is to transfer the optimal steering wheel angle to steering wheel torque.

The NMS model that Pick and Cole proposed is showed in Figure 2.13.

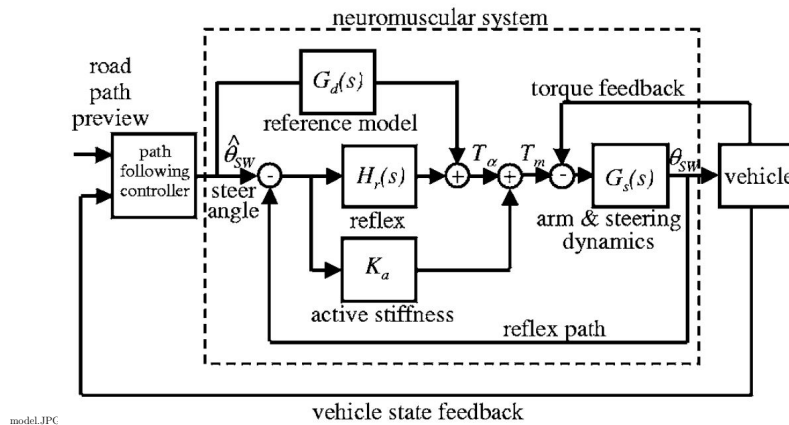


Figure 2.13: Driver Model with NMS Dynamics

It consists of 3 parts, reference model, reflex dynamics and active stiffness. The block *reference model* and *reflex* represent how the brain controls the muscle through different neurons (muscle activation). This so-called "Co activation" process [6], describes how the command sent to arms should be able to control the muscle force and muscle length at the same time via different neurons. The block *active stiffness* shows the stiffness of the muscle caused by the activation of the muscle.

This model demonstrates how different neurons work, as well as the mechanism of muscle activation. However, it is too complex for this study. Figure 2.14 illustrates

how the simplifications are made.

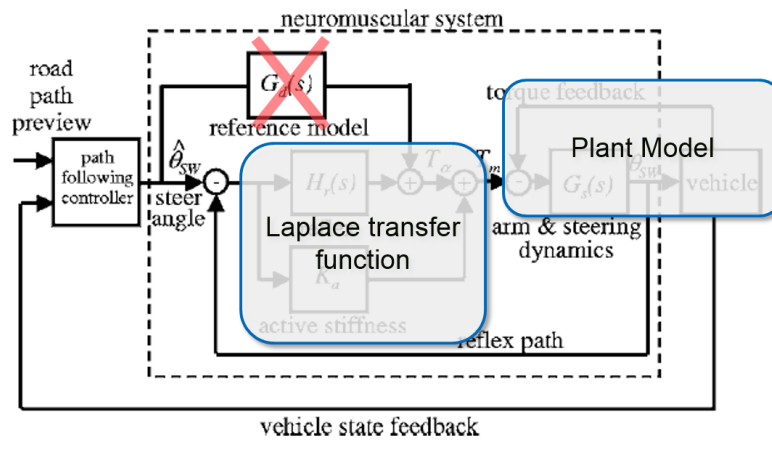


Figure 2.14: The simplification of the NMS model

Considering an alternative of the *reference model* block is to increase *active stiffness*, the block of reference model is thus negligible [5, 17]. *Active stiffness* is simply a gain and *reflex* is a first order filter. If these blocks are lumped together plus additionally the arm dynamics, which shows the damping, stiffness and the inertia of the arms, the complex NMS model in Figure 2.13 would be replaced by a second-order system $\frac{a_1 s^2 + a_2 s + a_3}{b_1 s^2 + b_2 s + b_3}$ ($b_1=1$), but with different numerators and denominators for different drivers. Note that the output of the NMS model in Figure 2.1 is steering wheel torque rather than the steering wheel angle in Figure 2.13. Therefore, the NMS model should be able to convert the error of steering wheel angle to the steering wheel torque. The entire NMS model is formulated as:

$$\frac{SWT}{\varepsilon_{SWA}} = \frac{a_1 s^2 + a_2 s + a_3}{b_1 s^2 + b_2 s + b_3} \cdot e^{-0.4s} \quad (2.24)$$

where SWT is the steering wheel torque output of the NMS (in Figure 2.15 showed as *Torq.*) and ε_{SWA} (in Figure 2.15 showed as *Diff*) is the difference of the optimal steering wheel angle and the current feedback of steering wheel angle.

The schematic block diagrams of the simplified NMS model is shown in figure,

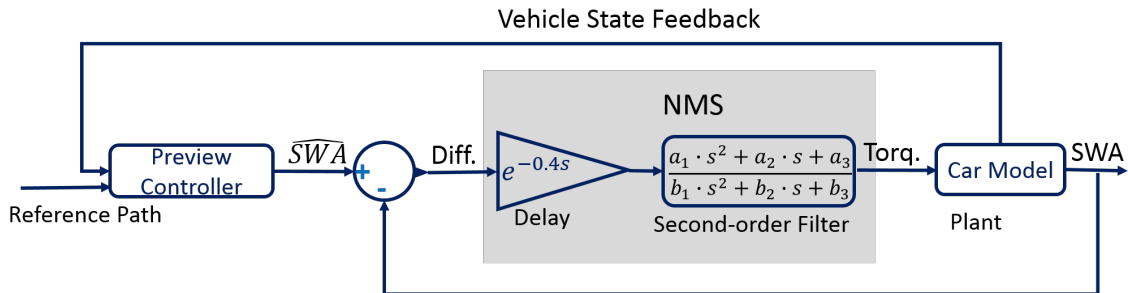


Figure 2.15: Schematic block diagram of the simplified design

The exact value of the numerators and denominators is varying from drivers to drivers, as the arm dynamic properties are different for individuals. These parameters (in total 5 except b_1) would be tuned, after the data of individual drivers have been obtained.

Chapter 3

Data Collection

This chapter explains the test conducted to collect the data of different skill sets of the drivers, in order to tune and verify the driver model. Most commonly used types in data collection are *test track experiments*, *driving simulator experiments* and *field-operational tests (FOTs)*[23]. The driver model are modeled considering a specific scenario, so it is important that the data should be collected for the same scenario for which the model is designed. Each data collection method has its own advantages and disadvantages, one needs to select a suitable method for data collection accordingly.

3.1 Test

In this thesis work, test track experiments were conducted in order to collect the data for the designed driver model. Two tests were conducted separately to study the driving skills of different drivers, broadly the drivers can be classified as skilled drivers and unskilled drivers. As the driver model was designed to check the effectiveness of the EMA function, theoretically the gain from the EMA function should be more for an unskilled driver than skilled driver (or gain is zero for ideal driver). Considering this aspect both skilled and unskilled drivers were asked to participate in the test, as it was important to gather the data of different driving skill sets.

3.1.1 Test Setup

It was required to have a suitable test track so that specific scenario test setup can be made considering all safety measures. The test was carried out at **AstaZero**, Sweden. It is the world's first full-scale test track where one can have a comprehensive test environment to evaluate the advanced safety system. The test drivers who participated in the test were ordinary drivers. 10 such drivers took part in the test. Among these 10 drivers, there were 3 drivers who had the driving experience for more than 20 years and had a experience of over 200000 km. Also few drivers were beginners and the others had an average number of years of driving experience. The test vehicle used for the experiment was a Volvo V40, the car was equipped with all the necessary sensors like GPS, Steering angle sensor (SAS), sensor to measure

steering column torque etc, to collect the data. Two tests were performed in order to collect the data and study the driver behaviour.

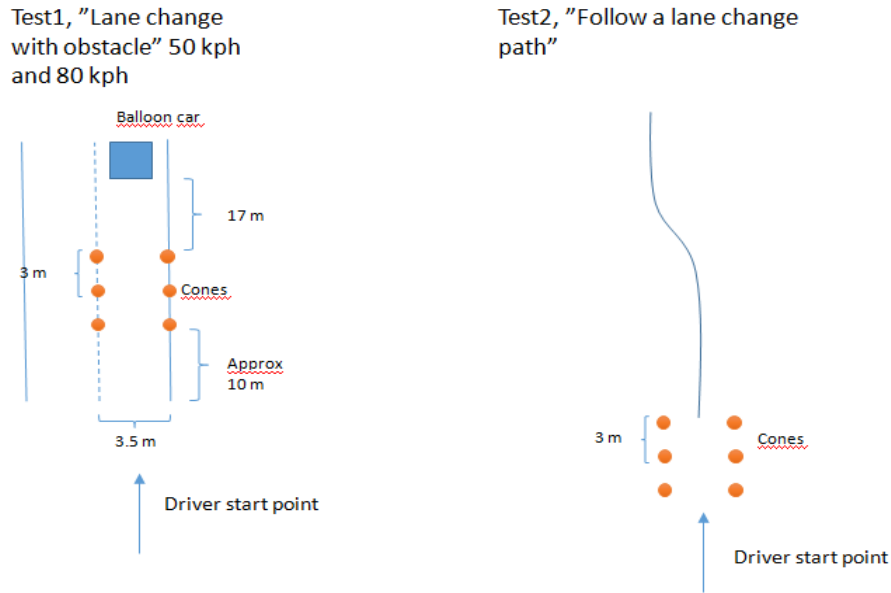


Figure 3.1: Test Setup

3.1.1.1 Test 1: Lane change with obstacle

An evasive manoeuvre scenario was set up in Test 1, a stationary balloon car was kept as an obstacle in the driving lane and drivers were asked to avoid the collision with the obstacle. It would be easier to perform the collision avoidance at lower velocity than at higher velocity. Therefore, the drivers were asked to perform at two different velocities i.e. at 50 kph and 80 kph, in order to collect the data at both situations. The test setup of Test 1 is shown in Figure 3.1: the drivers were asked to steer the vehicle from the third cone (the third cone from the bottom) and by the time they reach the first cone they were asked to maintain the speed of 50 kph and 80 kph respectively. The drivers were given instruction to avoid the obstacle only by steering and not to apply brakes while performing the task. The data collected in this test will be used to tune the parameters in the driver model.

3.1.1.2 Test 2: Follow a lane change path

The objective of Test 2 was to follow the reference path which had been drawn on the asphalt (road). The drivers were asked to perform this task by keeping a constant velocity of 70 kph. The drivers were told to follow this reference path only by steering and not taking any help by applying brakes. The coordinates of the reference path were taken from the path travelled by a professional driver at the speed of 70 kph, which was measured and collected in one of Volvo's previous tests. The reference path is shown in Figure 3.2. The main purpose of Test 2 was to analyze how differently drivers with different driving skill set will perform this task, when they have the same reference path. The classification of the test driver will take the

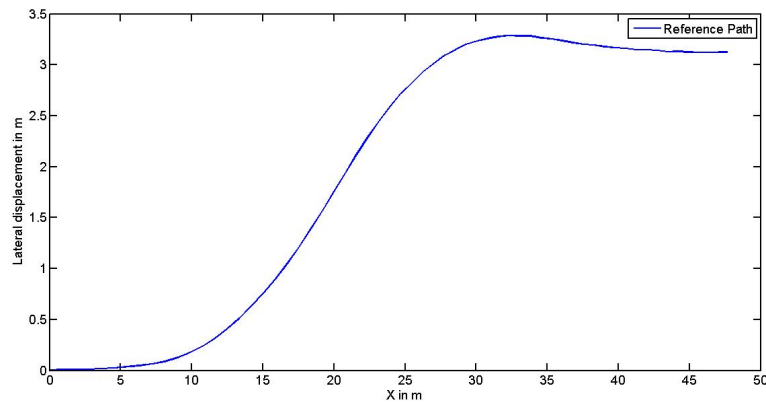


Figure 3.2: Reference path for test 2

results of this test into account.

When the human brain sees an image or a scene, it creates a replica of the image. Considering this fact, one can assume that the image of the reference path in all drivers' brains is the same. So ideally they all should follow the reference path more or less in the same way if their judgments to follow the path are appropriate.

In both tests, the values of many variables were collected, the following ones are interested in this thesis work:

1. Longitudinal Velocity (V_x)
2. Vehicle Position
3. Lateral Acceleration
4. Yaw angle
5. Yaw rate
6. Steering wheel torque (torsion bar torque)
7. Steering wheel angle

3.2 Analysis of test data

3.2.1 Test 1

3.2.1.1 Case 1: At velocity of 50 kph

In the test, the test drivers were asked to avoid the obstacle by only steering and keeping the constant velocity of 50 kph. There was no reference path for the test drivers to be followed in order to avoid the obstacle. Drivers were set free to follow their own mind path to follow and avoid the obstacle. The path travelled by all the

3. Data Collection

test drivers is shown in Figure 3.3, and the steering wheel angle applied by the test drivers is shown in Figure 3.4.

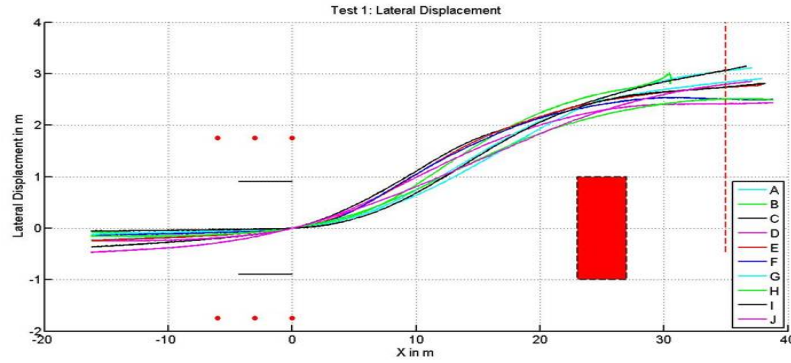


Figure 3.3: Path travelled by all the test drivers at speed of 50 kph

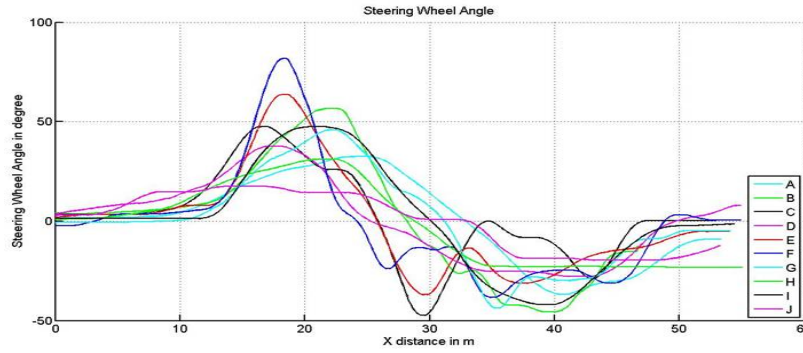


Figure 3.4: Steering Wheel Angle of all the test drivers at a velocity of 50 kph

The other important parameters are also studied in order to understand the driver behaviour during the test, the parameters are shown in Table 3.1.

Driver	Max SWA in degree	Max SWAR in rad/sec	Max Lateral acc in m/s^2	Min Lateral acc in m/s^2	Max Lateral Jerk in m/s^3	Avg Vx in kph	Min Vx in kph	Max Vx in kph
A	36.69	1.70	2.12	-2.37	3.69	50.19	49.72	50.58
B	56.48	2.87	2.63	-1.73	4.91	18.54	-0.22	44.42
C	47.60	3.84	2.26	-2.17	6.16	44.11	43.38	44.82
D	37.58	2.09	1.78	-1.42	2.98	40.98	38.01	41.94
E	63.68	3.48	3.40	-1.69	8.85	46.35	44.35	47.38
F	81.66	5.42	3.96	-1.87	9.99	45.28	44.20	46.22
G	45.80	2.54	1.87	-1.56	2.96	36.94	34.92	39.13
H	31.16	1.72	1.82	-1.60	2.46	46.85	46.37	47.59
I	47.38	2.25	2.78	-2.39	6.47	46.06	45.94	46.30
G	19.69	1.53	0.93	-1.04	1.68	42.27	41.58	43.06

Table 3.1: Parameter table for all test drivers for test 1 at speed of 50 kph

3.2.1.2 Case 2: At velocity of 80 kph

During this test, the test drivers were asked to avoid the obstacle with constant velocity of 80 kph and only by steering. Figure 3.5 shows path travelled by all the test drivers and the steering wheel angle is shown in Figure 3.6.

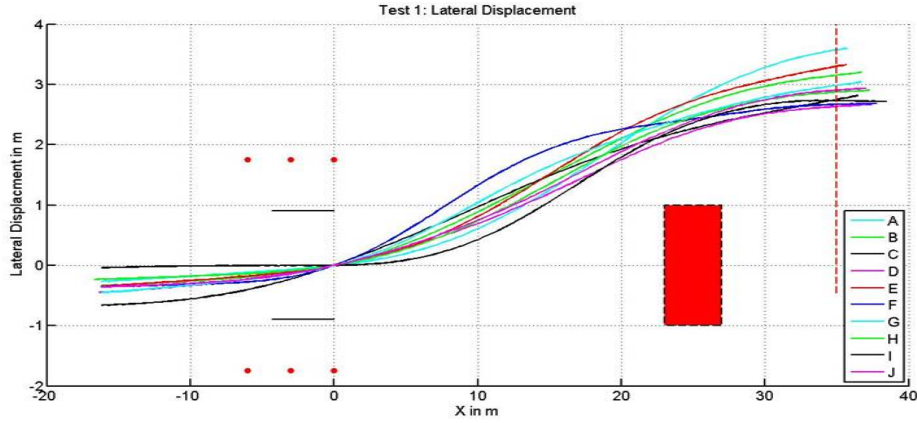


Figure 3.5: Path travelled by all the test drivers at speed of 80 kph

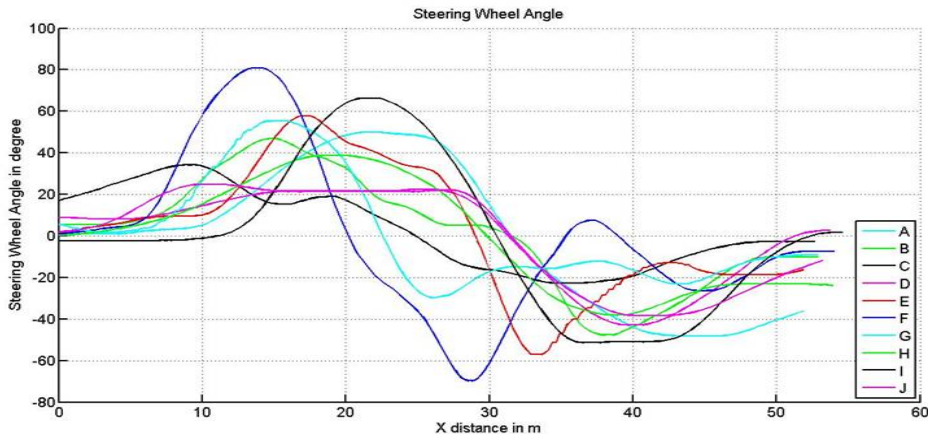


Figure 3.6: Steering wheel angle of all the test drivers at a velocity of 80 kph

Other parameters are listed in Table 3.2.

3.3 Test 2

In Test 2, all the test drivers were asked to follow the reference path with constant speed of 70 kph and they were instructed to perform the test only by steering. The resulting path travelled by the test drivers is shown in Figure 3.7. And the path travelled by the test drivers is different, even when the reference path is same for all of them. And also the steering wheel angle applied by the drivers to follow the reference path varies a lot from each other as shown in Figure 3.8.

3. Data Collection

Driver	Max SWA in degree	Max SWAR in rad/sec	Max Lateral acc in m/s^2	Min Lateral acc in m/s^2	Max Lateral Jerk m/s^3	Avg Vx in kph	Min Vx in kph	Max Vx in kph
A	49.8	4.2	5.57	-5.53	14.41	80.01	76.86	81
B	47.69	4.92	4.39	-4.95	11.85	84.03	81.76	84.82
C	34.28	3.33	2.95	-3.66	8.51	88.22	81.79	92.74
D	42.9	3.17	1.66	-5.58	10.4	79.96	78.05	82.3
E	57.88	7.32	5.62	-4.39	13	82.42	79.7	84.2
F	80.87	7.69	6.94	-4.9	18.15	74.82	72.14	76.18
G	55.38	5.88	4.92	-2.88	13.54	78.01	76.14	79.6
H	38.68	2.94	4.37	-3.65	10.05	77.42	75.24	79.34
I	66.36	5.12	6.58	-5.07	15.79	75.55	73.33	76.54
J	38.37	3.14	2.24	-4.37	6.52	76	74.45	77.04

Table 3.2: Parameter table for all test drivers for test 1 at speed of 80 kph

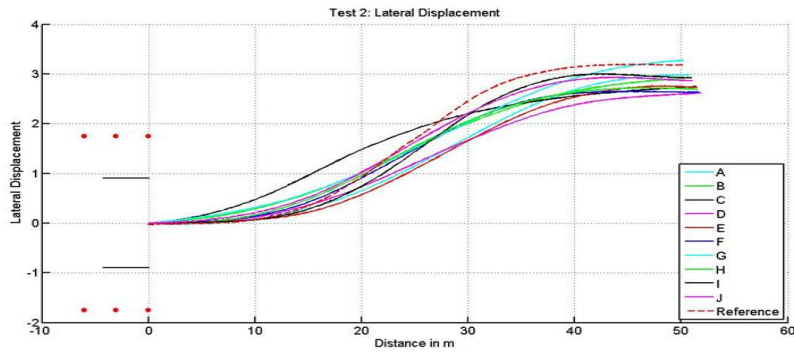


Figure 3.7: Path travelled by all the test drivers in order to follow the reference path

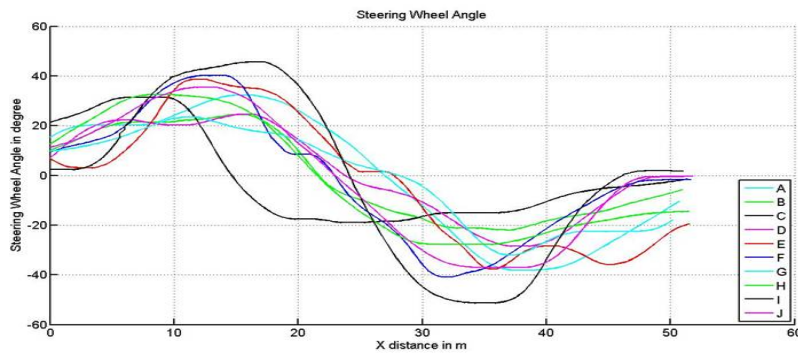


Figure 3.8: Steering wheel angle of the test drivers in order to follow the reference path

The red dash line in Figure 3.7 represents the reference path. After analysing the path of all the test drivers, it can be concluded that the drivers involved in this test had different driving skill sets. It was necessary to divide the test drivers into skilled

and unskilled drivers, based on the results obtained from this test. In order to study the behaviour of the drivers, the parameters like maximum steering wheel angle, maximum steering wheel angle rate, maximum lateral jerk and other parameters as shown in Table 3.3, were considered. But just by studying these parameters, one cannot classify the driver as skilled or unskilled, because driver *I* have maximum SWA, maximum SWAR and maximum lateral jerk. But still that driver *I* could follow the reference path very close enough, so there was no proper trend among these parameters and the path followed by the drivers. So the deviation from the reference path and path travelled by the different drivers were considered, as shown in Figure 3.9 and the deviation for all the test drivers is mentioned in Table 3.4. The deviation for driver *I* is least among all test drivers, also the steering wheel angle provided by the driver *I* is similar to a sine wave and by the numeric optimization result, it is known that the steering wheel angle should be similar to a sine wave. Along with these parameters, the experience of the driver is also considered while classifying the drivers into skilled and unskilled group. For example driver *I* was considered as a skilled driver as the driver had 200000 km of driving experience and least deviation from the reference and also the steering angle was similar to a sine wave.

Driver	Max SWA in degree	Max SWAR in rad/sec	Max Lateral acc in m/s^2	Min Lateral acc in m/s^2	Max Lateral Jerk m/s^3	Avg Vx in kph	Min Vx in kph	Max Vx in kph
A	38.06	3.18	3.25	-5.79	11.6	73.44	75.5	76.64
B	24.39	2.76	2.15	-3.22	9.68	67.72	70.42	72.32
C	31.29	3.51	1.45	-4.02	9.22	59.83	66.29	69.08
D	28.48	2.34	2.25	-3.85	10.74	64.55	65.8	66.85
E	38.59	3.61	3.08	-5.51	15.41	67.25	68.9	70.27
F	40.79	3.46	4.08	-5.43	11.77	67.61	68.21	68.8
G	32	1.95	1.88	-4.67	7.68	69.3	70.08	70.78
H	32.39	2.86	3.08	-3.84	9.47	64.44	67.18	68.9
I	51.29	3.73	5.02	-5.6	18.39	66.31	66.95	67.25
J	36.96	2.13	3.08	-4.87	14.27	64.98	65.7	66.24

Table 3.3: Parameter table for all test drivers for test 2 at speed of 70 kph

3. Data Collection

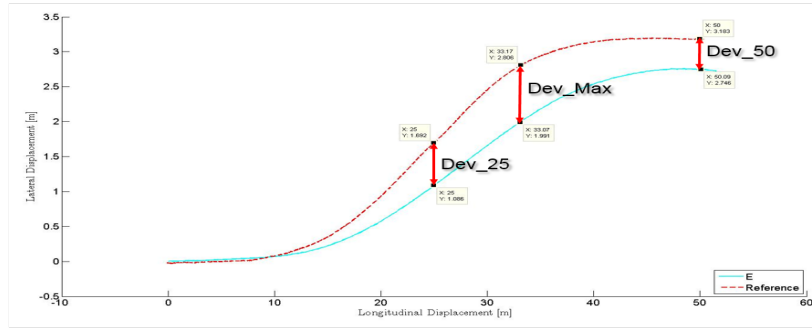


Figure 3.9: Deviation of the reference path and driver's path

Driver	Xmax in m	Maximum Deviation in m	Deviation at X=50m	Deviation at X=20m
A	31.941	0.754	0.201	0.535
B	34.537	0.559	0.265	0.167
C	40.485	0.588	0.449	-0.193
D	33.17	0.872	0.582	0.486
E	32.256	0.819	0.433	0.607
F	47.803	0.549	0.542	0.216
G	31.932	0.469	-0.09	0.192
H	36.219	0.525	0.472	0.143
I	30.414	0.285	0.251	0.269
J	50.262	0.308	0.309	0.063

Table 3.4: Deviation table for all test drivers for test 2 at speed of 70 kph

Based on this test the drivers were classified into skilled drivers and unskilled drivers group. The groups are shown below:

For the test of 50 kph:

Skilled: A, D, G, H, I, J

Unskilled: C, E, F

For the test of 80 kph:

Skilled: A, B, D, H, I, J

Unskilled: C, E, F, G

The skill of the driver varies based on the speed too, from the result G driver was skilled when speed was 50 kph and same driver was not able to perform well at high speed. From the result it can be said that driver skill is also dependent on the speed.

Among the skilled drivers' group the best driver was selected (the best driver is one who matched with requirements of skilled driver very well, for example driver I). The path travelled by the best driver will be used as a reference path for LQR controller and the parameters the in driver model will be tuned. The tuning methods

and the parameters selected to tune the driver model is explained in the following chapter.

Chapter 4

Tuning Parameters

The different driving strategies reflected in the preview controller are used by different drivers. In order to show such differences in the driver model, the parameters in the preview controller should be finely tuned. It is evident that the values of different physical properties of drivers' arm (NMS) should vary from one person to another. The tuning results regarding the value of different parameter sets will be studied and a brief analysis will be given accordingly.

Before the tuning, the vehicle model (the plant) should be verified as well, as the car model in CarMaker is not the same as the vehicle used in the test.

After the testing data has been obtained, the work of tuning parameters could start. At this stage, the parameters for different drivers will be tuned, in order to fit their performance in the simulation with the data got in the test. The virtual digital drivers (the driver model for different drivers), who are able to mimic the real driver in the test after tuning parameters, will be finally used to test the EMA function.

The method that is used to tune the parameters will be introduced in this chapter.

4.1 Tuning the Vehicle Model

As described in the last chapter, the test vehicle used is a Volvo V40. However, there is no such car model available in CarMaker. Therefore, a similar model is used, but some modifications should be made. The car model used in Carmaker is Ford Focus, because both Volvo V40 and Ford Focus were developed on the same platform.

The dimensions and the weight of the vehicle are set based on the official data of V40. Another parameter that needs to be tuned is the amplification of the hydraulic power steering in the steering system. After changing the values of parameters of the vehicle model in CarMaker, the vehicle should be able to generate the same trajectory as the one measured in the test, when the corresponding measured steering wheel torque is sent to the vehicle as input.

The result after tuning is shown in Figure 4.1

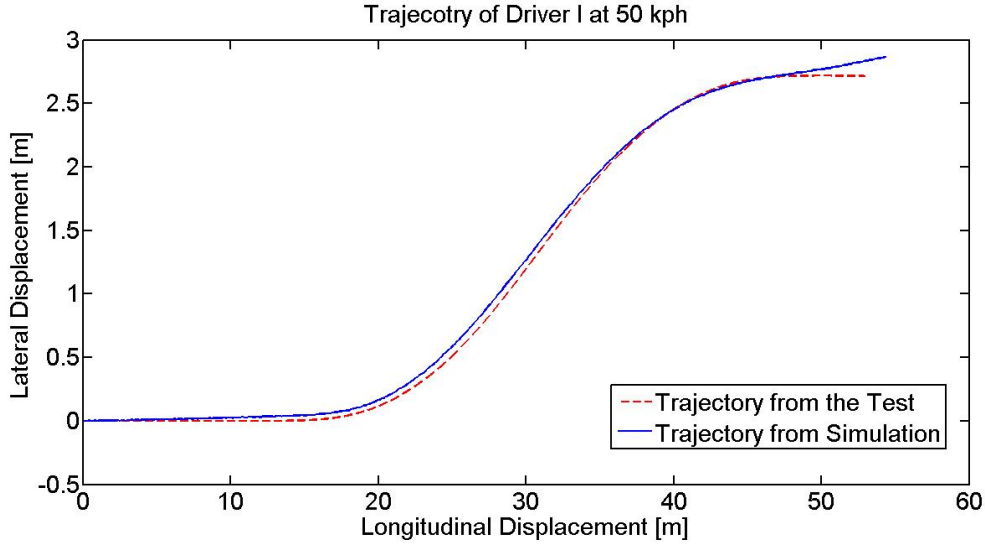


Figure 4.1: Verification of Car Model in CarMaker

The blue curve in Figure 4.1 is the trajectory from the test and the red dashed line is the trajectory from simulation by inputting the measured steering wheel torque sequence into the car model. If the parameters in CarMaker are well tuned, the two curves should be coincident. The result looks good and they match each other almost perfectly with merely a little deviation in the initial part, this is due to the initial yaw angle of the vehicle in the test is not strictly zero.

4.2 Tuning the Driver Model

In the driver model, there are in total 9 independent parameters (4 in preview controller, 5 in NMS model). The value of these parameters depends highly on the driver performance and driver skills. Therefore, the parameters should be tuned for each driver individually. However, it would become extremely difficult and time-consuming, if all the parameters are tuned manually. This problem will become even more severe, if the trend of how the parameters influence the model is not clear. Additionally, NMS model is a composite of arm dynamics and muscle activation, there is thus no explicit physical meaning of individual parameters in NMS model, which would make the problem more complex. Due to the problems that have shown up, the MATLAB function *fmincon* is introduced to solve above-mentioned problems.

The ultimate goal of tuning parameters is: after tuning the parameters, the NMS output (i.e. The steering wheel torque) should have the same trend and shape as the measured steering torque in the test, e.g. a sine-wave shape, if the reference path is sent to the driver model. The reference path is the same for all the test drivers for the same speed and it should be different from the one that the driver generated in the test (because almost no one could follow the reference path, according to

Test 2). This is to assure that the virtual driver has the similar steering strategy as what the real driver did. Then, the sequence of steering wheel torque is sent to the CarMaker model (i.e. the plant) and the vehicle should be able to generate the trajectory, which is the same as the one measured in the test.

The tuning is all based on the test data that was obtained before. However, the test was not perfect, the imperfections lays mainly in two aspects:

1. The initial yaw angle and initial steering wheel angle at the start point is not zero, which means that some drivers started to steer before he/she arrived at the start point;
2. The vehicle was not moving straight after the end point, so that the vehicle may not become completely stable in the end.

The imperfections will cause some problems while tuning. This will be discussed in the subsequent work.

4.2.1 Defining Reference Path

An assumption should be made first, i.e. in Test 1, all the drivers have the same reference path in their minds. For the speed of 50 kph and 80 kph cases, the reference path is different. The path is selected from the best-performed driver's path recorded in Test 1. "Best-performed" here means that the driver should:

1. Avoid the collision successfully and keep vehicle within the safe zone during the entire manoeuvre;
2. Enter the manoeuvre with almost zero steering wheel torque and yaw angle;
3. Have the sine-wave-like steering wheel torque input during the entire manoeuvre (according to the mathematical optimization in Dymola, the optimal steering wheel input for the evasive manoeuvre should be like a sine-wave);

Moreover, the Test 2's results should not be neglected. Another requirement is: The driver, whose path is used as the reference path, should be categorized into the "skilled driver group" according to test 2, so that the path that the driver generated in the Test 1 is exactly the same path that the driver generated in his mind. In other words, the best-performed driver should be able to follow the reference path.

After studying all the drivers' performance in both cases, Driver I and Driver H's path are used as the reference in the case of 50 kph and 80 kph respectively. Their paths and steering wheel torque profiles are shown in Figure 4.2 and Figure 4.3:

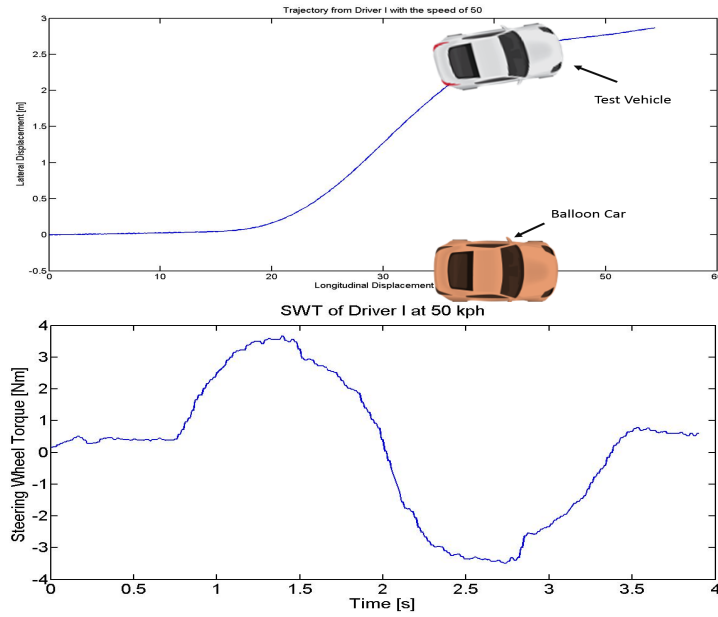


Figure 4.2: Driver I's Performance for the Case of 50 kph

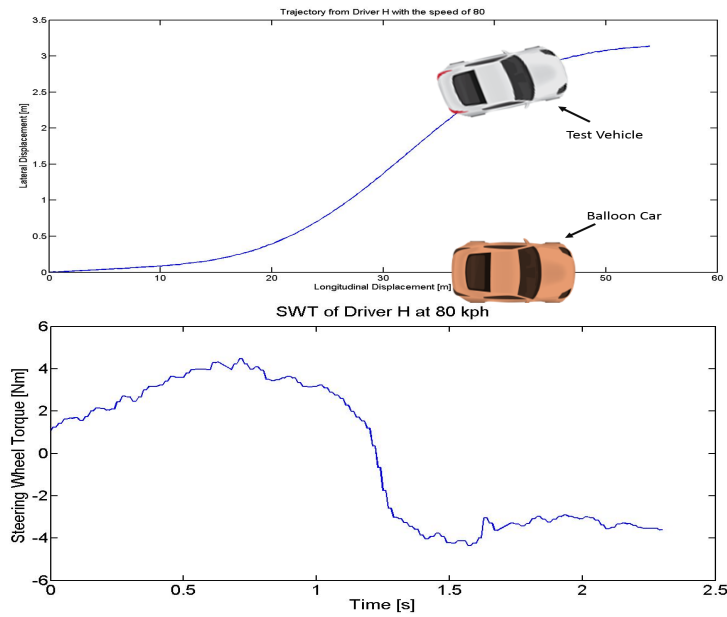


Figure 4.3: Driver H's performance for the case of 50 kph

4.2.2 Methods

The objective of tuning the driver model is that the driving strategy should be reflected by the parameters in the preview controller. If the steering wheel torque output of the driver model is exactly the same as the steering wheel torque that was measured in the test, or at least shows same trend with reasonable deviation, then the goal is achieved.

The method is illustrated in Figure 4.4:

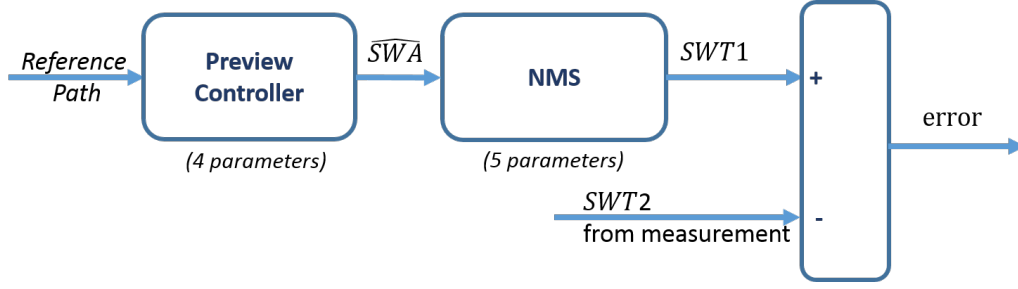


Figure 4.4: Schematic diagram of the tuning method

The block diagram is built based on the idea mentioned before. The reference path is the input of the driver model. It should be the same for all the test drivers for the same speed. The preview controller and the NMS model have 4 and 5 parameters respectively, that need to be tuned. The output of the NMS model is the estimated steering wheel torque ($SWT1$), which should be compared with the measured steering wheel torque from the test ($SWT2$). $SWT2$ is different from driver to driver.

This method is used in combination with the MATLAB function *fmincon*. "*fmincon*" is a tool in MATLAB used to solve constrained nonlinear optimization problem. *fmincon* finds the minimum point/value for a given constrained nonlinear optimization [24]. In this case, it aims to minimize the error showing in Figure 4.4, by assigning new value to the parameters at each iterations. Thus, $SWT1$ from simulation would be similar with $SWT2$ from measurement as much as possible.

While tuning, all the virtual drivers (the driver model) have the same reference path input, but with different driving strategies (different values of the parameter set in the driver model). Therefore, different steering wheel torque output sequences will be generated by different virtual drivers, but should be similar to the one that was generated in the test by the corresponding driver. Note that the controller also needs the states of the vehicle as feedback, which are from the test as well.

In short, the tuning is an open loop and thus no feedback. All the inputs are from the test measurement. The optimal values of the parameter set can be found by using the function "*fmincon*".

However, this method has mainly two problems:

1. It is assumed that all the drivers starts tuning with zero yaw angle and zero steering wheel torque. But in fact, it is not exactly true in the test. If the steering wheel torque profile from the test is sent to the car model in CarMaker, the trajectory that the vehicle generates is not the same as the one in the test, although the car model has been tuned. This is mainly because the initial yaw angle is not zero in the test (the first imperfection of the test mentioned before). But in CarMaker the vehicle starts from the origin with zero yaw angle. Therefore, even if the driver model has been perfectly tuned and send out the exactly the same steering wheel torque from the test, the vehicle still cannot generate the same trajectory recorded in the test;

2. There are in total 9 parameters, which is a huge burden to the computer. The function *fmincon* is also very sensitive to the initial value that was set in the code. Most of the time, it is not possible to estimate reasonable values.

Nevertheless, if the reference path is the same as the trajectory that the vehicle should follow, it would be much easier for MATLAB to tune, so the values of the parameter set for the best-performed driver can be obtained by this method (driver's initial yaw angle is almost zero, based on the definition of "best-performed driver"). On the other hand, if the preview controller and the NMS model can be tuned separately, only 4 or 5 parameters need to be tuned at each time. It would save lots of time and enable the MATLAB function *fmincon* to get better results. In order to do so, the output of the preview controller should be available, which is used to be compared with. However, this is hard to measure in the test, because the optimal steering wheel angle is the signal that the brain sends to the muscle. So the exact value is not obtainable.

Regarding these problems, the solutions come as below, which shows the steps that the tuning process will follow.

1. Send the measured steering wheel torque profiles (SWT_2) of all the drivers to the vehicle and generate the simulated paths ($path_1$);
2. Set $path_1$ as the reference path for corresponding drivers and send it to the preview controller;
3. Using MATLAB function *fmincon* to minimize the error and collect the values of the parameters for each drivers, as shown in Figure 4.4. Each set of tuned parameters could then mimic the corresponding driver's performance, as long as the reference path is the same as the $path_1$;
4. Set all the values the same as the optimization results (from *fmincon*) in preview controller, as well as in NMS model;
5. Connect the driver model to the car model in CarMaker and run the whole system. The reference path is the real path from the test $path_2$ this time, but with some modifications based on the assumptions:
 - (a) The initial yaw angle and initial steering wheel angle at the start point are zero;
 - (b) All the vehicle starts at the same point;
 - (c) The vehicle moves straight before the start point;
 - (d) The vehicle moves straight after the end point.
6. Check whether the vehicle could follow the reference path or not. If not, go back to Step 3 and change the initial values in function *fmincon*. Then repeat the process. If yes, collect the output of the preview controller and the output of the NMS model.

7. Set the reference path as the best-performed driver's path and tune the parameters in the preview controller by comparing the output with the data collected in the last step. Collect the optimization results from *fmincon*, i.e. the value of the parameters. The schematic diagram is shown in Figure 4.5.

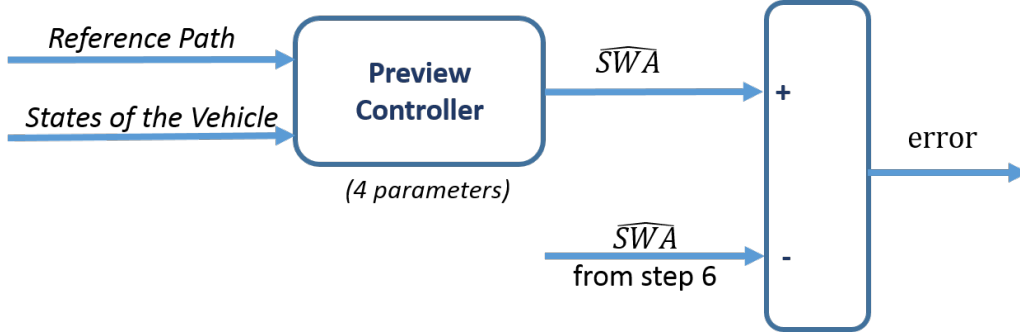


Figure 4.5: Schematic diagram of tuning preview controller

8. Fix the parameters in the preview controller as the values obtained in the last step and tune the parameters in the NMS model by comparing the output with the data collected in Step 6. Collecting the optimization results from *fmincon*. The schematic diagram is shown in Figure 4.6

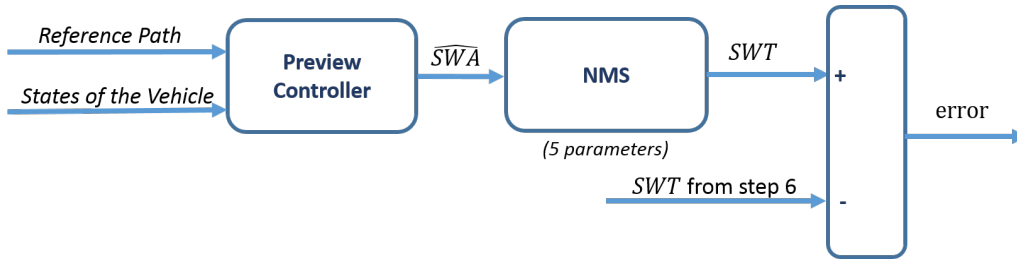


Figure 4.6: Schematic diagram of tuning NMS model

9. Check whether the individual driver could follow the measured trajectory in the test, after setting all the parameters as the same value as from the optimization and connecting the driver model to the car model in CarMaker. If not, go back to Step 7 and changing the initial value set in function *fmincon*. If so, check the steering output of NMS model has the similar trend as the measured one.

The new method could solve the problem mentioned before, but is complicated and thus time-consuming, because Step 3, which is the most difficult part, should be repeated at least 10 times for each speed. If some of the test drivers have the same driving strategy, e.g. a sine-wave-like steering torque profile, they could be classified into one group and one representative, especially the best-performed driver, is good enough to follow other group members' path and generate the necessary data (Step 5 to Step 9).

4.3 Results and Analysis

4.3.1 Simulation result and analysis

For the speed of 50 kph, the values of the parameters in the driver model is unavailable for Driver B and Driver C, whereas for the speed of 80kph, Driver F's value set is not available. The values by auto-tuning for the two cases are shown in Table 4.1 and Table 4.2 respectively:

Table 4.1: Values of the parameters for the speed of 50 kph

Driver	Q_a	Q_y	T [s]	L [m]	a_1	a_2	a_3	b_2	b_3
A	0	17.599	1.499	6.448	0	15.299	14.541	2.052	18.116
D	319.634	7.160	1.50	8.738	0.554	24.993	6.434	4.325	0
E	0	27.533	1.500	8.470	0.583	38.374	100	15.427	20.102
F	0	18.400	1.500	8.494	0	33.773	100	15.011	19.416
G	50.225	47.331	1.055	7.445	1.628	54.221	-20	19.293	6.462
H	4.046	11.211	1.445	8.738	0	21.497	0	5.061	5.561
I	50.234	42.873	1.316	7.969	0.021	40.149	0	13.493	20.125
J	0	17.569	1.404	8.738	0	16.876	0.034	3.797	8.466

Table 4.2: Values of the parameters for the speed of 80 kph

Driver	Q_a	Q_y	T [s]	L [m]	a_1	a_2	a_3	b_2	b_3
A	0.136	2.988	1.325	5.972	4.759	14.677	160.023	5.631	13.065
B	0.054	5.724	1.315	7.750	5.396	19.201	150.352	5.912	10.876
C	0.009	1.770	1.385	7.804	0.2424	25.535	-20	-0.764	0.347
D	0.235	2.022	1.285	8.738	3.872	5.067	63.122	0.6926	6.849
E	0.021	2.464	1.565	4.710	3.872	5.067	63.122	0.693	6.849
G	0.037	2.891	1.905	6.154	0	41.129	395.742	14.717	-7.618
H	4.538	3.464	1.325	8.738	5.063	7.001	89.873	1.922	8.243
I	8.729	4.244	0.918	7.254	3.518	37.841	161.507	8.925	10.393
J	3.615	4.057	1.145	8.466	5.108	14.298	113.899	3.858	8.657

It can be seen that Q_a is zero or almost zero for some drivers in some cases, which means that the driver only focused on the lateral displacement of the vehicle and doesn't penalize anything for the yaw angle of the vehicle. This is reflected in their corresponding steering torque profile.

Take Driver F at the speed of 50 kph for example, his steering torque profile is shown in Figure 4.7:

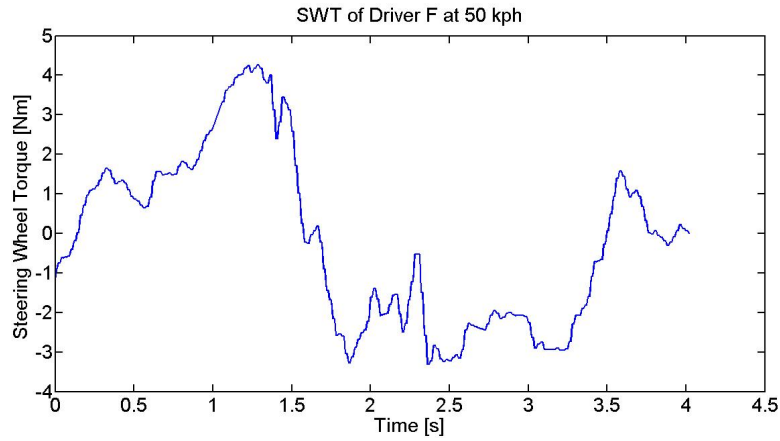


Figure 4.7: Measured steering torque of Driver F at the speed of 50 kph

Generally, the steering torque profile in figure 4.7 is like a sine-wave, but with too many high-order harmonics. This implies that the driver turned the vehicle more frequently and tried to make the vehicle follow the reference path by the means of only changing its lateral displacement.

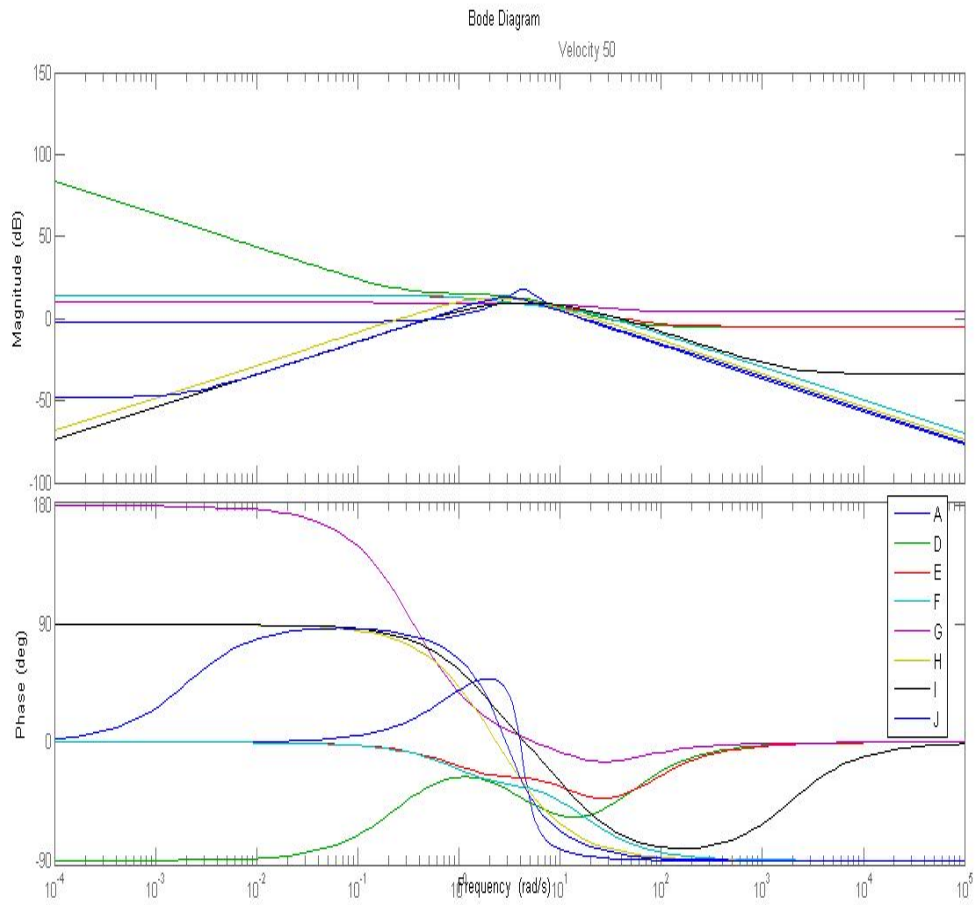


Figure 4.8: Bode Diagram for all the drivers at the speed of 50 kph

It is also noteworthy that the values of a_1 and a_3 for some drivers at the speed of 50 km/h are zero or almost zero. From the optimization result, it can be concluded that the skilled driver input to the vehicle resemble the sinusoidal wave, which means that the input will have a single frequency. From the steering torque profiles of skilled drivers (Driver H, I and J), one can observe that their frequency responses of NMS model not only resemble the sinusoidal wave, but also have almost no harmonics (only respond to a narrow range of frequencies). This coincides with the result of frequency analysis in Bode Diagram (Figure 4.8) and thus explaining why a_1 and a_3 coefficients of a second order function are zero for skilled drivers (or almost equal to zero). And for all drivers a_1 is almost zero in order to make the number of zeros less than the number of poles and thus attenuating the higher frequencies, which ensures that the entire system is stable at high frequency.

4.3.2 Evaluation of the result

According to the shape of the steering wheel torque measured in the test, the test drivers are categorized into two groups, i.e. sine-wave-like steering wheel torque and the others (sine-wave-like shape with higher-order harmonics). Typical sine-wave like and non-sine-wave like profiles of steering wheel torque can be seen in Figure 4.9 for the speed of 50 kph. Others can be found in Appendix A and Appendix C for the speed of 50 kph and 80 kph, respectively.

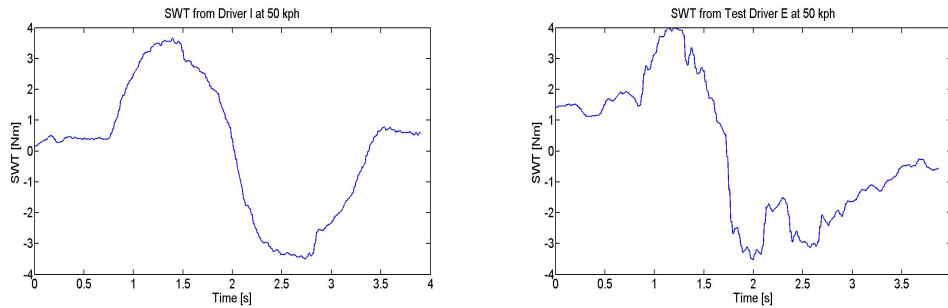


Figure 4.9: Typical steering wheel torque profile from two test drivers

After the parameters are tuned and the are obtained, two test driver's simulation result (the trajectory and the steering wheel torque) will be taken as an example for each case and shown as below.

The simulation result for the speed of 50 kph is shown in Figure 4.10 and Figure 4.11

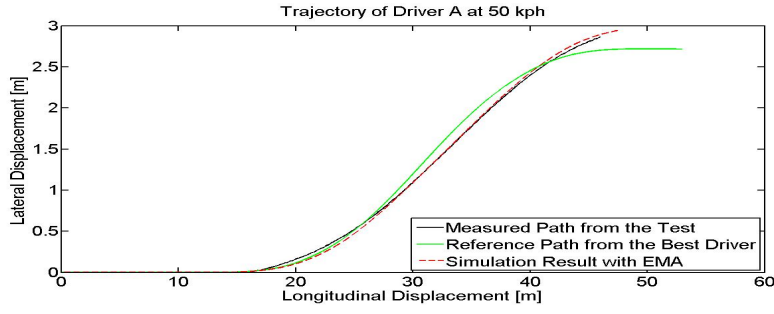


Figure 4.10: Trajectory of Driver A for the speed of 50 kph

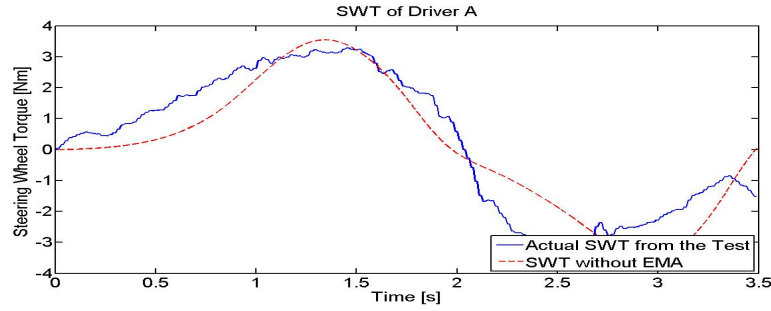


Figure 4.11: Steering wheel torque of Driver A for the speed of 50 kph

There are in total three curves in the trajectory plot: The black dash line is the actual path measured in the test but with some modifications (the $path_2$ mentioned in the last section), the red dash line is the simulation result after tuning the parameters and the green solid line is the reference path for the corresponding speed.

If the red dash line and the black dash line are coinciding, the simulation result could be considered as a good result.

On the other hand, the comparison of the steering wheel torque is also necessary. If the two curves have the same trend or shape, the conclusion can be drawn that the driver model can mimic the corresponding driver's performance and the tuning is successful.

The simulation result for the speed of 80 kph is shown in Figure 4.12 and Figure 4.13.

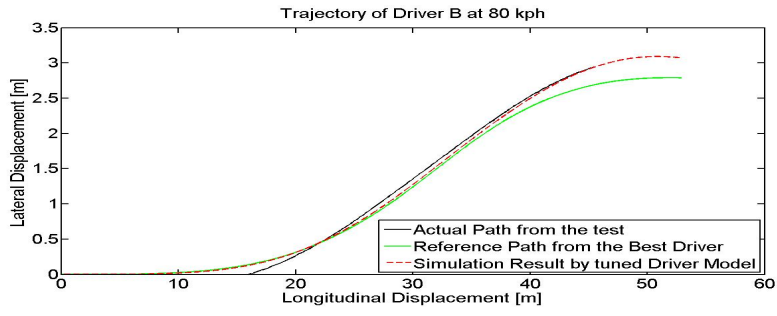


Figure 4.12: Trajectory of Driver B for the speed of 80 kph

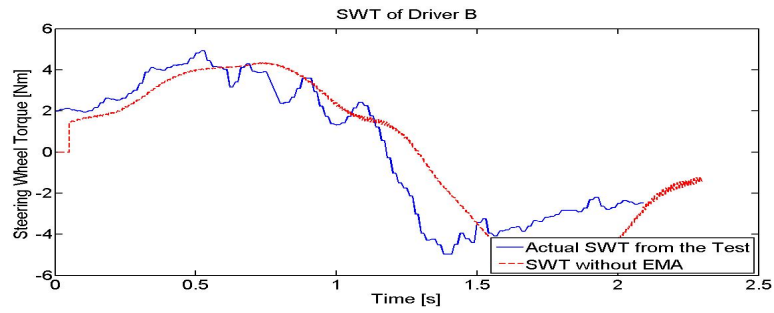


Figure 4.13: Steering wheel torque of Driver B for the speed of 80 kph

The interpretation of the plots is the same as the case of 50 kph.

Chapter 5

Results and Discussion

One of the objectives of this master thesis work is to evaluate the effectiveness of EMA function. In this chapter, a way to evaluate the effectiveness will be introduced first. Then, the test result of the effectiveness of EMA will be shown by using the driver model designed before with the tuned parameters. A simple roughly tuned EMA function is used rather than the real complex one, because in the simple EMA function the influence of individual parameters on the result could be studied and changed.

5.1 Evaluation criterion of the effectiveness of EMA

Before the effectiveness of EMA is tested, a standard should be developed in order to evaluate the effectiveness of the EMA function. Thus, an effective measurement metric ΔX is introduced shown in Figure 5.1. The metric quantifies the extra longitudinal distance given by the EMA function to the driver which in turn helps the driver to avoid the obstacle. Considering the driver is travelling at constant velocity, the extra time provided by the EMA function can be determined with help of ΔX , this extra time can be added to driver reaction time or extra time gained for the driver to react for the given situation.

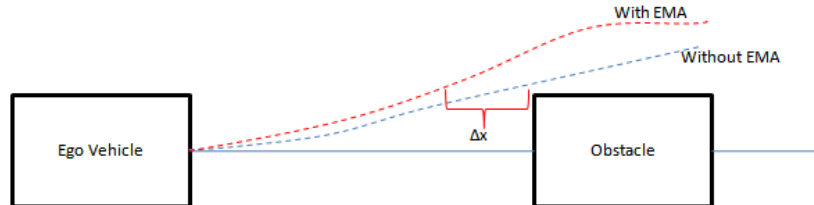


Figure 5.1: Metric Measurement

Theoretically this metric should be more for unskilled driver than the skilled driver.

5.2 Testing Results

The result shown in Figure 5.2 to Figure 5.4 is obtained by connecting the tuned driver model to the original EMA function without any changes of EMA. The EMA function is designed mainly based on the rate of change of the steering wheel angle. According to the result from Dymola, the optimal steering angle (or torque) should be like a sine wave, which means that the optimal driver will turn the steering wheel three times, first anticlockwise, then clockwise, and finally anticlockwise. Therefore, as long as the driver steers the vehicle evasively for each turnings, the EMA function should be triggered at least three times. Whether the EMA function should be triggered or not is decided by three variables, i.e. the steering wheel angular velocity, longitudinal velocity of the vehicle and the side slip angle of the rear axle. The results will be shown and discussed for the speed of 50 kph and 80 kph respectively.

For the lower speed, e.g. 50 kph, the EMA function is not triggered at all for all the skilled drivers. The outputs of the EMA function: the braking pressure and SWT, are zero during the entire maneuver. This implies that the EMA function plays little role at low speed. As the vehicle moves slowly (comparing to another case), the rate of change of the steering wheel angle is not large enough to trigger the EMA function.

For the speed of 80 kph, the result is completely different. EMA function is triggered for all the drivers, but triggered at the first turn of the steering wheel only for the Driver G. Figure 5.2 shows how the vehicle moves after connected to the original version of EMA. The output of the EMA function and the total steering wheel torque to the vehicle (torque from the driver plus the torque from the EMA output) are shown in Figure 5.3 and Figure 5.4.

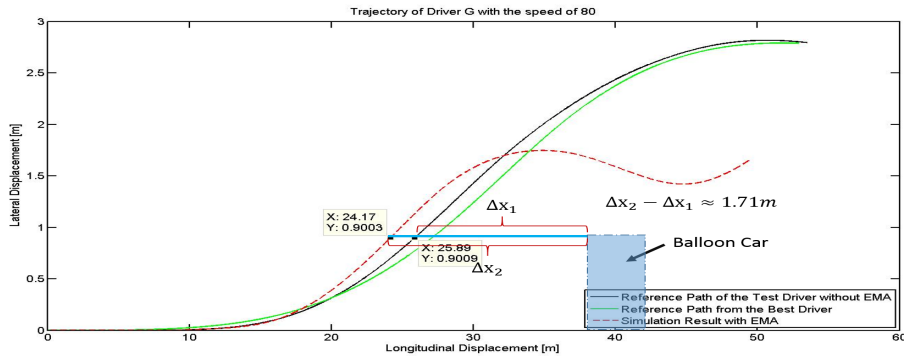


Figure 5.2: Trajectory of Driver G after the connection with EMA

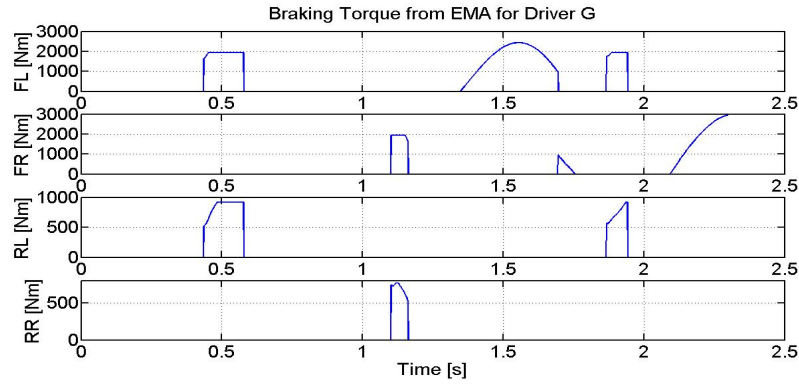


Figure 5.3: Braking pressures on individual wheel of Driver G for the speed of 80 kph

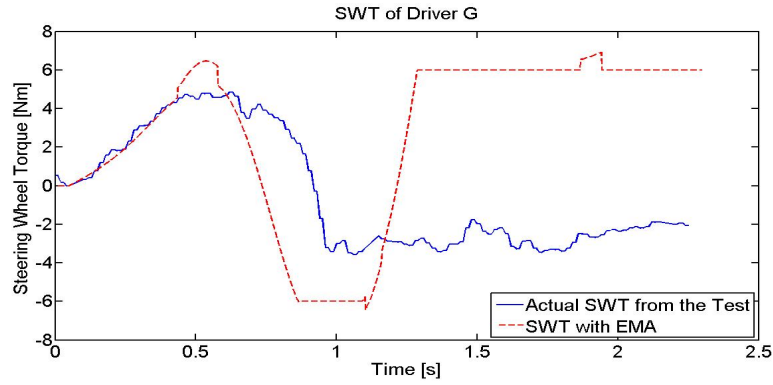


Figure 5.4: Steering wheel torque of Driver G for the speed of 80 kph

In Figure 5.2, although the EMA function is connected to the vehicle and Δx becomes larger, the driver does not benefit at all, because the vehicle will finally collide with the obstacle. The total steering wheel torque input to the vehicle model (Figure 5.4) could explain this: At 1.1 second, the driver starts turning the steering wheel anticlockwise, in order to make the vehicle not turn right anymore and move straight instead. However, the max torque that the driver could apply on the steering wheel is around 6 Nm, which is not enough to turn the vehicle and make the vehicle move as desired. As a result, the vehicle keeps turning right because the steering wheel angle is still a negative value. The problem of inadequate steering torque output from the driver could probably be solved with the help of the EMA, as the EMA could apply an extra torque on the torsion bar of the steering system. However, according to the steering wheel profile shown in Figure 5.4, the EMA function is not triggered until around 1.8 second, which is too late.

In order to make the EMA trigger earlier, the threshold of the steering wheel angle rate is reduced. This method also enables the EMA be in activated mode for a longer time, which means that the active-safety function could help the driver more than before. Figure 5.5 to Figure 5.7 show the performance of the driver with the rough-tuned EMA.

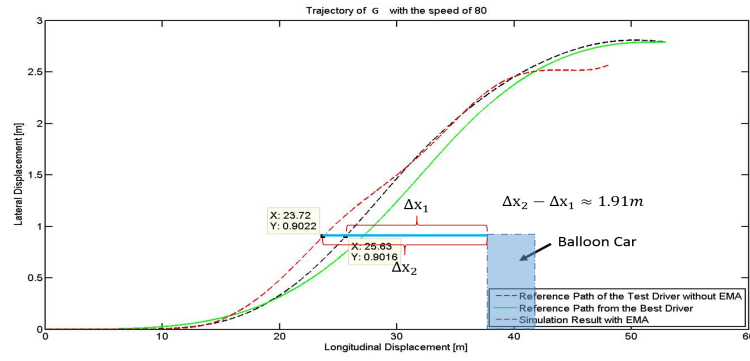


Figure 5.5: Trajectory of Driver G with tuned EMA

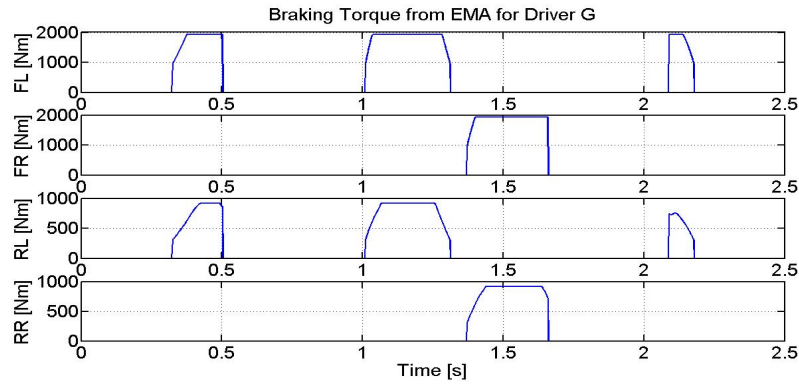


Figure 5.6: Braking pressures on individual wheel of Driver G with tuned EMA

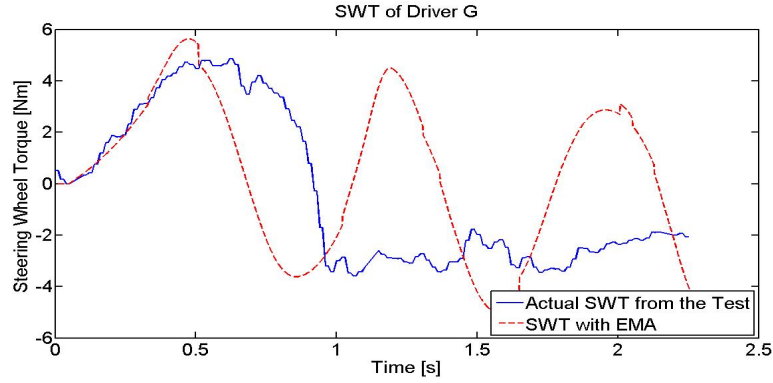


Figure 5.7: Steering wheel torque of Driver G with tuned EMA

The trajectory becomes much better than before, after tuning EMA. Moreover, after reducing the threshold, the EMA function is triggered, some earlier at the first turning of the steering wheel than before, and thus larger distance from the obstacle (Δx) is achieved.

Not only Driver G benefit from the EMA function, the EMA function also helps one more driver (Driver E) after the tuning. Driver E's path is shown in Figure 5.8.

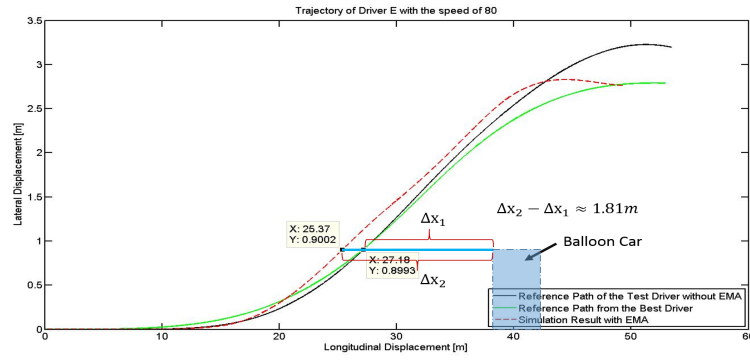


Figure 5.8: Trajectory of Driver E with tuned EMA

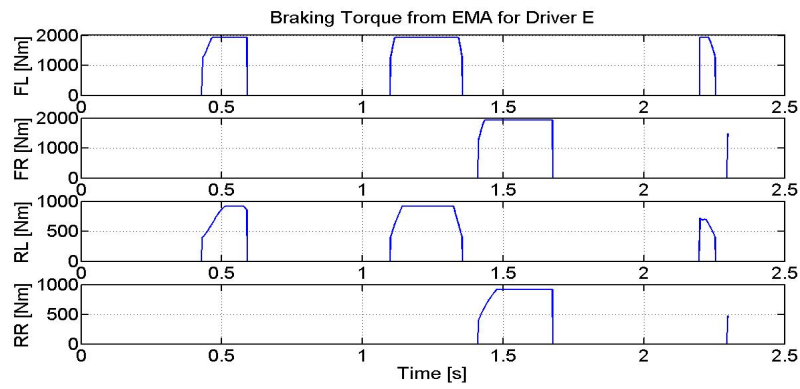


Figure 5.9: Steering wheel torque of Driver E with tuned EMA

However, except for the unskilled drivers, the EMA function doesn't improve Δx for the other relatively more skilled drivers, even if the threshold has been reduced to the reasonable value.

Chapter 6

Conclusion and scope for future work

This chapter provides the conclusion of the thesis work and also few points for the future work which needs to be focused on.

6.1 Conclusion

Based on the results obtained,

1. It is possible to evaluate the effectiveness of the EMA function by including the driver model in the simulation, after the driver model is verified, such that a preliminary tuning of EMA can be done before the experimental test, if necessary.
2. It can be seen that the EMA function that were tested in this thesis work benefits the unskilled drivers more than the skilled drivers, for EMA function can make the vehicle turn earlier for unskilled drivers. This could be seen by a larger ΔX shown in Figure 5.5.
3. The steering wheel angle rate is the most important variable of the EMA among all 3 variables that could trigger the EMA function. Only when the threshold of steering wheel angle rate is reduced, the EMA can help one more driver, according to the study before, i.e. Driver E shown in Figure 5.8.
4. For the lower-speed case (50 kph), the EMA function is not triggered at all for all the drivers.
5. For the higher-speed case (80 kph), the EMA function plays more role on helping the unskilled drivers (Driver G and E) than the skilled drivers, after tuning the EMA.
6. EMA should be finely tuned based on different cases, in order to help unskilled drivers.

6.2 Future Work

In the thesis work it is shown that EMA function benefits an unskilled driver more than the skilled driver, but due to the limitation of the scope of the thesis work and time, few aspects were not considered in the work. In order to determine the exact benefit of the EMA function for unskilled drivers, it is suggested to include the following aspects:

6.2.1 Parameters of NMS model

The parameters for an NMS model obtained in the thesis work is based on the optimization carried out for a collected set of data. As the data collected is for a particular scenario and also at a certain speed, these parameters holds for that speed and scenario. As a result, one cannot use the same parameters for a driver for another scenario or for a different speed case. Additionally, these parameters do not represent the any physical significance, for example the parameters $a1, a2, a3$ does not represent the stiffness or damping coefficient of the driver muscle.

6.2.2 Testing methods

During the analysis of the data collected from field experiment it was observed that there were some drawbacks in the test method followed in the thesis work.

1. Most of the drivers did not have a steering wheel angle and yaw angle at zero at the start point of the test. During post processing of the data it was hard to evaluate drivers as skilled driver or unskilled driver, because few may have a benefit in avoiding obstacle as their initial yaw angle is not zero. So it is recommended to have a test with increased number of cones at the start (starting cones as shown in Figure 3.1) such that driver drives a vehicle with yaw angle and steering angle equal to zero. Also one can reduce the width of the road so that the driver will drive straight until the end of the cone and then driver can steer.
2. It would also be better, if more cones are placed straight at the end, in order to make the vehicle move straight. This is used to make sure that the driver stabilize the vehicle at the end as much as possible.
3. A stationary balloon car was used as an obstacle in this test setup, this is not a strictly evasive manoeuvre. Because evasive manoeuvre is a situation where driver will face unexpected situation and react to it. Due to practical limitation, this kind of situation was not able to create in the test, but it is strongly recommended to have a test with the strictly evasive manoeuvre situation, so that the actual behaviour of a driver at such situation can be evaluated.
4. None of the drivers participated in the test collided with the front balloon car, which is not possible in reality. The ideal unskilled driver would be the one who would collide or almost collide with the balloon car. If such a driver had

participated in the test, then evaluating the effectiveness of the EMA would be more interesting and make it closer to reality. Because the function is designed especially for such unskilled drivers, it is necessary to have such driver in the test, in to determine the exact benefit of the function .

6.2.3 Simulation and testing environment should be same

It is necessary to have testing and simulation environment as close as possible or else it will be difficult to get an exact parameters of the drivers. As seen in the thesis work, a generic car model in CarMaker is tuned in order to make the car model as close as possible to the car used for experiment. But still one cannot guarantee that they both are exactly same. Thus, if the model is same as the car used for testing, then the results would be more reliable and convincing. Also the EMA model used in this thesis is a simplified version. It is necessary to use the same model of the EMA as in production, so that one can evaluate the benefit from the EMA function in a more appropriate way.

6.2.4 Updating the reference path (driver brain path)

In the thesis work it was assumed that the driver will have the same escape path/reference path in the mind throughout the manoeuvre. But in fact, in a real scenario, the driver will update the reference path when the states of the vehicle have changed. So in order to make the driver model close to reality, the it is recommended to include the updating reference path in the driver model and then evaluate how the EMA function will benefit the driver.

6.2.5 Curved Road

The entire work is to study the effectiveness of EMA on a straight road. However, drivers may make an evasive manoeuvre on a curved road as well. If the EMA function needs to be tested in such a scenario, there is no guarantee that the driver model developed in this thesis work will perform perfectly, because it is not tested for an evasive manoeuvre on a curved road.

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Appendix A

Comparison of the driver model output and the measured result for the speed of 50 kph without EMA

In this chapter, the profiles of the trajectory and the steering wheel torque of different drivers will be illustrated (for the speed of 50 kph), in order to examine whether the simulation result has a good consistency with the test result.

In each figure, the left one shows the comparison of trajectories from both simulation (the red dashed line) and the test (the black solid line). The reference path could also be seen as a green solid line. The x-axis shows the longitudinal displacement in meter, whereas the y-axis shows the lateral displacement of the vehicle. The right one illustrates the profiles of the steering wheel torque, where the blue line represents the data collected from the test and the red dashed line shows the simulation result. The x-axis indicates the time in second, while the y-axis is the amplitude of the steering wheel torque (SWT).

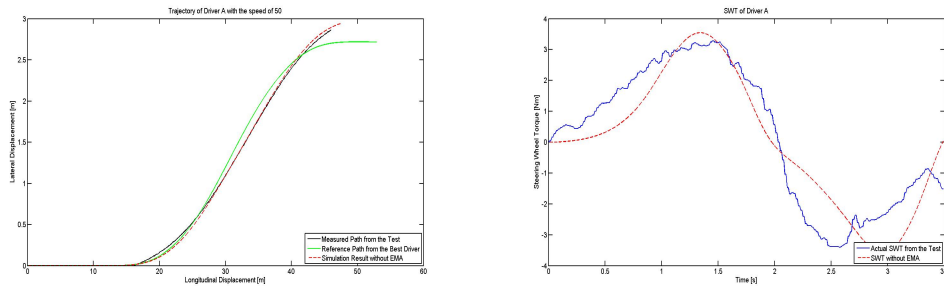


Figure A.1: Trajectory and steering wheel torque from Driver A without EMA

A. Comparison of the driver model output and the measured result for the speed of 50 kph without EMA

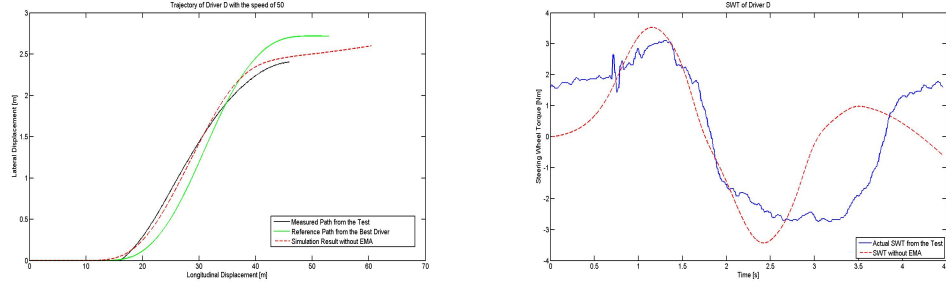


Figure A.2: Trajectory and steering wheel torque from Driver D without EMA

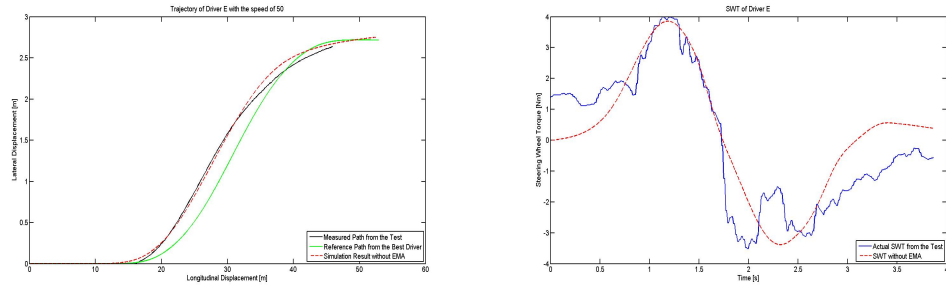


Figure A.3: Trajectory and steering wheel torque from Driver E without EMA

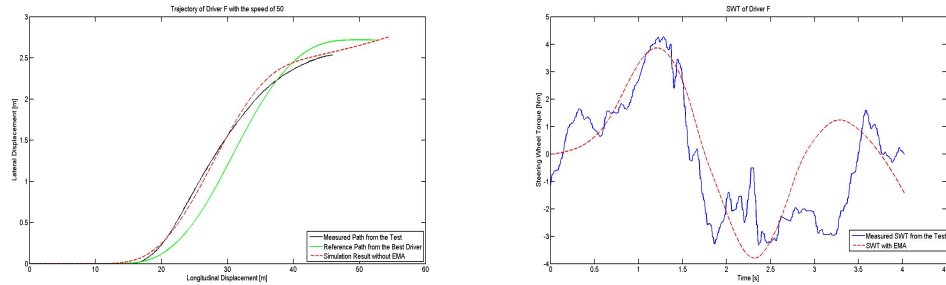


Figure A.4: Trajectory and steering wheel torque from Driver F without EMA

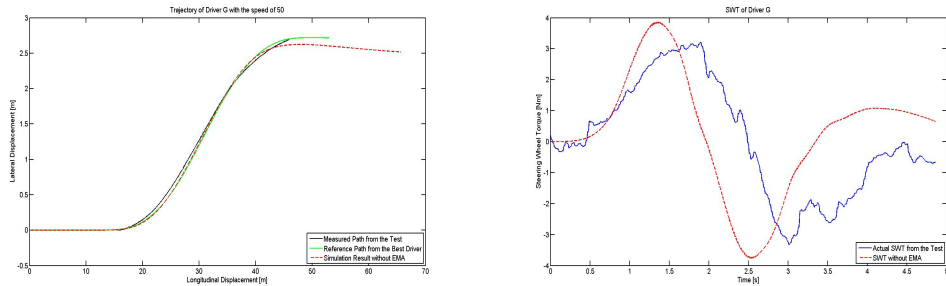


Figure A.5: Trajectory and steering wheel torque from Driver G without EMA

A. Comparison of the driver model output and the measured result for the speed of 50 kph without EMA

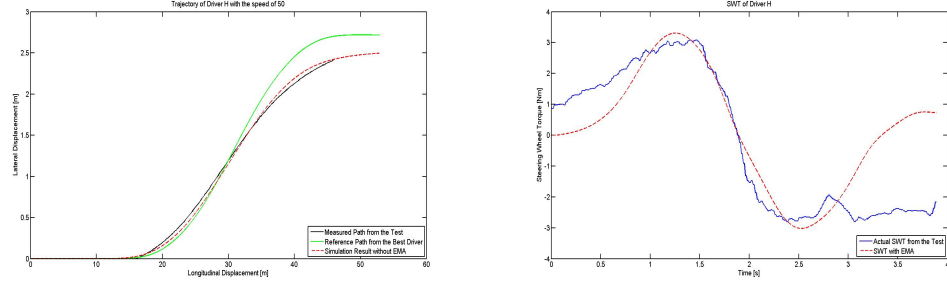


Figure A.6: Trajectory and steering wheel torque from Driver H without EMA

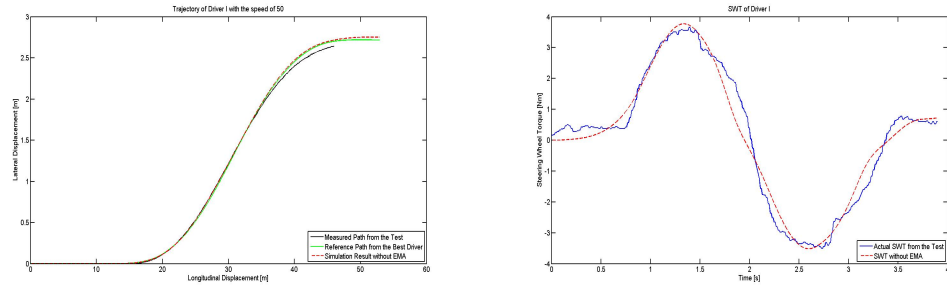


Figure A.7: Trajectory and steering wheel torque from Driver I without EMA

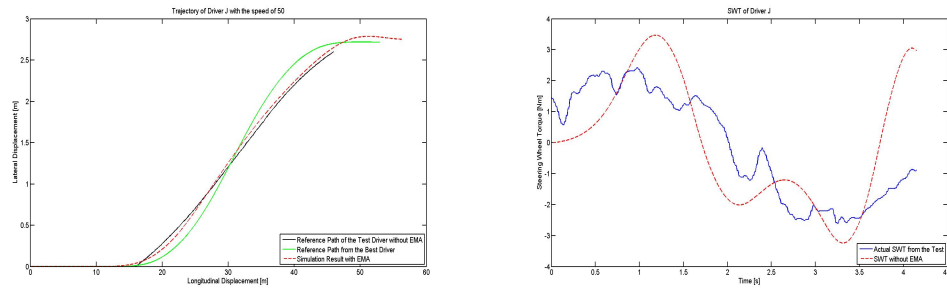


Figure A.8: Trajectory and steering wheel torque from Driver J without EMA

A. Comparison of the driver model output and the measured result for the speed of 50 kph without EMA

Appendix B

Comparison of the driver model output with and without EMA for the speed of 50 kph

In this chapter, the effectiveness of the EMA function will be shown for the speed of 50 kph.

In each figure, the left one shows the trajectories of the reference path (green solid line), the simulation result without EMA (black solid line) and the simulation result with EMA (red dashed line). The x-axis is the longitudinal displacement in meter, whereas the y-axis is the lateral displacement in meter. The right one shows how the braking torques (Nm) on individual wheel work. In all the cases, the braking torque is zero, which means that the EMA function has not been triggered at all. Thus, the steering torque profiles with and without EMA should be same.

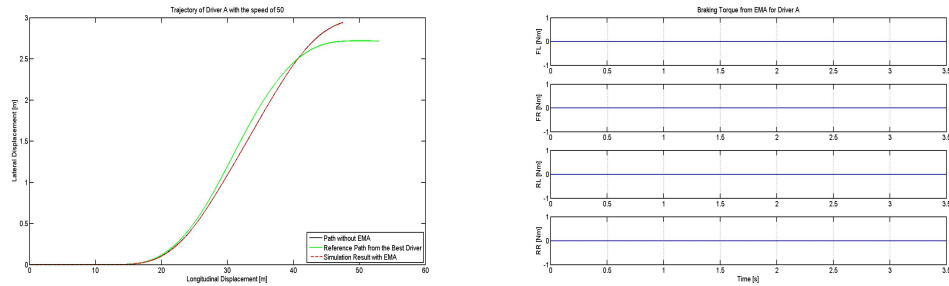


Figure B.1: Trajectory and braking torque from Driver A with EMA

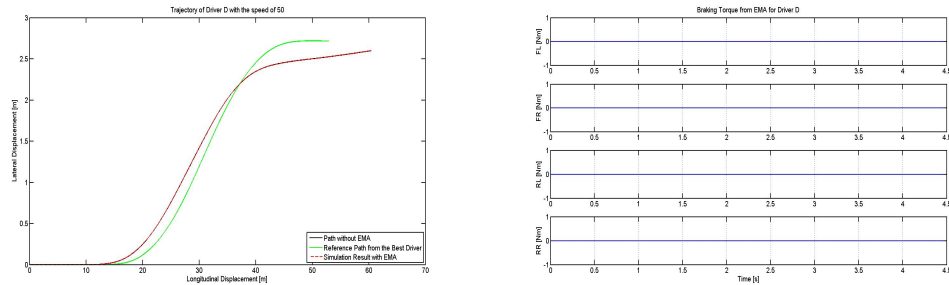


Figure B.2: Trajectory and braking torque from Driver D with EMA

B. Comparison of the driver model output with and without EMA for the speed of 50 kph

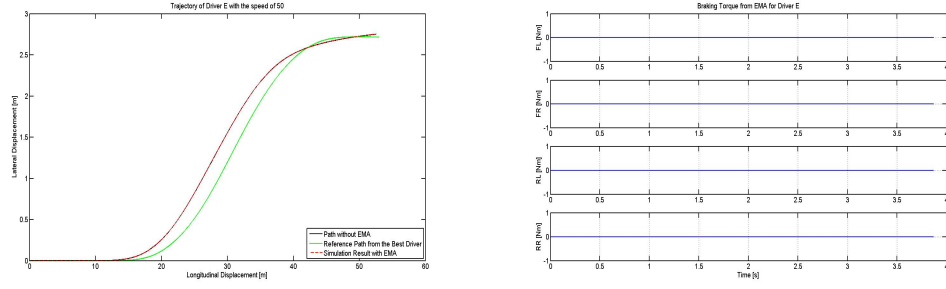


Figure B.3: Trajectory and braking torque from Driver E with EMA

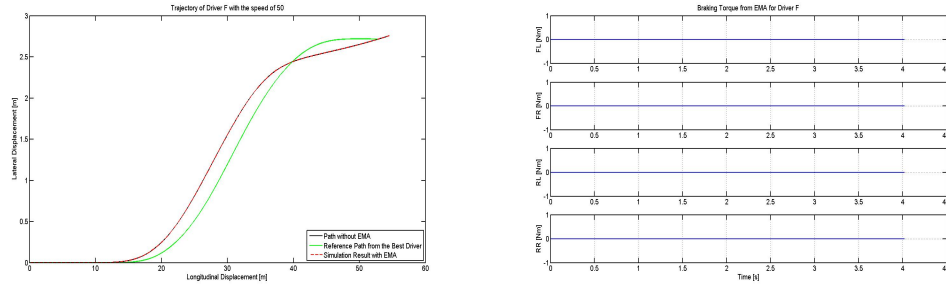


Figure B.4: Trajectory and braking torque from Driver F with EMA

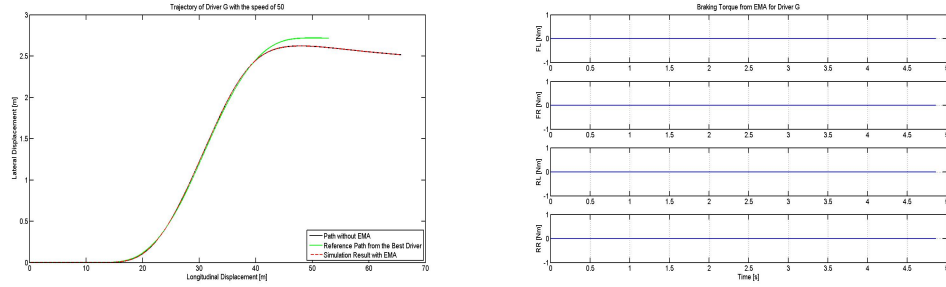


Figure B.5: Trajectory and braking torque from Driver G with EMA

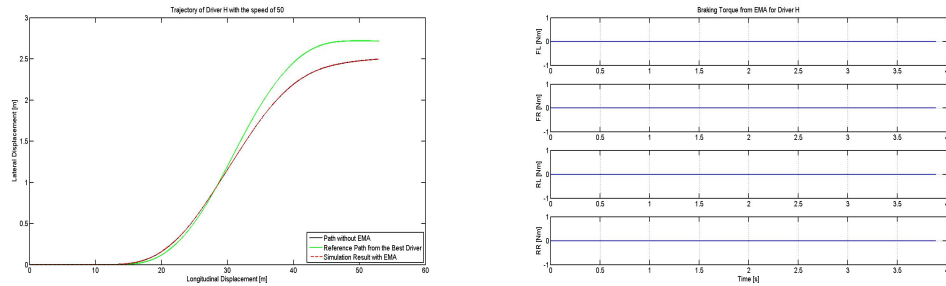


Figure B.6: Trajectory and braking torque from Driver H with EMA

B. Comparison of the driver model output with and without EMA for the speed of 50 kph

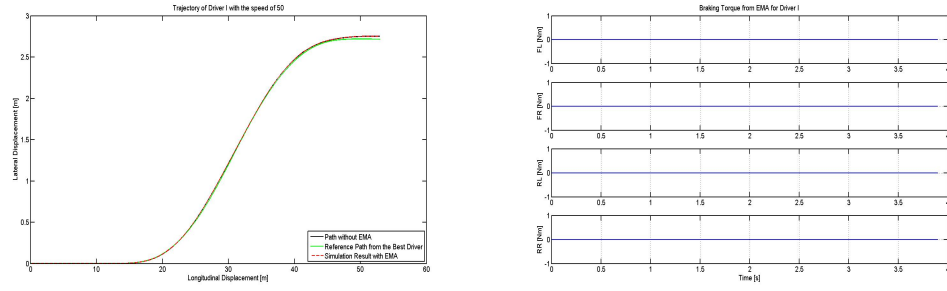


Figure B.7: Trajectory and braking torque from Driver I with EMA

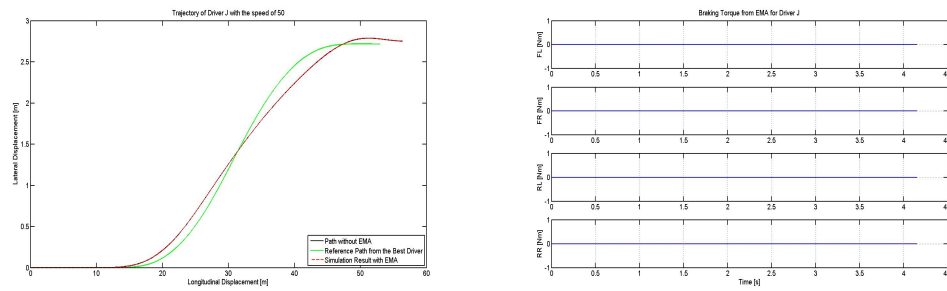


Figure B.8: Trajectory and braking torque from Driver J with EMA

B. Comparison of the driver model output with and without EMA for the speed of 50 kph

Appendix C

Comparison of the driver model output and the measured result for the speed of 80 kph without EMA

In this chapter, the profiles of the trajectory and the steering wheel torque of different drivers will be illustrated for the speed of 80 kph. The interpretation of each figure are the same as for the speed of 50 kph.

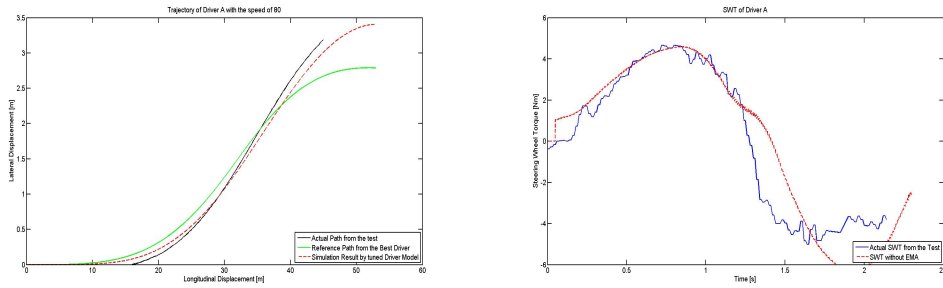


Figure C.1: Trajectory and steering wheel torque from Driver A without EMA

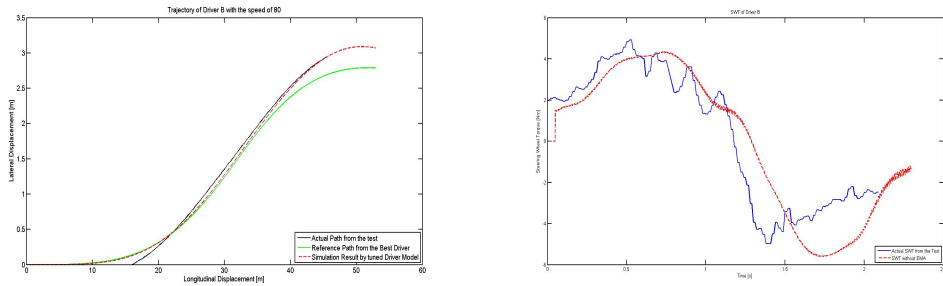


Figure C.2: Trajectory and steering wheel torque from Driver B without EMA

C. Comparison of the driver model output and the measured result for the speed of 80 kph without EMA

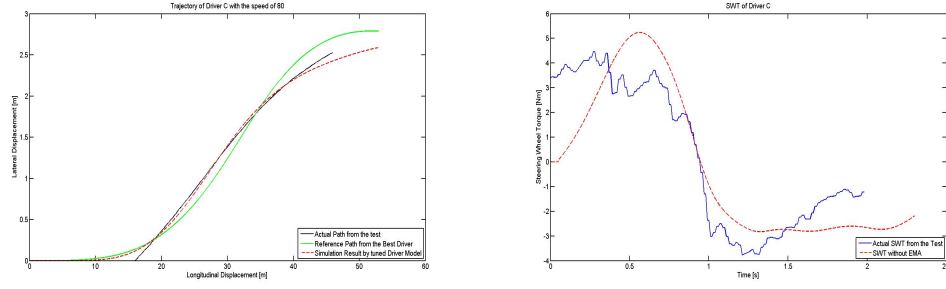


Figure C.3: Trajectory and steering wheel torque from Driver C without EMA

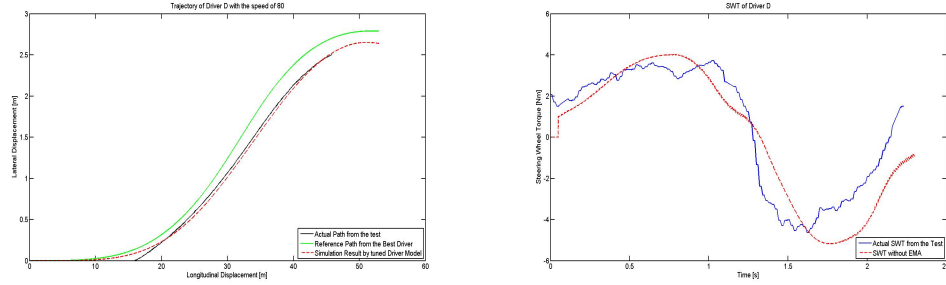


Figure C.4: Trajectory and steering wheel torque from Driver D without EMA

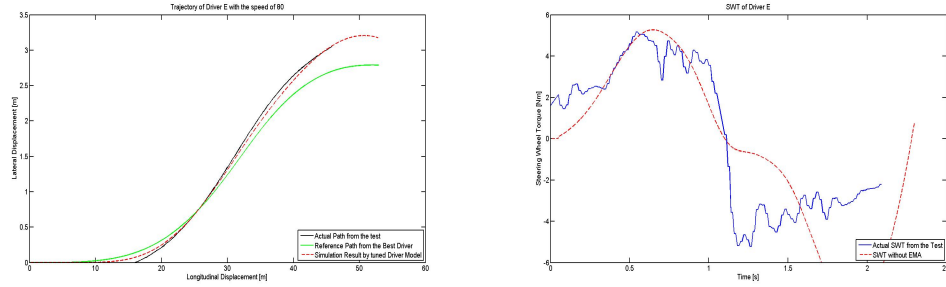


Figure C.5: Trajectory and steering wheel torque from Driver E without EMA

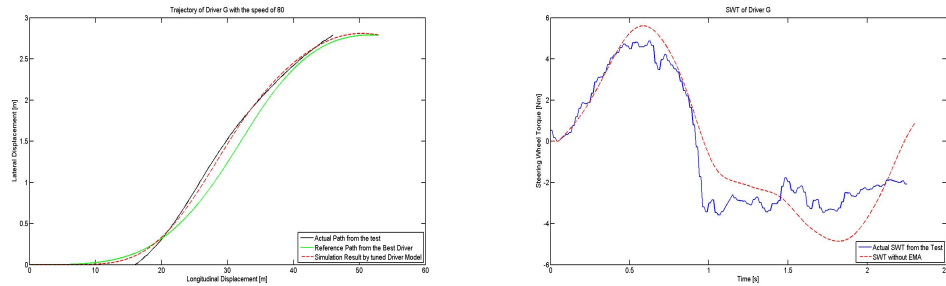


Figure C.6: Trajectory and steering wheel torque from Driver G without EMA

C. Comparison of the driver model output and the measured result for the speed of 80 kph without EMA

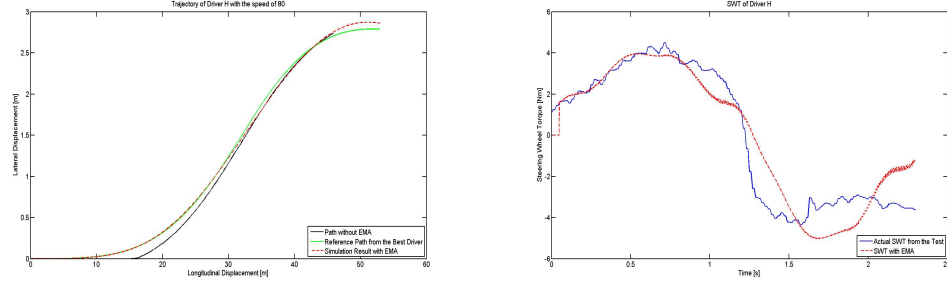


Figure C.7: Trajectory and steering wheel torque from Driver H without EMA

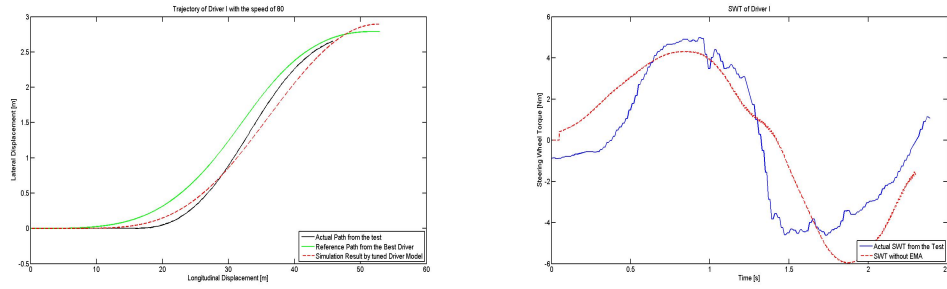


Figure C.8: Trajectory and steering wheel torque from Driver I without EMA

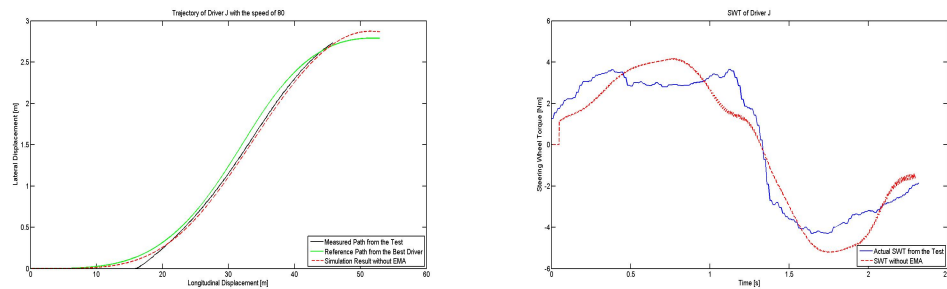


Figure C.9: Trajectory and steering wheel torque from Driver J without EMA

C. Comparison of the driver model output and the measured result for the speed of 80 kph without EMA

Appendix D

Comparison of the driver model output with and without EMA for the speed of 80 kph

In this chapter, the effectiveness of the EMA function will be shown for the speed of 80 kph.

Apart from the profiles of the trajectory and the braking torque with the same interpretation as for the speed of 50 kph, the profiles of steering wheel torque (Nm) against time (s) is shown on the bottom left of each figure. As the EMA function is triggered for all the cases, especially for the unskilled drivers, the red dashed line (steering torque with EMA) deviates from the blue one (steering wheel torque without EMA).

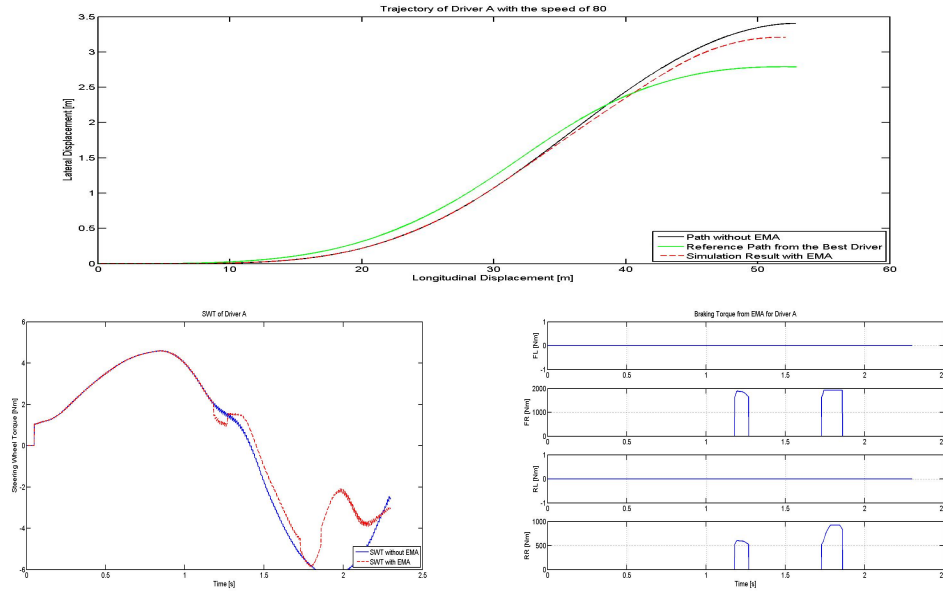


Figure D.1: Trajectory, SWT and braking torque from Driver A with EMA

D. Comparison of the driver model output with and without EMA for the speed of 80 kph

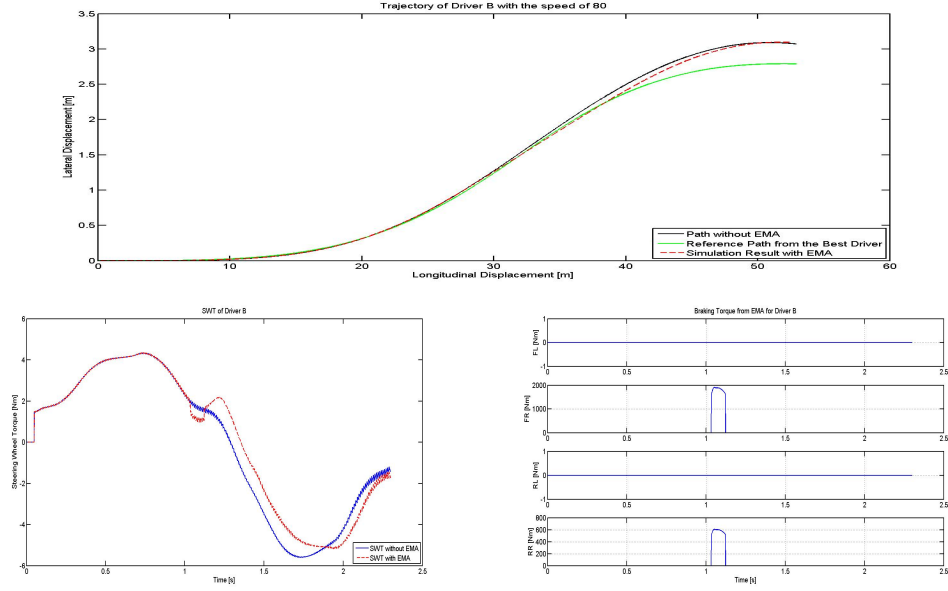


Figure D.2: Trajectory, SWT and braking torque from Driver B with EMA

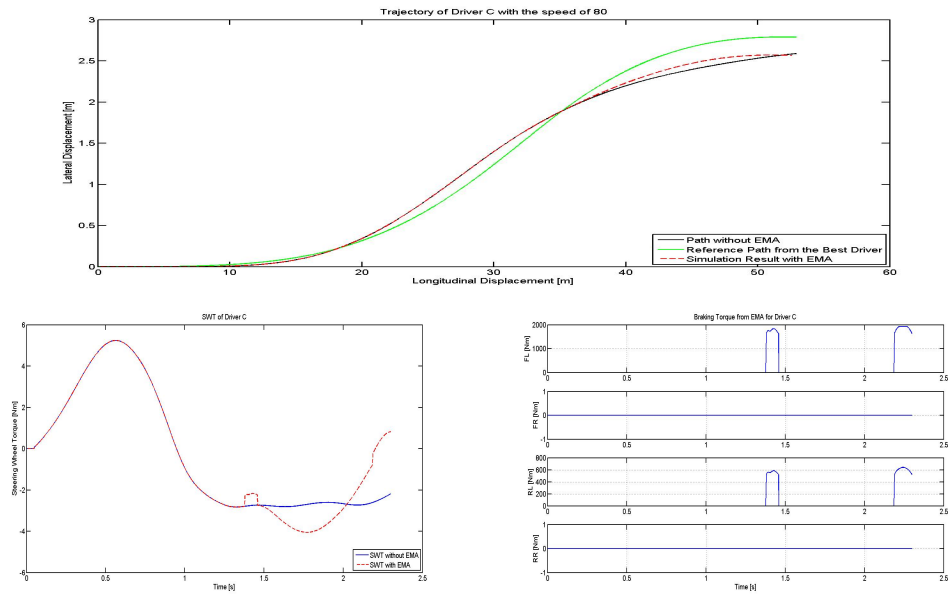


Figure D.3: Trajectory, SWT and braking torque from Driver C with EMA

D. Comparison of the driver model output with and without EMA for the speed of 80 kph

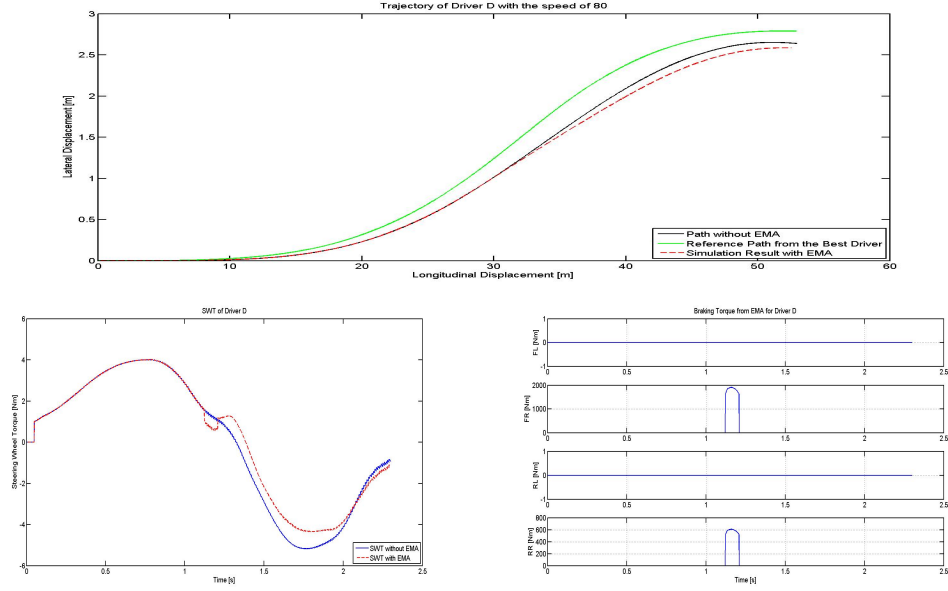


Figure D.4: Trajectory, SWT and braking torque from Driver D with EMA

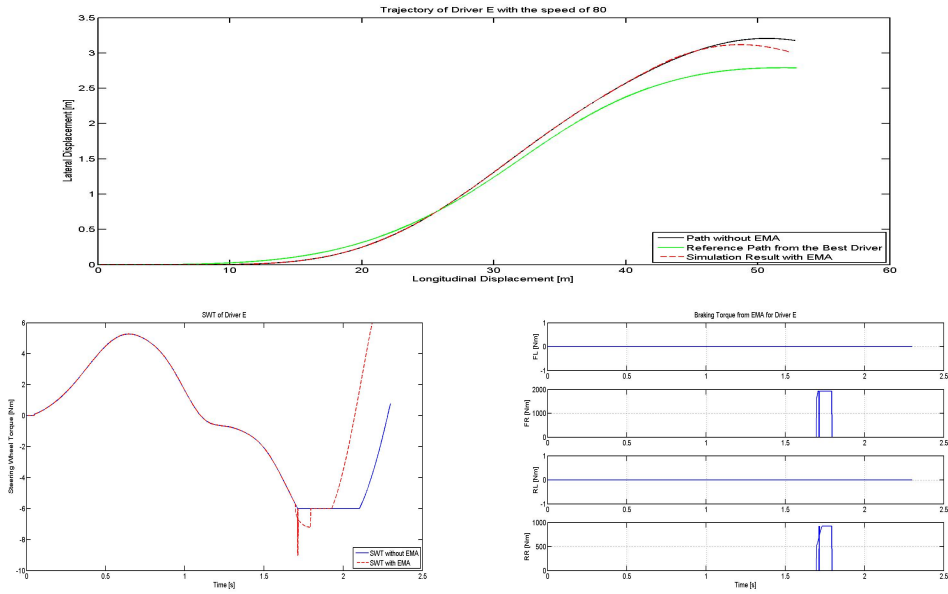


Figure D.5: Trajectory, SWT and braking torque from Driver E with EMA

D. Comparison of the driver model output with and without EMA for the speed of 80 kph

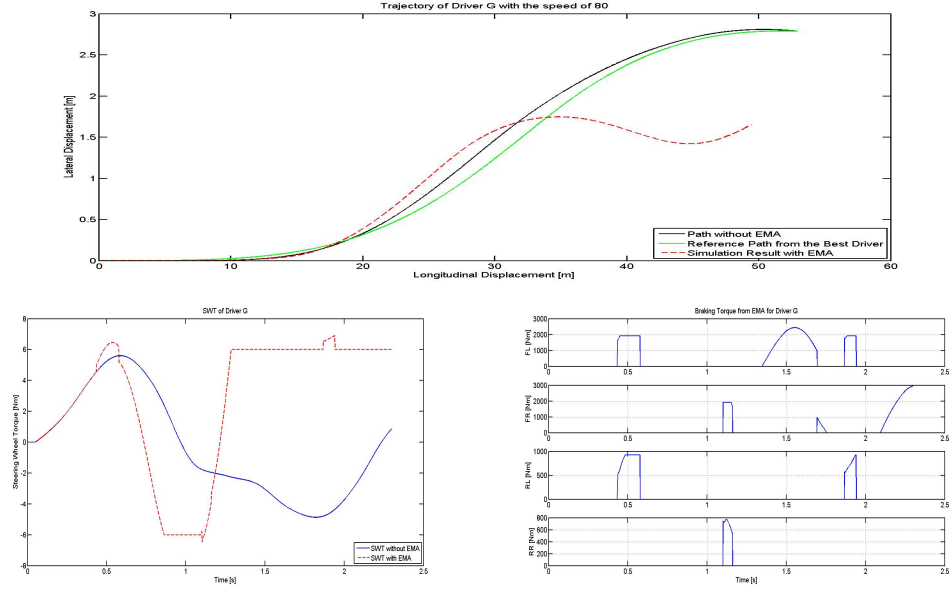


Figure D.6: Trajectory, SWT and braking torque from Driver G with EMA

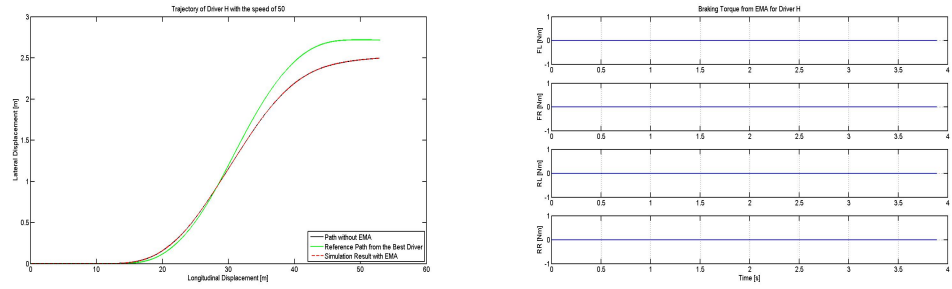


Figure D.7: Trajectory, SWT and braking torque from Driver H with EMA

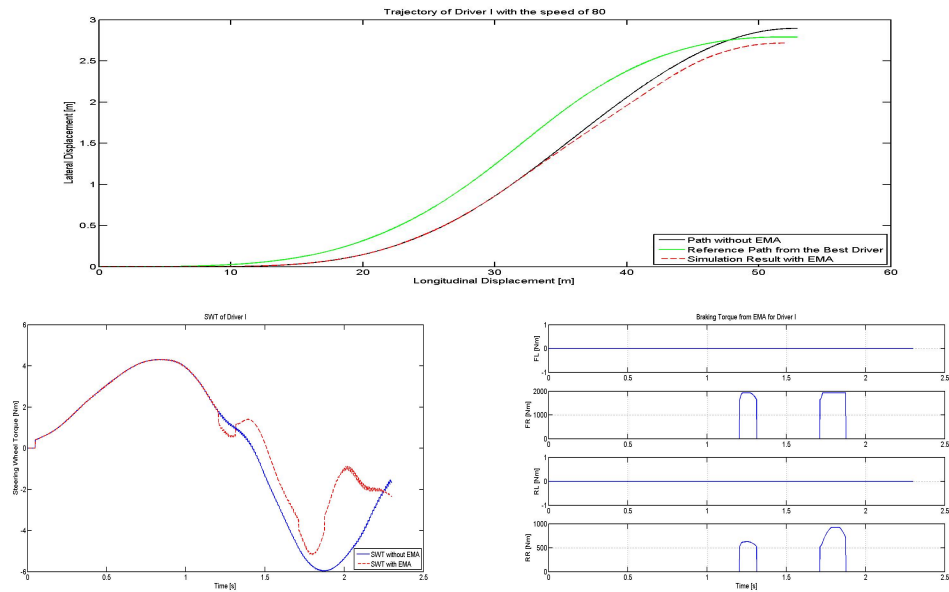


Figure D.8: Trajectory, SWT and braking torque from Driver I with EMA

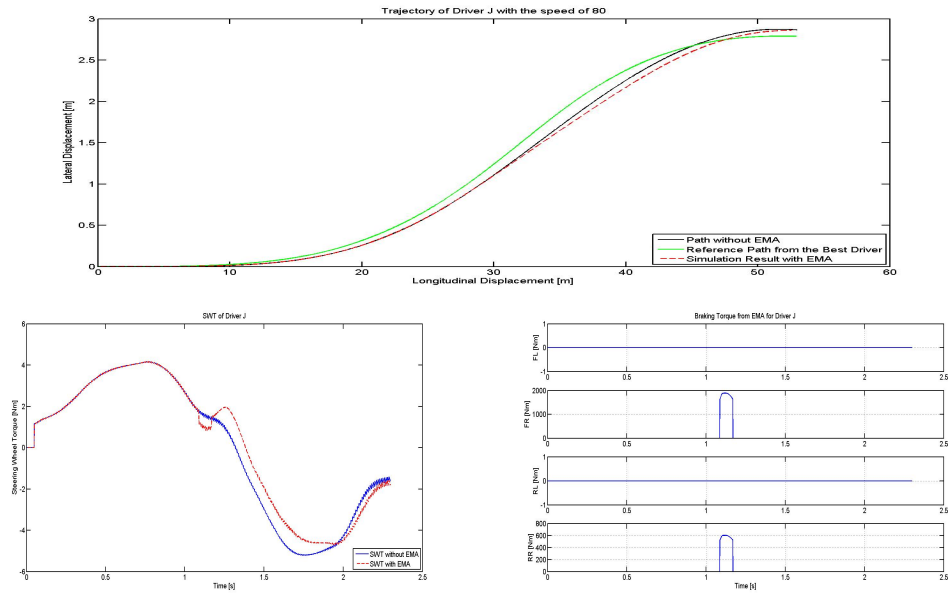


Figure D.9: Trajectory, SWT and braking torque from Driver J with EMA