Steering controller identification and design for human-like overtaking

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Steering controller identification and design for human-like overtaking

MASTER OF SCIENCE THESIS

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DAVI project, which is the abbreviation for Dutch Automated Vehicle Initiative, aims to explore, improve and demonstrate automated driving on public roads. The ultimate goal of the project is to achieve a full autonomous vehicle without any driver, but only users on it. Compared with traditional human driving, automated driving is an appealing topic due to its advantages of enhancing road safety, increasing road capacity and reinforcing driving comfort.

Concentrating on overtaking on a two-lane highway, this particular study investigates driver’s steering behavior and experimentally develop a customized controller.

In a typical configuration of driver model, the assumption, that a driver conceives a trajectory before the process of overtaking, is problematic in this case due to inaccurate reflection of driving behavior and computational complexity. As an alternative to this method, a target and control scheme is implemented to mimic human overtaking behavior. First, data from driving simulator experiments are provided by over 40 participants, where each driver performs a series of four consecutive overtaking (FCO). Second, parameters of the steering controller are identified to match the overtaking data exhibited in the driving simulator. Furthermore, the controller analysis is carried out to test the performance. Finally, an operating system designed for customized overtaking is programmed using MATLAB guide. A human-machine interface demonstrates how the system is applied to a real autonomous vehicle. The closed-loop simulation result suggests key characteristics of overtaking are properly captured and computational speed of the algorithm is sufficiently fast, thus indicates a solution to practical autonomous overtaking.
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Yujie Zhang
Chapter 1

Introduction

This subject is studied and conducted as one of the many subtasks of Dutch Automated Vehicle Initiative (DAVI), the abbreviation for Dutch Automated Vehicle Initiative. The objective of the DAVI project is to investigate, improve and demonstrate automated driving on public roads. As an ultimate goal, we would like to achieve a full autonomous vehicle without any driver, but only users on it. With a certain destination assigned by the operator, a user friendly operating environment can be established through instruments such as buttons and knobs that are used to tune adjustable parameters.

Despite of problematic challenges such as control robustness and legal liability, automated driving are appealing topics due to its advantages of enhancing road safety, increasing road capacity and reinforcing driving pleasure and comfort[2].

Among all the challenges in the aspect of technology, overtaking on a highway road is one of the most risky maneuver for an autonomous vehicle, because the action to be taken depends on a great quantity of factors such as: current state of the host vehicle, positions and speed of the surrounding vehicles, etc. Driving on the highway, drivers tend to behave differently in the same overtaking scenario, thus different steering controllers are demanded by various user groups. For instance, various distance headway and lateral spacing are desired by diverse users, largely depending on their driving styles. It is therefore necessary to develop a driver steering model, which can be customized, to capture and represent drivers’ overtaking behavior.

1-1 Literature Review

Overtaking maneuvers are implemented by a driver due to multiple factors, such as: requirement for intended turns, speed advantage, etc. However, overtaking behavior is not widely studied in the field of autonomous driving. Inspecting this field, human factor engineers usually focus on the high-level driver behavior of cognitive processing and decision-making[3].
Postulating that the instruction of overtaking is given by the higher-level controller, this thesis takes one specific perspective of the topic: developing a customized controller that models steering behavior during overtaking on a double-lane highway.

As prior attempts on modeling human steering controller, many control methods have been proposed to capture the driving behavior based on the data collected from both road tests and driving simulators. For example, proposed in [4], driver models are developed using neural networks, which defines the steering angle as a function of the time-delayed heading angle and deviation of lateral position from a desired trajectory. In [5], using the approach of reinforcement learning, the steering maneuver of the driver model is learnt from a reward, which is evaluated whether or not the vehicle is on the road. Besides, hybrid driver models [6] and hierarchical driver models [7] are discussed within the scope of the topic.

In the aforementioned researches, the proposed driver steering models share a common configuration, which is illustrated in Fig. 1-1. This typical configuration comprises three major presumed elements: trajectory planning, prediction horizon and steering controller. According to this assumption, a driver follows an imaginary trajectory in his mind before the lane-change maneuver. The generated trajectory proves feasible for the controller to follow [4]-[8], but it doesn’t coincide with most of the cases in lane-changing maneuver. For example, as tested in [9], it is unveiled that the steering angle is much smoother than that of the real test. In other words, this proves all types trajectories investigated in [9] are not able to reflect the real human steering behavior.

Another assumption that drivers look ahead of a certain distance as prediction, introduced in [8], resembles real driving behavior during overtaking [10]. Based on this concept, in [9], instead of following a prescribed trajectory that imitates the real one, a target and control scheme is proposed. In [9], it is assumed that during the process of overtaking, after the decision is made, the driver determines to reach the middle of the other lane without the whole trajectory conceived in his mind. The basic principle for the human steering model is to set a target on the other lane according to one’s own predication horizon and adjust the heading angle of the vehicle to reach the constantly moving target. Following the target and control scheme, it turns out that the target angle error (the discrepancy between desired heading angle and real heading angle) is almost proportional to steering rate that is exhibited in the test data. Therefore, a steering rate controller is suggested and validated in closed-loop simulation. With a proper horizon distance, the controller with the identified parameter can accurately capture driver’s steering behavior, including the non-linear, high-frequency content in the steering angle that can not be reflected in the model with trajectory planning.
In terms of lane changing performance, the target and control scheme provides two advantages over the traditional structure: one is to better capture the features of steering behavior, the other is to lighten the computational complexity by eliminating the element of trajectory planning. The first advantage is not so pertinent since we don’t focus on replicating the exact behavior of human steering. However, the second one is significant when the method is implemented in real autonomous driving, which makes the algorithm suitable for short sampling time.

In my study, still following the target and control scheme, my work differs from what is conducted in [9] in two distinct aspects: Firstly, instead of investigating lane-changing maneuver in sharp curves, the subject in this case is overtaking maneuver, which is a much smoother procedure. Secondly, this paper also focuses on implementation of a customized steering controller on an autonomous vehicle, which is not covered in the aforementioned scheme.

1-2 Problem Statement

This paper aims to investigate driver’s steering behavior and to experimentally develop a customized controller that can mimic driver’s key steering mechanisms from a control engineering point of view.

Due to the nature of stochastic driving behavior, it is difficult to capture the key characteristics during overtaking. Rising to this challenge, we set up the main requirements that meet the target of this thesis:

1. accurate reflection of drivers’ overtaking procedure
2. a fast and simple solution to autonomous overtaking

The first requirement involves establishment of the driver model, while the second one concerns design of the customized controller.

As a starting point, data from driving simulator experiments are provided by over 40 participants, where each driver performs a series of four consecutive overtaking (FCO) under different driving conditions with a constant speed. According to the collected datasets, a human-like steering model is established following a target and control scheme.

In terms of controller selection, an insight into open-loop data facilitates analysing the characteristics of drivers and determines the type of controller that is implemented. Given a certain type of controller (proportional-derivative (PD) controller), parameters are tuned to fit the experiment data of FCO in closed-loop identification.

For the application of the customized controller on a real autonomous vehicle, a tuning facility such as a slider is placed in the car to adjust parameters of the controller, which aids selection of the driving style. Finally, as a demonstration of the simple operating system, a human-machine simulation interface is created in Matlab, presenting the function of the customized steering controller.

Note that in order to avoid content overlap with other researches conducted within DAVI project, the validation of the vehicle dynamic model is not amplified and the safety concern during overtaking is not examined thoroughly in the paper.
The paper is organized in a sequential fashion: Chapter 2 introduces data and vehicle model for the driving simulator. Chapter 3 illustrates identification and analysis of the steering controller. Chapter 4 describes the design of the customized controller using on an autonomous vehicle. Last but not the least, conclusions and future work are suggested in Chapter 5.
In the previous chapter, the basic motivation and target of the thesis are introduced. For the next, data collection is preliminary, yet crucial to further analysis because it determines the control scheme that is implemented. As the data collection method chosen in our study, fundamentals of the driving simulator are elaborated. Besides, in order to make the content of the whole thesis compact, albeit not inspected thoroughly, the vehicle model identified for the driving simulator is included in this chapter.

2-1 Driving Simulator

As far as data collection method is concerned, validity and controllability are two commonly applied indexes[1]. With regard to data collection methods, validity is the degree in which the method measures what it claims to measure. In general, the following types of validity can be distinguished for the purpose of road data collection, namely:

- test validity (construct validity, content validity, criterion validity);

- experimental validity (internal validity, external validity);

One type of the test validity is construct validity. Construct validity refers to the extent to which operationalizations of a construct actually do measure what is intended. As steering driving behavior during overtaking can not be perceived as a construct, this type of validity is less important.

Another type of test validity is content validity. Content validity is a non-statistical type of validity that involves the systematic examination of the content of the data collection method in order to determine whether it covers a representative sample of the behavior domain to be measured[11]. This aspect of validity is particularly important regarding the steering behavior of the drivers during overtaking. The consecutive lane-changing maneuvers, prove to be
informative and demanding in [9], capture sufficient characteristics of the steering behavior. This operation, to be examined in the driving simulator, is qualified to represent overtaking on the highway in most cases. Emergency braking and lane change are not considered in our study since safety evaluation throughout the overtaking process needs to be introduced to perform the tasks, which is out of the research scope.

Finally, criterion validity can be categorized as a type of test validity. It compares the data with other measures or outcomes (the criteria) already held to be valid. The validated experiment results in [9] can not be used as criterion because that paper focuses on sharp cornering maneuver other than smooth lane change. In the context of steering behavior during overtaking, this element of test validity is less important since no other report involved overtaking with a target and control scheme.

Beside test validity, two types of experimental validity are investigated. One is internal validity. It reflects the extent to which a causal conclusion based on a study is warranted. This is a crucial element in this case because a steering controller is deemed adequate if it can replicate the key characteristics of a driver.

The other type is external validity. It concerns the extent to which the results of a study can be held to be true for other cases, for example to different people, places or times. In this particular study, controllers with different parameters are intended for different people, so external validity is not required. However, overtaking performed in different scenarios are tested as an examination of external validity.

Validity plays an important role in the choice of the appropriate data collection method, so is controllability. It is beneficial to maintain a high degree of controllability in experiment in order to simulate the real driving situation as well as simplify the process of data analysis.

Two data collection methods are considered for the study of steering behavior: instrumented vehicle and driving simulator. These two approaches distinguish from each other in terms of validity and controllability. As shown in a simple graph in Fig. 2-1 quoted from [1], the performance of a certain method can be recognized as a trade-off between external validity and controllability. In general, a method with a higher level of controllability normally has a lower degree of external validity. For example, tests on instrumented vehicles can almost completely reflect driving behavior exhibited in real life, which have a high level of validity. However, due to the nature of this method, the traffic scenario can hardly be manipulated, which limited the level of controllability.
As mentioned in the introduction chapter, this paper intends to investigate different drivers’ behavior during overtaking. For the purpose that the steering behavior of various drivers can be comparable to each other, the overtaking operation should be undertaken in more or less the same scenario. Therefore, we observe in this case how a driver overtakes three consecutive obstacle vehicles arranged in a position shown in Fig. 2-2, with enough overtaking gap and with constant speed. The specifics of the experiment will be elaborated in the next subsection.

According to the experiment settings described above, in this particular context, the method of driving simulator is selected because of higher controllability and lower experimental cost. As mentioned before, tests done with a driving simulator is highly controllable. Due to the fact that the study focuses on drivers’ diverse steering behavior exhibited in the same overtaking task, a driving simulator is required since it can provide participants with tests under similar or even the same scenario. This feature makes drivers’ performance in different

*Figure 2-1: External validity and controllability of measures of empirical longitudinal driving behavior[1]*

*Figure 2-2: observation subject: four-consecutive-overtaking performance*
driving styles comparable to each other. In addition to this, another factor that counts in the choice is experimental cost. If the research is conducted using the instrumented vehicles, a considerable amount of fuel would be consumed just to examine steering behavior of one driver during overtaking.

Despite of the aforementioned advantages, a validation study with regard to steering behavior during overtaking using the Advanced Driving Simulator has not yet been performed. Besides, according to the driving simulator experiments that are concluded in [12], in general, driving simulators only possess relative validity.

The driving simulator used in the three experiments consists of three screens which are, compared to each other, placed at an angle of 120 degrees, a driver’s seat mock-up and hardware and software interfacing of this mock-up to a central computer system (Fig. 2-3). This central computer system consists of two personal computers (a controller personal computer with a Graphical User Interface and a Traffic personal computer) which are connected through a Local Area Network (LAN).

![Fixed base Driving Simulator](image)

**Figure 2-3:** Fixed base Driving Simulator

From the driver’s seat the view of the driving environment consists of a projection of in total 210 degrees horizontally and 45 degrees vertically. The used software was developed by StSoftware. The software consists of several modules, namely: StRoadDesign, StScenario, StControl, StTraffic and StRender. The driving environments are designed with StRoadDesign. This tool generates a geometrically correlated graphical and logical database required for the traffic module and the graphical rendering module.

The actual test drives are generated with StScenario. StScenario makes use of a scripting language. This scenario controls the module StControl, which provides control over the simulation module StTraffic. StTraffic finally computes the dynamic traffic system based on intelligent agents based technology. During the test drives the graphics are rendered through StRender at a 60 fps frame rate.
2-1 Driving Simulator

2-1-1 Experiment design

In the driving simulator experiment, we investigate how a driver performs a four-consecutive-overtaking (four consecutive overtaking (FCO)) in a stable traffic scenario. FCO performance on a two-lane highway is observed in this case because it is informative and demanding, similar to the scenario described in [9], which exhibits a driver’s key attribute in overtaking.

In terms of overtaking type, constant overtaking, as one of the two commonly performed overtaking on a highway[13], is performed in this experiment for the sake of simplicity and driving comfort. Distinguished from accelerative overtaking, where the host vehicle follows the impeding vehicle and increases speed to complete the overtaking, constant overtaking travels at a higher constant speed compared to the obstacle vehicle and carries out the overtaking without slowing down. For the sake of simplicity, overtaking performance with a constant speed, 120 km/h, is investigated since most of overtaking is executed with an invariant speed.

Intended to study steering behavior during ordinary overtaking (not emergency overtaking), three scenarios are designed where obstacle vehicles run with different speeds, one of which is depicted in Fig.2-4a. A sufficient gap of 50 m between the two overtaken cars is reserved to avoid irregular performance of steering. With enough space for overtaking maneuver, the controlled variable in three traffic scenarios is the speed of obstacle vehicles. Each scenario consists of three vehicles to be overtaken, which are travelling at the same speed. The host vehicle is supposed to make a four-consecutive-overtaking maneuver (FCO), overtaking three groups of slower vehicles that travels respectively at 70 km/h, 80 km/h, and 90 km/h.

The steering controller are fashioned to meet the requirements of various driving situations. Besides, participants are requested to perform the same task of FCO with the disturbance of simulated side wind. This extra disturbance is added to test if the performance of the controller has advantage over human drivers.

As far as the participants are concerned, 41 master students and researchers take part in the experiments and finish FCO tasks without a single crash observed. During the simulator test which lasts for about 6 minutes, the states of host and obstacle vehicles are recorded for further analysis. The vehicle states, that are applied in vehicle model and controller identification, are respectively explained in the relevant sections. A picture of first-person view is captured during overtaking, as illustrated in Fig.2-4b. The double dashed white line makes the middle area of a lane more prominent, therefore facilitates confirming the location of the host vehicle and prevents a driver from wandering in the lane.

![Figure 2-4: Overtaking experiment in driving simulator](image)
2-2 Vehicle Model

A precise vehicle model, that represents the physics engine running inside the driving simulator, is required for the closed-loop analysis of the controller, which is illustrated in Fig.3-7. We discuss in this section the process of development and identification of the vehicle model in driving simulator.

2-2-1 4 Contact Point Vehicle Model

In this experiment, a four contact point vehicle model, which is simplified from a 6 degree of freedom (DoF) complex vehicle model, is implemented for parameter identification. This model is established by Simone Manazza and Paolo Gottardis (two colleagues working on vehicle dynamics aspect in DAVI programme). The model proves to be validate due to the fact that the output states of the model are consistent to what are measured on a real vehicle on a road test.

The dynamic model developed here consists of five connected subsystems: one vehicle body and four wheels, which are rigidly coupled to the vehicle body. The model is symmetrical about the vehicle body’s longitudinal axis. The rear wheels, which are driven by a torque, cannot be steered and are therefore aligned with the vehicle body’s longitudinal axis. The front wheels can be steered according to the bicycle steering model and the vehicle motion is constrained to horizontal movements only.

As illustrated in Fig.2-5, different coordinate systems for all the five subsystems are defined. The road reference coordinate system is defined with respect to a fixed point on the highway, where x is the direction in which the highway stretches, y is the direction on the road plane perpendicular to the road borders and z is perpendicular to the road plane. In addition, each wheel has its own coordinate system. Each of the four wheels always touches the horizontal road plane with a single point. These points are called wheel ground contact points, which
suggests the name of this vehicle model. Relative to the CoG coordinate system, the wheels are allowed to freely rotate to the degree indicated by steering angles of left front wheel \( \delta_{fl} \) and right front wheel \( \delta_{fr} \). Due to the fact that overtaking process is normally performed with small steering angle (emergency situation is not considered), the steering angle \( \delta \) for front wheels can be simplified as:

\[
\delta = \delta_{fl} = \delta_{fr}
\]  \hspace{1cm} (2-1)

Another simplification is made because of constant overtaking. In this particular situation, we consider the driving torque ideally counteracts the resisting torque generated by the combination of friction on the contact point and aerodynamic force, etc. Thus the resultant force on the longitudinal axis of the front wheels is always zero throughout the experiment.

According to the prescribed vehicle model structure, six input-output vehicle states are used, also shown in Fig.2-5 as well as the table below.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( V_{xg} )</td>
<td>CoG velocity in x direction of road reference frame</td>
</tr>
<tr>
<td>( V_{yg} )</td>
<td>CoG velocity in y direction of road reference frame</td>
</tr>
<tr>
<td>( \psi )</td>
<td>CoG yaw rate (in radius per second)</td>
</tr>
<tr>
<td>( \psi )</td>
<td>CoG yaw angle (in radius)</td>
</tr>
<tr>
<td>( X_g )</td>
<td>CoG disposition in x direction of road reference frame</td>
</tr>
<tr>
<td>( Y_g )</td>
<td>CoG disposition in y direction of road reference frame</td>
</tr>
</tbody>
</table>

Table 2-1: list of input-output vehicle states

In addition to the vehicle states, variables of the vehicle are introduced for the derivation of the 4 point contact vehicle model, which are specified in Tab. A-2.

In the following, the process of building the 4 point contact model will be elaborated. We consider it a sequence of force transmission after the operation (steering angle alternation) is assigned. When a driver turns the steering wheel to a certain angle, the steering angle for each tyre can be calculated,

\[
\delta = \frac{st \cdot \pi/180}{\tau}
\]  \hspace{1cm} (2-2)

where \( \delta \) is in degree because the angle of steering wheel collected from simulator is in degree. Given the initial states of the vehicle and steering angle of the tyres at the moment, we evaluate velocities in every wheel ground contact point,

\[
\begin{align*}
V_{x_{fl}} &= (V_{xg} + \psi \cdot C_f) \cdot \cos \delta + (V_{yg} + \psi \cdot a) \cdot \sin \delta \\
V_{x_{fr}} &= (V_{xg} - \psi \cdot C_f) \cdot \cos \delta + (V_{yg} + \psi \cdot a) \cdot \sin \delta \\
V_{x_{rl}} &= V_{xg} + \psi \cdot C_r \\
V_{x_{rr}} &= V_{xg} - \psi \cdot C_r
\end{align*}
\]  \hspace{1cm} (2-3)
The tyre side slip angle, $\alpha$, is defined as the angle between the wheel longitudinal axis and the wheel velocity for each tyre,

$$\alpha_{fl} = \tan^{-1} \frac{V_{yf}}{V_{xf}},$$
$$\alpha_{fr} = \tan^{-1} \frac{V_{yf}}{V_{xr}},$$
$$\alpha_{rl} = \tan^{-1} \frac{V_{yf}}{V_{xr}},$$
$$\alpha_{rr} = \tan^{-1} \frac{V_{yf}}{V_{xr}}$$

(2-5)

Based on the characteristics of the tyre, given the tyre side slip angle, the forces acting on the tyre can be computed. This part is described in a separate section specified a tyre model. Introducing the result of the lateral and longitudinal forces on each tyre yielded from the tyre model, forces transferred from vehicle load to the wheel hub are calculated,

$$F_{xm_{fl}} = F_{xf} \cdot \cos \delta - F_{yf} \cdot \delta$$
$$F_{xm_{fr}} = F_{xf} \cdot \cos \delta - F_{yf} \cdot \delta$$
$$F_{xm_{rl}} = F_{xf}$$
$$F_{xm_{rr}} = F_{xf}$$

(2-6)

From these forces, the resultant force on the CoG and the torque on the CoG around the vertical axis $z$ are obtained,

$$F_{xt} = F_{xm_{fl}} + F_{xm_{fr}} + F_{xm_{rl}} + F_{xm_{rr}}$$
$$F_{yt} = F_{ym_{fl}} + F_{ym_{fr}} + F_{ym_{rl}} + F_{ym_{rr}}$$

(2-7)

$$M_z = (F_{xm_{fl}} - F_{xm_{fr}}) \cdot C_f + (F_{xm_{rl}} - F_{xm_{rr}}) \cdot C_r$$
$$+ (F_{xm_{fl}} - F_{xm_{fr}}) \cdot a - (F_{xm_{rl}} - F_{xm_{rr}}) \cdot b$$

(2-8)

So far all the physical quantities, which are required for the integration of the six states, are computed. We acquire the derivative of the six input states:

$$\dot{x}_1 = \dot{V}_x = \frac{F_x}{M_t} + \psi \cdot V_{yg}$$
$$\dot{x}_2 = \dot{V}_y = \frac{F_y}{M_t} - \psi \cdot V_{xg}$$
$$\dot{x}_3 = \dot{\psi} = \frac{M_z}{J_z}$$
$$\dot{x}_4 = \dot{\psi}$$
$$\dot{x}_5 = \dot{V}_x = V_g \cdot \cos(\beta + \psi)$$
$$\dot{x}_6 = \dot{V}_y = V_g \cdot \sin(\beta + \psi)$$

(2-9)
where \( V_g \) is the scalar resultant computed as \( V_g = \sqrt{V_{gx}^2 + V_{gy}^2} \) and the body side slip angle is \( \beta = \tan^{-1}(\frac{V_{gy}}{V_{gx}}) \). Through integration of the states in Eqn. 2-9, the corresponding vehicle states at the moment is achieved. In MATLAB, this process is accomplished using function ode45.

2-2-2 Tyre Model

The tyre model in this case is developed and validated by Simone Manazza and Paolo Gottardin in accordance with a Pirelli tyre. The data is recorded from tyre experiments on test bench. In order to describe the measured data with great accuracy, the tyre model proposed in [14] is applied. This model is later validated in [15].

Delivered from the load of the vehicle, the forces exerted on the wheel at the wheel ground contact points are determined by the characteristic of the tyre. The tyre model can be amplified in the process of load transfer.

First of all, the vertical forces respectively on the front and rear track are,

\[
F_{zf} = \frac{M_t \cdot g \cdot b}{p}, \quad F_{zr} = \frac{M_t \cdot g \cdot a}{p} \tag{2-10}
\]

Due to the fact that the vehicle in this experiment is running at a constant speed, pitch and roll momentum are not generated and stays zero. The load of the front and rear track of the vehicle are uniformly distributed to the four wheels,

\[
F_{zf_l} = \frac{F_{zf}}{2}, \quad F_{zf_r} = \frac{F_{zf}}{2}, \quad F_{zr_l} = \frac{F_{zr}}{2}, \quad F_{zr_r} = \frac{F_{zr}}{2} \tag{2-11}
\]

The forces transferred from the vehicle load to the tyre are represented as Eq. 2-12:

\[
\begin{align*}
F_{yf_l} &= -D_{yf_l} \cdot \sin(C_{yf_l} \cdot \tan^{-1}(B_{yf_l} \cdot \alpha_{f_l} - E_{yf_l} \cdot (B_{yf_l} \cdot \alpha_{f_l} - \tan^{-1}(B_{yf_l} \cdot \alpha_{f_l})))) \\
F_{yf_r} &= -D_{yf_r} \cdot \sin(C_{yf_r} \cdot \tan^{-1}(B_{yf_r} \cdot \alpha_{f_r} - E_{yf_r} \cdot (B_{yf_r} \cdot \alpha_{f_r} - \tan^{-1}(B_{yf_r} \cdot \alpha_{f_r})))) \\
F_{yr_l} &= -D_{yr_l} \cdot \sin(C_{yr_l} \cdot \tan^{-1}(B_{yr_l} \cdot \alpha_{r_l} - E_{yr_l} \cdot (B_{yr_l} \cdot \alpha_{r_l} - \tan^{-1}(B_{yr_l} \cdot \alpha_{r_l})))) \\
F_{yr_r} &= -D_{yr_r} \cdot \sin(C_{yr_r} \cdot \tan^{-1}(B_{yr_r} \cdot \alpha_{r_r} - E_{yr_r} \cdot (B_{yr_r} \cdot \alpha_{r_r} - \tan^{-1}(B_{yr_r} \cdot \alpha_{r_r})))) \tag{2-12}
\end{align*}
\]

where \( B, C, D, E \), listed in Tab. A-1, are the coefficients to be tuned to fit the test data.
The peak factor $D$, in particular, is determined as,

$$
\mu_{fl} = PD_{y_{fl}} + PD_{y_{2f}} \cdot \frac{F_{z_{fl}} - F_{z_{n}}}{F_{z_{n}}}
$$

$$
\mu_{fr} = PD_{y_{fr}} + PD_{y_{2r}} \cdot \frac{F_{z_{fr}} - F_{z_{n}}}{F_{z_{n}}}
$$

$$
\mu_{rl} = PD_{y_{rl}} + PD_{y_{2r}} \cdot \frac{F_{z_{rl}} - F_{z_{n}}}{F_{z_{n}}}
$$

$$
\mu_{rr} = PD_{y_{rr}} + PD_{y_{2c}} \cdot \frac{F_{z_{rr}} - F_{z_{n}}}{F_{z_{n}}}
$$

(2-13)

$$
D_{y_{fl}} = \mu_{fl} \cdot F_{z_{fl}}
$$

$$
D_{y_{fr}} = \mu_{fr} \cdot F_{z_{fr}}
$$

$$
D_{y_{rl}} = \mu_{rl} \cdot F_{z_{rl}}
$$

$$
D_{y_{rr}} = \mu_{rr} \cdot F_{z_{rr}}
$$

(2-14)

It is noted that longitudinal forces on the four wheels are taken as zero since the vehicle in the whole process is travelling at a constant speed.

### 2-2-3 Vehicle Model Identification

We describe above the complete mathematical expression of the vehicle model. This model needs to be identified to fit the output data of the driving simulator. The identified model are applied to mimic the physical model in the simulator, which is a crucial part in closed-loop simulation demonstrated in Fig.3-7. The vehicle states are integrated using a sample time of $T_v = 0.1\text{s}$, which is the same as the one in data collected from driving simulator.

It is noted that the values of parameters in the tyre model tested on the Pirelli tyre in the last subsection are introduced without change. We still use this tyre model because physical quantities related to tyre model identification, such as angular velocity and tractive force of each tyre, are not directly accessible to the experiment on the driving simulator. Judging from the identification results, these parameters, listed in Tab.A-1, proves to be effective when they are applied in combination with the identified vehicle parameters.

In this subsection, we focus on the parameter identification of the aforementioned 4 contact point vehicle model, which is listed in Tab.B-2. As a starting point, these parameters are identified using MATLAB function *lsqnonlin*, where the least square error between the lateral position of the identified model and the simulator output at the same time instant are evaluated as the goodness of fitting. The optimization problem is presented as follows:

$$
\min_{\tau} \sum_{t \in \mathbb{T}} (y_m(t) - y_e(t))^2
$$

(2-15)

where $\mathbb{T}$ is the set of all the time instants, which are extracted from overtaking in the three traffic scenarios.

There are two reasons this variable is selected: Firstly, to achieve the desired lateral position accurately is the most important target during overtaking, which becomes the ultimate goal of a driver’s maneuver and ensures safety. Secondly, observed from the trial identification
data, compared to other parameters such as heading angle and lateral velocity of the host vehicle, it is more difficult to fit the lateral position data of the estimated model output to that of the real simulator output. In another word, if the goodness of fitting is satisfactory in terms of lateral position, the accuracy of other physical quantities can also be guaranteed.

Setting the parameters to be identified, using MATLAB function \texttt{lsqnonlin}, the result of the trial identification is examined in Fig. 2-6. Here we use the phrase, the trial identification, because the result of identification for this stage needs to be evaluated to see if any modification in identification method is required.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{trial_identification.png}
\caption{Result of Trial Identification with six parameters of driver No.1}
\end{figure}

We observe comparison of predicted and measured data of three output channels: lateral position, heading angle and lateral velocity, which are key characteristics of the lateral movement of a vehicle. Each column of the figures corresponds to one FCO performance in a specific scenario. The value of the six parameters evaluated on the real road test data (examined by Simone) are chosen as the initial value.

Results in Fig.2-6 indicate the poor quality of the trial fitting. However, the outcome is not unexpected when using function \texttt{lsqnonlin} because the vehicle model illustrated in the last subsection is nonlinear and the algorithm can easily fall into a local optimal when solving a nonlinear optimization problem. This phenomenon exists because \texttt{lsqnonlin} finds a solution near the origin using the gradient to determine the search direction. Despite the goodness of fitting is not satisfactory, a hint is given in Tab.2-2 that we can focus on the identification of steering ratio $\tau$ since other parameters in this case do not make a difference in the variation of
the least square error. This is also suggested by the fact that the basic shape of the predicted
data is similar to that of the measured data. The curve fitting can be achieved by properly
fitting the steering ratio because the amplitude of the steering action is regulated by the
steering ratio $\tau$.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Initial Value</th>
<th>Identified Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_f$</td>
<td>0.796m</td>
<td>0.796m</td>
</tr>
<tr>
<td>$C_r$</td>
<td>0.796m</td>
<td>0.796m</td>
</tr>
<tr>
<td>$a$</td>
<td>1.235m</td>
<td>1.235m</td>
</tr>
<tr>
<td>$b$</td>
<td>1.465m</td>
<td>1.465m</td>
</tr>
<tr>
<td>$\tau$</td>
<td>23.1</td>
<td>24.523</td>
</tr>
<tr>
<td>$M_t$</td>
<td>1880kg</td>
<td>1880.01kg</td>
</tr>
</tbody>
</table>

Table 2-2: Result of Trial Identification for the 4 Contact Point Vehicle Model

For the identification of the second stage, to avoid the result that the algorithm ends up with
a local optimal, we apply traverse to all the possible values for steering ratio identification.
Observed in Fig.2-6, the amplitude of value in predicted data is much greater than that in
measured ones, which indicates a smaller steering angle of the wheel if the same amount of
angle of the steering wheel is applied. From the definition of $\tau$, the ratio between the turn
of the steering wheel (in degrees) or handlebars and the turn of the wheels (in degrees)[16], the
steering ratio should be increased if we attempt to achieve a smaller steering angle.

We scan the steering ratio value from 24.5, suggested by the result of the first stage in Tab.2-2,
to 34.5, using the interval of 0.1 for the speed of the algorithm. If the outcome of the second
stage is still not satisfactory, a larger scale or a smaller interval is requested.

<table>
<thead>
<tr>
<th>Lateral Position</th>
<th>Heading Angle</th>
<th>Lateral Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>93.5465</td>
<td>96.4577</td>
<td>97.9528</td>
</tr>
<tr>
<td>99.5403</td>
<td>99.5327</td>
<td>99.7191</td>
</tr>
<tr>
<td>97.3184</td>
<td>97.8074</td>
<td>98.6170</td>
</tr>
</tbody>
</table>

Table 2-3: VAF value comparing predicted and measure data for driver NO.1 (in percentage)

The result of steering ratio identification for driver NO.1 is listed in Tab.B-1, where the
steering ratio that yields the best fit (least square error) is 31.5. The Variance Accounted
For (variance accounted for (VAF)) value of the three output channels in three scenarios
for driver NO.1 is listed in Tab.2-3, where each row refers to FCO in one specific scenario.
VAF value in each case is close to 1, which indicates the degree of curve fitting is quite high.
Besides, output comparison with $\tau = 31.5$ is shown in Fig.2-7. According to this figure, the
discrepancies of value and profile of the predicted and measured data are all small, which
reassures the aforementioned consequence.
After the internal validation, introducing the data exhibited by other drivers, the external validation of the simulator model are evaluated on the basis of FCO using the steering ratio identified for driver NO.1. Although data of all the participants are examined, validation results of only 5 drivers are demonstrated in Appendix B constrained by the length of the paper.

It is observed from every driver that the error of the lateral position is always greater than that of the lateral velocity. This is caused by the trivial cumulative error of the velocity, which also leads to the fact that the estimation of predicted lateral position deteriorates with time within one FCO. Despite of the flaw, among all the cross validation results, VAF value of lateral position in any case is above 90%, while the value of heading angle and lateral velocity are above 96%, which is accurate enough for the established vehicle model to reproduce the outcome generated by the driving simulator.

2-3 Summary

At the beginning of the chapter, the applied data collection method and scenarios are illustrated. To make the introduction of driving simulator method compact, the vehicle model used in the simulator is identified. It is noted that the identified steering ratio and other parameters determined in the first stage are not necessarily the correct value of the driving simulator. In terms of ordinary consecutive overtaking, combined with the existing tyre
model, this identified value is the best one that makes the predicted lateral position match
the measured lateral position. As a preliminary research of vehicle dynamics, this chapter
provides a method of how to develop a vehicle model suitable for an autonomous vehicle.
Moreover, possible solutions are suggested for parameter identification of the model, which
yields a result accurate enough for the overtaking experiment. In the subsequent task in
DAVI, accessible to test data of tractive force and friction, the parameters of the tyre model
can be identified with greater accuracy, which will further improve the 4 contact point vehicle
model.
Chapter 3

Controller Identification for Human Steering

With the data collected from the driving simulator experiment, for the next, we observe the fundamentals of the driving behavior and intend to establish a model applying the target and control scheme proposed in [9].

In the literature review mentioned in the first chapter, during lane change/overtaking maneuver, it is generally assumed that the drivers plan a reference trajectory first, then adjust the steering angle to follow it, which is illustrated in Fig.3-1.

However, according to the data collected from real lane change maneuver in [9], closed-loop simulation results show that the non-linear component in steering angle cannot be accurately reflected under this assumption. In other words, the simulated steering angle is much smoother than the one detected during real driving. In this particular study, accurate replication of the measured steering angle is not the most important task because the high frequency component, if precisely formulated, results in unstable driving behavior and damages the steering system. The lateral position is considered the most significant quantity because inaccurate control of it leads to collision with obstacles on a highway. Therefore, regarding the overtaking task, we propose two criteria of the controller identified for the human driver: to replicate the outline of the driver’s overtaking trajectory in each scenario, which is indicated

Figure 3-1: typical configuration of a driver steering model
by a high VAF value in terms of lateral position; to ensure accurate tracking of the target line, which is implied by a low steady-state error.

Suggested in [9], instead of planning the whole overtaking trajectory in advance, drivers evaluate target points as references for lane changing. In this paper, we constructs the steering controller following the scheme in [9]. Since the trajectory planning element in the traditional configuration of a steering model is eliminated, this method saves much computational time. We examine in the following whether or not the identified controller can reflect the driving behavior in overtaking, which is determined by the two aforementioned criterion. Moreover, the step response is simulated in two situations, excluding and including disturbance, to check the performance of the identified controller.

3-1 Target Line Control Strategy

Fig. 3-2 illustrates the proposed target points as control references during a FCO maneuver.

![Figure 3-2: Target sets (dotted line along the lane centerline)](image)

The thin red dotted line along the center of the lane is the target set a driver intends to follow when they overtake the obstacle vehicles. All the FCO maneuver fall into two categories: lane keeping and lane changing maneuver. When the host vehicle is travelling from A to B, the driver follows the target set where point A is located and performs the lane keeping maneuver. As soon as it arrives at point B, due to safety concerns, the driver determines to switch to another lane. Then from point B to C, the driver operates a lane changing maneuver, where the target set is the dotted line in which point C is located.

In the Fig. 3-1, the preview/prediction module is included to mimic human’s preview and predictive behavior. The preview behavior refers to that the human drivers perceive future path information within a finite future distance. In this particular study, the concept of prediction is still implemented to mimic human driving behavior and determine the reference point at a certain time instant. In the driver steering model, a target point on the center of another lane a certain distance (prediction horizon) away from the current position is pursued by the driver in real driving task. Given the prediction horizon distance, $d(t)$, of a driver, the preview target point $T_i \left(x_T(t), y_T(t)\right)$ for a certain vehicle position $i$ can be determined according to the current position of the vehicle $\left(x_T(t), y_T(t)\right)$,

$$
\left\| \begin{bmatrix} x_T(t) - x(t) \\ y_T(t) - y(t) \end{bmatrix} \right\| = d(t) \quad \text{and} \quad \begin{bmatrix} x_T(t) \\ y_T(t) \end{bmatrix} \in \Pi
$$

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where Π is the center line of the vehicle is turning into. Target points perceived by a driver at a certain time instant can be observed in figure 3-2, where A, B and C are the position of the vehicle and TA, TB and TC the corresponding position of the target point.

Now that the target point is defined as a reference, it is necessary that we convert it to a physical quantity that the steering controller can regulate. Therefore, the definition of target heading angle is described below.

Given vehicle current position \( (x(t), y(t)) \), yaw rate \( \omega(t) \), speed \( v(t) \) and the target point \( T(x_T(t), y_T(t)) \), and assuming the vehicle maintains its current yaw rate \( \omega(t) \) and speed \( v(t) \), (that is, the vehicle travels along a curve with a fixed radius \( R(t) = \frac{v(t)}{\omega(t)} \)), the target heading angle \( \theta_d \) is the heading angle that ensures the vehicle will reach the target \( T \).

![Figure 3-3: Computation of the target heading angle](image)

As depicted in Fig. 3-3, \( \beta \) is the angle between the road extension direction and the line connected by the vehicle position and the target point; \( \gamma \) is the angle generated by current vehicle yaw rate \( \omega(t) \). The target heading angle is computed as:

\[
\theta_d = \beta + \gamma = \arctan\left(\frac{y_T(t) - y(t)}{x_T(t) - x(t)}\right) + \arcsin\left(\frac{d(t)}{2R(t)}\right) \tag{3-2}
\]

Therefore, postulating target heading angle as the desired heading angle, the reference target point is translated into the desired heading angle, which can be regulated through the steering controller. The task of the controller is to minimize the error between the actual heading angle and the target heading angle, which is represented in Eq. 3-3.

\[
\theta_e(t) = \theta_d(t) - \theta(t) \tag{3-3}
\]

where \( \theta(t) \) is the actual heading angle.

### 3-2 Controller Type Selection

After the variable to be regulated is determined, a certain type of controller can be selected analysing the relationship between the controller input (desired heading angle \( \theta_d(t) \)) and
output (vehicle steering angle $\delta(t)$). Fig. 3-4 illustrates the structure of open-loop analysis based on FCO data collected from driving simulator tests.

Introduced in the previous chapter, FCO data consist of host vehicle information including the vehicle positions, heading angle, yaw rate, vehicle speed and steering angle and obstacle vehicle information containing vehicle position and speed. At a certain time instant $t$, the target set $\Pi$ is determined by the current vehicle position $(x(t), y(t))$ and the decision of lane change. Assigning a proper prediction horizon $d$ to a driver, the preview target point is computed based on Eq. 3-1. Accordingly, the target heading angle $\theta_d$ at this time instant is then computed extracting yaw rate $\omega(t)$ and speed $v$ of the host vehicle from the test data. Finally, the target angle error, considered the input to the controller, is calculated from $\theta_d$ and the current vehicle heading angle $\theta(t)$.

Fig. 3-5 and Fig. 3-6a show the four consecutive overtaking (FCO) conducted by driver No.1 under the condition where speed of the obstacle vehicles are 70km/h, while Fig. 3-6b illustrates FCO performed where speed of the obstacle vehicles are 80km/h. As observed from the result, when the prediction distance is appropriately selected (50m) in the analysis, the steering angle for the most of the time is more or less proportional to the heading angle error, no matter what traffic condition a driver is in. Hence, we assume that it is possible to use one parameter to approximate steering behavior of a driver in the whole FCO process. This suggests that a $P$ controller, $\delta(t) = k_p \cdot \theta_e(t)$, is suitable to mimic a human driver performance. Due to the fact that the reference point jumps suddenly from one lane to another when switching the target set, $D$ controller, $\delta(t) = k_d \cdot \dot{\theta}_e(t)$, is combined with $P$ controller to boost up the response.

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In Fig. 3-6b, at the beginning of the FCO maneuver (value of horizontal axis $< 810m$), the steering angle is almost zero when the heading angle is enormous. This is because there is discrepancy between the target switching moment used by the driver and the one used in the analysis. At the beginning of the overtaking, a driver tends to give a steering angle much greater than the one applied in lane-keeping maneuver, so we may use this distinct steering angle to determine the target switching moment. However, this angle is sometimes difficult to detect because some drivers implements a small steering angle until the vehicle deviates several meters from the original lane. In the open-loop analysis and the subsequent analysis, we consider the instant when the vehicle heading angle $\theta(t) > 0.15^\circ$ as the target switching moment. Now it is understandable the problem discussed at the beginning of this paragraph: the algorithm in open-loop analysis misjudges that the overtaking begins while actually the...
controller takes no action. If the target switching moment is correctly determined, the steering angle given by a driver increases with the target heading error in the most of the time.

3-3 Controller Identification

The above observation suggests a $PD$ controller. Combined with the preview distance $d$, there are three parameters to be identified. Given the target set determined by FCO data extracted from the driving simulator test, these three parameters of the steering controller are tuned so that the lateral position of the controlled vehicle model matches the one from the test data. The same variable is chosen as in vehicle model identification because of the significance of lateral position mentioned in the last chapter still applies. The configuration of the closed-loop simulation is illustrated in Fig. 3-7. The controller sample times used is $T_s = 0.3s$, which is selected within the commonly applied range of time interval from 0.05s to 0.5s[17]. To reduce accumulative discretization error, the sample time used in vehicle state integration, $T_v = 0.1s$, is smaller than the controller sample time. With sample time $T_v$, at any time instant, instead of using the ‘switching target set’ section in Fig. 3-4, the target set is predefined by obtaining the target switching moment from FCO data in simulator tests.

After the preview target and target angle error are sequentially computed, the error is sent to and regulated by the steering controller. The steering angle is then implemented as an input to the vehicle model to generate vehicle states for the next time instant. Finally, the lateral position of the simulation for FCO process is compared to that from the driving simulator test with a global search of the three parameters.

Before the two approaches of global search are elaborated, it is noted that two types of drivers are discriminated no matter what identification method is applied, which are respectively illustrated in Fig. 3-8 and Fig. 3-9. As observed in Fig. 3-8, the goodness of fit for the third overtaking scenario is 78.8077%, not as good as the other two situations, where VAF value is 96.1873% and 97.7095%. On the contrary, one set of parameters fit well for driver NO.5 in all the scenarios, which is listed in Tab. 3-1. This indicates that one part of the drivers behave consistently, while the other part drive accordingly to a specific traffic scenario. Due to the
stochastic driving behavior observed during overtaking, it is impossible to use the proposed controller scheme to cover all the drivers. In this study, we focus on the consistent type of drivers. A standard for consistence is set at 85%: if VAF values of one set of parameters fitting the three scenarios are all above 85%, the controller is perceived adequate to mimic human steering behavior. The goal of the identification is to find a set of controller parameters that represents one consistent driver. In this study, 15 drivers are identified as consistent, which is shown in Tab.C-1. The exhaustive process of identification is discussed in the next section.

Due to the fact the outcome of controller identification are more or less the same within the consistent driver group, one representative is chosen for further analysis. Data from driver NO.5 are selected because it’s informative. For example, we observed the phenomena of oversteering and understeering from Fig.3-9c, which are not always performed by other drivers. Subsequently, the controller identification and analysis is based on driver NO.5 in the consistent group if not specified.

![Identification results for an adaptive driver](image1)

**Figure 3-8:** Identification results for an adaptive driver

![Identification results for driver NO.5](image2)

**Figure 3-9:** Identification results for driver NO.5

### 3-3-1 Two-level Global Search

Firstly, a global search is divided into two levels for the sake of computational simplicity. The three parameters to be identified are globally scanned with relatively big interval. After the
optimal of the first level is found with the least square error between the measured and the estimated lateral position in all the three scenarios, the second level search algorithm starts with the suboptimal and examines values with smaller interval around the origin.

Suggested in [9], preview distance $d$ are checked around 20m with an interval of 3m. Compared to the scenario designed in [9], the overtaking is performed at a much higher speed and with a smoother steering behavior, thus the drivers are supposed to implement a much longer preview distance. In the first level of search, distance range from 40m to 72m is implemented with an interval of 4m. To determine the range of $k_p$, we take the test data from driver NO.1 as an example: 83 percent of steering angle values are within the scope of $2.7 \theta_e(t) < \theta(t) < 6.6 \theta_e(t)$. This suggests the domain of $k_p$ is from 2.7 to 6.6 with the interval of 0.3. Besides, $k_d$ is examined from 0 to 3 the interval of 0.3, which is smaller than the value of $k_p$ because the it acts as an auxiliary controller that boosts up the response when switching the target set.

The mathematical expression of the optimization problem for the first-level identification is,

$$\min_{d,k_p,k_d} \sum_{t \in \mathbb{T}} (y_m(t) - y_e(t))^2$$

subject to. $40 < d < 72$

$$2.7 < k_p < 6.6$$

$$0 < k_d < 3$$

where $\mathbb{T}$ is the set of all the time instants, which are extracted from overtaking in the three traffic scenarios.

The interval and scope of the second level search are narrowed down to: $d_{sub} - 2 < d < d_{sub} + 2$ with step size 1m, $k_{p_{sub}} - 0.4 < k_p < k_{p_{sub}} + 0.4$ with step size 0.1 and $k_{d_{sub}} - 0.4 < k_d < k_{d_{sub}} + 0.4$ with step size 0.1. The mathematical expression of the optimization problem for the first-level identification is,

$$\min_{d,k_p,k_d} \sum_{t \in \mathbb{T}} (y_m(t) - y_e(t))^2$$

subject to. $d_{sub} - 2 < d < d_{sub} + 2$

$$k_{p_{sub}} - 0.4 < k_p < k_{p_{sub}} + 0.4$$

$$k_{d_{sub}} - 0.4 < k_d < k_{d_{sub}} + 0.4$$

where $d_{sub}$ is the optimal solution for $d$ of the first-level identification, $k_{p_{sub}}$ is the optimal solution for $k_p$ of the first-level identification and $k_{d_{sub}}$ is the optimal solution for $k_d$ of the first-level identification.

The detailed result and computational time of the method are illustrated in Tab. 3-1 and Fig. 3-10. It is expected that the identification for just one driver still takes a long time because we have to repeat the overtaking process 1692 times ($9 \times 13 \times 11 + 5 \times 9 \times 9$) for a two-level global search. For the purpose of alleviating computational complexity, a multi-start global search method is introduced.

### 3-3-2 Multi-start Global Search

Multi-start algorithm is implemented to efficiently solve the optimization problem with the expression that is described in Eq. 3-4. The global search algorithm, illustrated in [18], is
performed by the Matlab function Multistart that runs the following steps: generate start points, run local solver and check stopping conditions.

**Generate Start Points**  With a user assigned number \( k \), \( k \) start points are uniformly generated within the bounds of the three parameters defined in Eq. 3-4.

**Run Local Solver**  With \( k \) generated start points, the algorithm runs the local solver, fmincon, which is explained in the last chapter in the identification of the vehicle model.

**Check Stopping Conditions**  The stopping criterion for every local solver conforms with that of fmincon:

\[
|x_i - x_{i+1}| < \text{TolX}
\]
\[
|f(x_i) - f(x_{i+1})| < \text{TolFun}
\]

(3-6)

where \( \text{TolX} \) and \( \text{TolFun} \) are the lower bound on the change in the value of the step size and the objective function, which is set at the default value \( 10^{-6} \).

The global search algorithm stops when it runs out of start points.

After the algorithm reaches the stopping criterion, the best result with the least square error is given comparing the final value of each start point. The exhaustive identification results for driver NO.5, using the two distinct algorithms, are illustrated in Tab. 3-1 and Fig. 3-11.
Hereby, high VAF values are yielded using both approaches. The outcome guarantee that the outline of the overtaking trajectory is captured, thus the driver’s steering behavior is reflected. Another criteria that regulates the controller identification is accurate target line tracking. The fact, that this criteria is achieved, is amplified in the section of controller analysis.

Concerning the quality of identification results for driver NO.5, in terms of VAF value of the lateral position, the two approaches don’t make too much a difference. Neither do the parameters. However, the computational time gives multistart method the edge, which implies that it provides accurate solutions in a much shorter time. In addition, the aforementioned results are tested using Intel i5-2400 CPU at 3.1GHz. Another advantage of the multistart method is that it can be computed in parallel without communication, where each start point can be assigned to one local processor as the origin of the optimization problem. The algorithm will be even faster if computed in a distributed way. Communication among processing units is not required because the algorithm reaches a local optimal without the knowledge from the neighbouring unit.

### 3-4 Controller Analysis

In this section, the performance of the steering controller is investigated. Due to the fact that the MIMO vehicle model is governed by nonlinear differential equations and a wide range of the six vehicle states is of interest in our study, it is difficult to linearize the vehicle model.
around an equilibrium point and conduct the frequency domain analysis as in SISO close-loop evaluation. We concentrate on time domain simulation results. Data from driver NO.5 are specifically examined as an example because of space constraints.

### 3-4-1 Time domain analysis

First of all, we observe the resemblance of the driving behavior. As mentioned before, the lateral position plays the most important role in overtaking, the result of which is illustrated in Fig. 3-12a, 3-13a and 3-14a. The delay of tracking in terms of lateral position occurs near the end of the first lane change. On one hand, the controller tends to generate a trajectory that turns more sharply at the beginning than in the end of a lane change, which is observed in Fig. 3-12b, because the heading angle error is the greatest when the target set is switched to another lane. On the other hand, the driver’s steering behavior at both ends are sometimes closer to each other. This explains why the delay takes place. Despite of the noticeable gap between the two curves during the second lane change of the FCO, most of the time the trajectory generated by the controller, which applies a target and control scheme, overlaps properly with the one collected from test data according to the high value of VAF. The fact, that the characteristic of driving behavior is correctly captured, can also be observed through other vehicle outputs in Fig. 3-12 beside the lateral position. The outline of the measure and predicted curves, in terms of the three output variables, are similar to each other. Although the peak amplitude of the three variables are more or less the same throughout the FCO, less start and stop steering behavior (nonlinear behavior) is observed in estimated steering angle. This implies that the controller finish the overtaking task with smoother steering maneuver. More importantly, the controller prevents the vehicle from being unstably regulated, which are separately illustrated in Fig.3-12a and in Fig.3-14a. At the end of FCO in the first case (around highway = 550m), the introduction of the PD controller avoids oversteering, which leads to the undesirable overshoot in lateral position. In the second case, around highway = 2300m in Fig.3-14a, the phenomenon of understeering, caused by misestimation of the target line position, is precluded in the presence of the controller.

![Figure 3-12: Comparison result of driver NO.5 with scenario NO.1](image)

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In terms of time response, we test step response with various target set (from 2.5m to 4m) on each driver in the consistent group, two examples of which are shown in Fig.3-15.

In this case, the standard of rise time and settling time are difficult to set since various lane transition time are requested by different driver needs. We focus on the error in position, which is characterized by the overshoot and steady state error of the step response. The details of these two measures for 15 drivers are illustrated in Fig.3-16a and Fig3-16b.
The horizontal axis represents the driver number within the consistent driver group, while the vertical one indicates the value of corresponding index. The errorbar in Fig.3-16a, the max lateral error, is the discrepancy between lateral position and reference position measured at the overshoot. The max lateral error increases with the growth in reference. In other words, the lower bound of the errorbar indicates the error with 2.5m reference, while the upper bound represents the one with 4m reference. Apart from driver NO.1, all the drivers in consistent group conform to the standard that maximum overshoot is under 5%, which promises a stable and smooth trajectory. After the max overshoot of lateral position, the error is decreasingly regulated to the steady state error. The speed of adjustment is relatively slow, as shown in Fig.3-15, which is not harmful to performance since even the max lateral error is small enough to be acceptable in overtaking task. The steady state error in Fig.3-16b is measured at $t = 10s$. Beside driver NO.1, the value are all under 0.02m, which indicates the controller with identified parameters is capable of tracking the reference accurately. It is a coincidence that the percentage overshoot (overshoot over reference) and steady state error are invariant for one driver, independent of the value of reference. This phenomenon, which is normally observed in a linear system, implies that it is possible in this case to linearize the vehicle model around a specific equilibrium point. The linearization is not expanded here, but may lead to interesting study and discussion in the field of overtaking in the future. In addition to this, it is revealed in Fig.3-16 that the step response of controllers identified for driver NO.1 is not satisfactory, which indicates the driving style is too aggressive for overtaking. This set of parameters is considered as an outlier in terms of driving safety.

![Graph](image1)

**Figure 3-16:** Step response of consistent driver group

### 3-4-2 Disturbance rejection

Sudden disturbance can be added to the system in order to test the robust performance of the identified controller. We insert step disturbance as long as 1s with the amplitude of 5° to the steering wheel, which functions as a strong gust of wind. Steering disturbance is used instead of wind because it can be directly introduced to the vehicle model as an input. The overtaking performance of driver NO.5, under the influence of the steering disturbance during each lane change, is illustrated in Fig.3-17 along with the disturbance, which is shown as cyan

![Graph](image2)
step.

Shown in Fig3-17a and Fig3-17b, the controller can hardly follow the disturbed trajectory produced by the driver because the typical driving habit examined in normal conditions is violated due to the introduction of simulated wind disturbance. In the comparable case in Fig3-17c, where the VAF value is as high as 92.70%, the lateral acceleration applied by the controller is far less than that performed by a driver in Fig.3-18c. As a comfort index widely implemented in the automotive field [19], less amount of lateral acceleration in every scenario suggests that, compared with a human driver, the steering controller provides a more comfortable overtaking trajectory in case of disturbance.

![Figure 3-17: FCO of driver NO.5 with disturbance](image)

![Figure 3-18: Lateral acceleration of driver NO.5 with disturbance](image)

Same as the sequence of analysis in the last subsection, next we examine step response in condition of the disturbance. The same amount of disturbance on steering angle is applied, but the time we insert it is altered. We intend to test the robustness of the controller against disturbance in the worst case, where the introduction of the disturbance causes the maximum error in lateral position. Based on the study of step response of the controller without disturbance, the worst case occurs if the disturbance is inserted at the maximum overshoot. What is illustrated in Fig.3-19a is a typical trajectory under the influence of the disturbance. For the sake of simplicity, we only consider the situation when reference = 3.5m.
Figure 3-19: Step response for insistent driver group with disturbance

As shown in Fig.3-19a, before the simulating wind disturbance, depicted as a green step, is inserted, the response is the same as evaluated in time domain analysis. However, due to the disturbance, the vehicle is forced to deviate from the desired target set and adjusted back to the line. Fig.3-19b illustrates the adjustment time that is counted from the end of disturbance to the instant the vehicle reaches 5% or 2% error boundary of the reference (3.5m). We observe that the adjustment time required to achieve the 5% boundary (0.175m), which is a slight deviation from the target, are less than 3s for the consistent driver group. This suggests the quick adjustment of the controller against the possible disturbance. Besides, the vehicle in simulation proceeds from 5% to 2% boundary within 1s in all the cases, which indicates the lateral position continues to converge to the reference. We accomplish fast regulation without the problem of unstability.
Chapter 4

Customized Controller Design for Autonomous Overtaking

In this chapter, we consider the basic of human machine interface as a trial to practical application of the controller to the autonomous vehicle. A simple operating system is developed with tunable sliders that regulate the parameters of the steering controller. Each slider is assigned an intuitive meaning, which makes the user easier to comprehend the function of the controller and overtake on his own demand.

4-1 Curve Fitting

As listed in Tab.C-1, three parameters are identified for the consistent driver group. If we manage to find the relationship among the parameters, the number of variables to be regulated can be reduced. For instance, if the value of $k_d$ can be represented as a function of horizon distance and $k_p$, the interface boils down to two controllable variables (two sliders) instead of three, which spares the effort in overtaking maneuver.

For the sake of simplicity, we use a linear model to try to fit the three-dimensional points to a plane, which is shown in Eq.4-1, accompanied with the fitting result. According to the model, linear least squares is selected as an approach to fit the statistical model to data. In the least squares method, the unknown parameters are estimated by minimizing the sum of the squared deviations between the data and the model. With $D$ controller functioning as an auxiliary controller that boosts up performance at the start of lane change, horizon distance and $k_p$ are used as variables because they are more significant and more intuitive for application. Horizon distance corresponds with the target point to be reached in the overtaking and the value of $k_p$ indicates fastness.
Due to the poor performance in terms of step response in simulation, driver NO.1 in the consistent group is labelled as an outlier, which is illustrated in Fig.4-2b. Beside Fig.4-1, which shows the distribution of the identified parameters and the plane, Tab.4-1 specifies the plane fitting quality of the two situations: plane fitting result with and without the outlier. Despite the method of least square regression is sensitive to outliers, the low numerical value of sum-of-square error (SSE) and root-mean-square error (RMSE) and high numerical value of R-square implies a good approximation of the identified parameter data, following the revelation of the outlier.

\[ f(x, y) = p_0 + p_1 \cdot x + p_1 \cdot y \]  

(a) With outlier  
(b) Without outlier

**Figure 4-1: Parameters fitting to a plane**

The three indexes indicate goodness of fit: SSE, sum of squared errors of prediction, is a measure of the discrepancy between the data and an estimation model; R-square, the coefficient of determination, is the proportion of variability in a data set that is accounted for by a statistical model; RMSE, root-mean-square error, represents the sample standard deviation of the differences between predicted values and observed values. The noticeable difference between the two situations suggests that the outlier plays an important role in this case. The fit result excluding the outlier has lower SSE and RMSE values, which indicates a tighter fit to the data, and higher R-square value, which reveals the observed outcomes are

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<th>excluding outlier</th>
</tr>
</thead>
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<td>0.18</td>
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<tr>
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<td>0.007821</td>
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</tr>
<tr>
<td>RMSE</td>
<td>0.0353</td>
<td>0.0250</td>
</tr>
</tbody>
</table>

**Table 4-1: Plane fitting result**

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better replicated. Based on the aforementioned advantages of the linear model without the outlier, it is used to represent the relationship among the identified parameters.

High percentage of fitting suggests that the controller parameters in this case, where the vehicle overtakes at a constant speed with sufficient gaps, follow a certain law despite of the fact that they belong to different drivers. Further research can be conducted on the relationship among the controller parameters identified for various drivers.

Through the plane fitting, three parameters are simplified to two with explicit meanings, which lays the ground work for application to autonomous overtaking.

4-2 Matlab Toolbox

In this section, a MATLAB guide is designed to mimic the function of the human-machine interface of the customized overtaking system. This is a demonstration of how the operating system works in the real autonomous vehicle.

Since the number of controllable variables are reduced to two, the parameters of the steering controller, \( d \) and \( k_p \), are respectively assigned to two sliders with labels, namely ‘horizon’ and ‘fastness’, which helps users to better understand the basic function of the slider.

Apart from the controller parameters, considered as an input to the system, the target set in this case is always the center of the lane the vehicle turns into. The target line can be more accurately determined according to the real-time safety analysis, which is out of the research scope of this paper.

Another factor, that is simply defined beforehand due to the same reason, is the starting instant of overtaking. We apply the time-to-collision notion as a safety indicator. The time-to-collision (time-to-collision (TTC)) concept was introduced in 1971 by the US researcher Hayward[20]. A TTC value at an instant \( t \) is defined as the time that remains until a collision between two vehicles would have occurred if speed difference is maintained. The time-to-collision of a vehicle-driver combination \( i \) at instant \( t \) with respect to a leading vehicle \( i - 1 \) can be calculated with:

\[
TTC_i = \frac{x_{i-1}(t) - x_i(t) - l_i}{v_i(t) - v_{i-1}(t)} \forall v_i(t) > v_{i-1}(t) \tag{4-2}
\]

where \( v \) denotes the vehicle speed, \( x \) the position and \( l \) the vehicle length.

In applying TTC to determine the starting time, a threshold value should be chosen to distinguish relatively safe and critical encounters. Hirst and Graham [21] report that a time-to-collision measure of 4s could be used to discriminate between cases where drivers unintentionally find themselves in a dangerous situation from cases where drivers remain in control. The results show that a TTC warning criterion of 4 or 5s results in too many false alarms. The study reveals that a TTC-value of 3s produced the least number of alarms although in some cases critical situations were observed. Therefore, the reference target set is switched to another lane when the safety indicator TTC attenuates to the threshold of 3.5s. We don’t expect the user to abandon the overtaking halfway because a more comprehensive real-time safety analysis is still required to make the decision.

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The simulated overtaking module is programmed with the graphical user interfaces, MATLAB guide, which demonstrates a possible solution to autonomous overtaking maneuver. The intuitive interface is illustrated in Fig. 4-2. With the intuitive meaning of each unit, the system is easy for new users to learn, eliminating the need to have deep insight into the function of the steering controller. We use the simulation to demonstrate the process that an autonomous vehicle overtakes obstacles at a constant speed with a tunable steering controller. A finite number of obstacle vehicles are placed arbitrarily on the highway at a random constant speed. In the following, we provide the function of the individual unit in the operating system and introduce the general steps in application.

4-2-1 Introduction to individual unit

The feature of each module in the operating system is listed as follows.

**Main screen** Display the position and trajectory of the vehicles. The horizontal axis represents the travel distance along the straight highway and the vertical axis the relative distance to the right boarder of the right lane.

**Initial Velocity** Set the velocity of the vehicle. Default value is $120\text{km/h}$ if not specified. The velocity can not be altered during the overtaking as we assume the vehicle travels at constant speed. We apply the controller parameters identified at $v = 120\text{km/h}$. Further study on variation of parameters subject to vehicle speed is not included in this paper.

**Horizon and fastness sliders** Determine the preview distance $d$ and parameter $k_p$ of the steering controller. Default values are $60m$ and $4.5$ if not specified. The adjustable interval of $d$ and $k_p$ are expanded to $[d_{\text{min}} - 5m, d_{\text{max}} + 5m]$ and $[k_{p_{\text{min}}} - 0.5, k_{p_{\text{max}}} + 0.5]$ to cover a wider range of driver types, where $d$ and $k_p$ denote identified parameters for all the consistent drivers. $k_p$, if applied to a real vehicle, can be interpreted as 'fastness' and scaled from 0 to 1 for better understanding and simpler application of the system. The value of current tuning position is displayed next to the sliders.
Start button  Commence the simulation after the initial velocity and controller parameters are set.

Continue button  Resume the simulation after the controller parameters are readjusted.

We pause the simulation when TTC indicator reaches threshold and display the trajectory span of the current horizon, which illustrates the possible position of the vehicle in the subsequent overtaking. The user can adjust the parameters according to what is observed on the main screen. The simulation proceeds after the continue button is pressed.

4-2-2 General application procedure

First of all, enter the velocity of the host vehicle to be tested. Then press the start button to commence the simulation with desired speed and subsequently the mini movie is displayed on the main screen, depicting the host vehicle advancing on the highway. Apart from the vehicle represented by a rectangular, a circle within the rectangular describes CoG of a vehicle and the cross shows the current target, which forms a red dashed trajectory in combination of the antecedents from the past. The picture pauses at the moment when the threshold of TTC indicator is reached, namely, the time that the overtaking begins. In order to illustrate the possible position of the host vehicle during overtaking, the trajectory span with a fixed prediction horizon is shown on the screen. The trajectories of the vehicle is calculated varying the value of $k_p$ from the minimum to the maximum, therefore a span is generated. Knowing the possible position when implementing different $k_p$, the user can select a value for $k_p$ that is appropriate for overtaking or tune the horizon slider to renew the span and find a value of $d$ that is more desirable. The values, which are currently selected, are displayed next to the sliders. After a couple of proper parameters are determined, the user can press the continue button to resume the simulation. The process of pause and play will be repeated every time the host vehicle passes an obstacle until the end of the simulation.

4-2-3 Summary

At the beginning of the thesis, the requirement concerning the customized controller design is fast and simple solution to autonomous overtaking. Through curve fitting, an intuitive and simple operating system is achieved. In terms of fast solution, high computational speed is requested for applications on a real autonomous vehicle. According to the test on MATLAB, the total time, which is spent for plotting trajectories for a certain horizon, is always less than 0.9s. This lefts enough time for a use to tune the operating system. Considering the time invested in visualization, the output of the PD controller can be generated even faster excluding that part. The elapsed time from input to output is less than 0.004s, which is far shorter than the normal sampling time in a steering controller such as 0.3s.
Conclusions and Recommendations

5-1 Conclusions

In this paper, we investigate a driver model that can represent steering behavior on normal overtaking tasks (smooth overtaking that is not undertaken in emergency) and apply it to autonomous vehicles. In the literature, the researchers establish the driver model in lane change using different algorithms with the same structure that includes three assumed elements: trajectory planning, prediction and steering controller. However, a new approach, namely target and control scheme, is proposed in [9] eliminating the trajectory planning part. Due to the fact that the model provided in the new approach is capable of capturing drivers’ steering behavior with simpler structure, this scheme is applied. We attempt to identify a steering controller that reflects the key characteristics of the driving behavior during overtaking with this new structure, namely, matches the model outputs in simulation with the experiment data from the driving simulator.

Based on the significance of lateral position in overtaking, two criteria are suggested for controller identification: reflection of the outline of the overtaking trajectory and accurate tracking of the target line the vehicle turns into.

Due to the fact that the identification assignment is complex and demanding, two global search algorithms, two level search and multi-start search, are compared to come up with a better solution. Tested with 41 participants who performs the overtaking on the driving simulator, it turns out that the multi-start global search algorithm yields results of similar quality with the speed at least 1.5 times faster than the two level one.

Based on this finding, two groups of drivers are distinguished from each other using the multi-start global search. We focus one of the driver groups: the consistent driver group, where the outline of overtaking trajectories in different traffic scenarios can be simulated by one controller. Within this driver group of 15 drivers, VAF value, between vehicle lateral position observed in the controller output and experiment data, are consistently high and over 85%. This result implies that the identified controller provides an authentic reflection of the overtaking trajectory in all the scenarios.
Using the steering controller parameters identified for the consistent driver group, we examine the step response of each driver model with or without simulated wind disturbance. In the situation with disturbance, excluding the solitary outlier, the maximum overshoot is under 5% and the steady state error less than 0.02m, which illustrates the accurate tracking of the target line. Combined with the result that reached in the last paragraph, we draw the conclusion that the identified controller is able to reflect the key characteristics of driver’s overtaking behavior.

Inserting the disturbance, the readjustment time of the controller is consistently under 2.2s. This outcome rules out the problem of instability. Besides, generating similar overtaking trajectories, less amount of lateral acceleration is observed in predicted model output than in experiment data, which indicates a more comfortable overtaking operation.

According to the aforementioned conclusion that the identified controller captures the key characteristics of driver’s overtaking behavior, a simple operating system is designed for overtaking in autonomous vehicles. Parameters of the steering controller, which are translated into intuitive meanings instead of terms in cybernetics, are tunable via the sliders on the interface. This operating system is demonstrated using a GUI program in MATLAB and the exhaustive manual is provided in the paper. Smooth overtaking trajectories and fast computation time indicate that the controller proposed in target and control scheme is suitable for application of customized overtaking in autonomous vehicles on real highway.

5-2 Recommendations for future work

First of all, as a preliminary to closed-loop controller identification, the method of establishment of the vehicle model needs to be altered when applied to a real autonomous vehicle. Physical quantities such as mass and steering ratio of the vehicle are filled with the corresponding vehicle parameters to improve degree of accuracy.

Secondly, this thesis focuses on a relatively small range of overtaking fashion: the host vehicle passes the obstacles at a constant speed of 120km/h. Further exploration can be carried out in the field of overtaking with a scope of constant speed and accelerative overtaking.

Thirdly, in terms of controller identification method, the efficiency of multi-start global search can be improved if we reveal the relationship between computational speed and number of starting points. Additionally, the algorithm can be computed in a distributed way for better efficiency.

Last but not the least, the operating system designed for autonomous overtaking, which seems promising, requires validation result from the road test before application on an autonomous vehicle. The steering controller is based on the identification result testing on a driving simulator. However, in a practical situation, the performance of the whole system are assessed under the influence of complicated traffic scenarios and demanding requirements.
## Variable List for Vehicle Model

### A-1 Tyre Model

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<th>Symbol</th>
<th>Description</th>
<th>Value</th>
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<td>-0.12</td>
</tr>
<tr>
<td>$PD_{y_{rl}}$</td>
<td>lateral friction coefficient of rear tyres at nominal load</td>
<td>1.2075</td>
</tr>
<tr>
<td>$PD_{y_{rr}}$</td>
<td>variation of lateral friction coefficient of rear tyres with load</td>
<td>-0.12</td>
</tr>
</tbody>
</table>

*Table A-1: variable list for tyre model*
## 4 Contact Point Model

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_f$</td>
<td>half length of the front track</td>
</tr>
<tr>
<td>$C_r$</td>
<td>half length of the rear track</td>
</tr>
<tr>
<td>$a$</td>
<td>distance from the front track to CoG</td>
</tr>
<tr>
<td>$b$</td>
<td>distance from the rear track to CoG</td>
</tr>
<tr>
<td>$p$</td>
<td>distance between the front track and the rear track</td>
</tr>
<tr>
<td>$\alpha_{fl}$</td>
<td>slip angle of the front left tyre</td>
</tr>
<tr>
<td>$\alpha_{fr}$</td>
<td>slip angle of the front right tyre</td>
</tr>
<tr>
<td>$\alpha_{rl}$</td>
<td>slip angle of the rear left tyre</td>
</tr>
<tr>
<td>$\alpha_{rr}$</td>
<td>slip angle of the rear right tyre</td>
</tr>
<tr>
<td>$V_{x,fl}$</td>
<td>longitudinal speed of the front left tyre</td>
</tr>
<tr>
<td>$V_{x,fr}$</td>
<td>longitudinal speed of the front right tyre</td>
</tr>
<tr>
<td>$V_{x,rl}$</td>
<td>longitudinal speed of the rear left tyre</td>
</tr>
<tr>
<td>$V_{x,rr}$</td>
<td>longitudinal speed of the rear right tyre</td>
</tr>
<tr>
<td>$V_y$</td>
<td>lateral speed of each tyre</td>
</tr>
<tr>
<td>$F_{z,fl}$</td>
<td>vertical force on the front left tyre</td>
</tr>
<tr>
<td>$F_{z,fr}$</td>
<td>vertical force on the front right tyre</td>
</tr>
<tr>
<td>$F_{z,rl}$</td>
<td>vertical force on the rear left tyre</td>
</tr>
<tr>
<td>$F_{z,rr}$</td>
<td>vertical force on the rear right tyre</td>
</tr>
<tr>
<td>$F_x$</td>
<td>longitudinal force on the wheel hub</td>
</tr>
<tr>
<td>$F_y$</td>
<td>longitudinal force on the wheel hub</td>
</tr>
<tr>
<td>$F_{xm}$</td>
<td>force on the wheel hub x direction in the road reference frame</td>
</tr>
<tr>
<td>$F_{ym}$</td>
<td>force on the wheel hub y direction in the road reference frame</td>
</tr>
<tr>
<td>$F_{xt}$</td>
<td>force on CoG x direction in the road reference frame</td>
</tr>
<tr>
<td>$F_{yt}$</td>
<td>force on CoG y direction in the road reference frame</td>
</tr>
<tr>
<td>$M_z$</td>
<td>torque on CoG around the vertical axis</td>
</tr>
<tr>
<td>$V_g$</td>
<td>resultant velocity of CoG (scalar)</td>
</tr>
<tr>
<td>$\tau$</td>
<td>steering ratio</td>
</tr>
<tr>
<td>$st$</td>
<td>angle of the steering wheel (in degree)</td>
</tr>
<tr>
<td>$M_t$</td>
<td>total mass of the host vehicle</td>
</tr>
<tr>
<td>$V_g$</td>
<td>the scalar resultant velocity of CoG</td>
</tr>
<tr>
<td>$\beta$</td>
<td>the body side slip angle at CoG</td>
</tr>
</tbody>
</table>

*Table A-2: list of vehicle variables*
Appendix B

Identification Result for the Simulator Model

B-1 Steering Ratio Identification

<table>
<thead>
<tr>
<th>Value</th>
<th>LSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>24.5</td>
<td>523.6432</td>
</tr>
<tr>
<td>25.5</td>
<td>407.1812</td>
</tr>
<tr>
<td>26.5</td>
<td>433.0128</td>
</tr>
<tr>
<td>27.5</td>
<td>297.4363</td>
</tr>
<tr>
<td>28.5</td>
<td>180.5358</td>
</tr>
<tr>
<td>29.5</td>
<td>204.2702</td>
</tr>
<tr>
<td>30.5</td>
<td>117.7156</td>
</tr>
<tr>
<td>31.5</td>
<td>83.3670</td>
</tr>
<tr>
<td>32.5</td>
<td>168.9577</td>
</tr>
<tr>
<td>33.5</td>
<td>109.5877</td>
</tr>
<tr>
<td>34.5</td>
<td>90.1960</td>
</tr>
</tbody>
</table>

Table B-1: list of identified steering ratio for driver NO.1

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_f$</td>
<td>half length of the front track</td>
<td>0.796m</td>
</tr>
<tr>
<td>$C_r$</td>
<td>half length of the rear track</td>
<td>0.796m</td>
</tr>
<tr>
<td>$a$</td>
<td>distance from the front track to CoG</td>
<td>1.235m</td>
</tr>
<tr>
<td>$b$</td>
<td>distance from the rear track to CoG</td>
<td>1.465m</td>
</tr>
<tr>
<td>$\tau$</td>
<td>steering ratio</td>
<td>31.5</td>
</tr>
<tr>
<td>$M_t$</td>
<td>total mass of the host vehicle</td>
<td>1880kg</td>
</tr>
</tbody>
</table>

Table B-2: Result of Parameter Identification for the 4 Contact Point Vehicle Model
B-2 Cross Validation

![Graphs showing the results of steering ratio identification for drivers No.2 and No.3.](image)

**Figure B-1**: Result of Steering Ratio Identification of driver No.2

**Figure B-2**: Result of Steering Ratio Identification of driver No.3
Figure B-3: Result of Steering Ratio Identification of driver No.4

Figure B-4: Result of Steering Ratio Identification of driver No.5
Figure B-5: Result of Steering Ratio Identification of driver No.6

<table>
<thead>
<tr>
<th>Lateral Position</th>
<th>Heading Angle</th>
<th>Lateral Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>97.3755</td>
<td>96.3404</td>
<td>98.8854</td>
</tr>
<tr>
<td>99.6249</td>
<td>99.6897</td>
<td>99.6366</td>
</tr>
<tr>
<td>97.5783</td>
<td>97.1766</td>
<td>98.5758</td>
</tr>
</tbody>
</table>

Table B-3: VAF value comparing predicted and measure data for driver NO.2 (in percentage)

<table>
<thead>
<tr>
<th>Lateral Position</th>
<th>Heading Angle</th>
<th>Lateral Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>97.6512</td>
<td>98.6746</td>
<td>99.1300</td>
</tr>
<tr>
<td>99.4503</td>
<td>99.4169</td>
<td>99.5041</td>
</tr>
<tr>
<td>99.3002</td>
<td>99.4220</td>
<td>99.4685</td>
</tr>
</tbody>
</table>

Table B-4: VAF value comparing predicted and measure data for driver NO.3 (in percentage)

<table>
<thead>
<tr>
<th>Lateral Position</th>
<th>Heading Angle</th>
<th>Lateral Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>96.9912</td>
<td>97.5826</td>
<td>98.1235</td>
</tr>
<tr>
<td>99.2648</td>
<td>99.1353</td>
<td>99.1235</td>
</tr>
<tr>
<td>99.4024</td>
<td>99.4153</td>
<td>99.5418</td>
</tr>
</tbody>
</table>

Table B-5: VAF value comparing predicted and measure data for driver NO.4 (in percentage)
Table B-6: VAF value comparing predicted and measure data for driver NO.5 (in percentage)

<table>
<thead>
<tr>
<th>Lateral Position</th>
<th>Heading Angle</th>
<th>Lateral Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>90.1525</td>
<td>95.8116</td>
<td>97.9378</td>
</tr>
<tr>
<td>99.0751</td>
<td>99.2235</td>
<td>99.3055</td>
</tr>
<tr>
<td>99.3001</td>
<td>99.3853</td>
<td>99.4890</td>
</tr>
</tbody>
</table>

Table B-7: VAF value comparing predicted and measure data for driver NO.6 (in percentage)

<table>
<thead>
<tr>
<th>Lateral Position</th>
<th>Heading Angle</th>
<th>Lateral Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>95.5237</td>
<td>98.3019</td>
<td>98.4268</td>
</tr>
<tr>
<td>99.2528</td>
<td>99.3468</td>
<td>99.3516</td>
</tr>
<tr>
<td>99.4496</td>
<td>99.5445</td>
<td>99.5880</td>
</tr>
<tr>
<td>driver NO.</td>
<td>horizon (m)</td>
<td>$k_p$</td>
</tr>
<tr>
<td>------------</td>
<td>-------------</td>
<td>---------</td>
</tr>
<tr>
<td>1</td>
<td>59.3825</td>
<td>3.6823</td>
</tr>
<tr>
<td>2</td>
<td>59.9377</td>
<td>4.8524</td>
</tr>
<tr>
<td>3</td>
<td>61.7339</td>
<td>5.1351</td>
</tr>
<tr>
<td>4</td>
<td>69.4009</td>
<td>5.2544</td>
</tr>
<tr>
<td>5</td>
<td>66.3087</td>
<td>4.2607</td>
</tr>
<tr>
<td>6</td>
<td>66.9426</td>
<td>5.0133</td>
</tr>
<tr>
<td>7</td>
<td>65.6235</td>
<td>5.0130</td>
</tr>
<tr>
<td>8</td>
<td>61.8888</td>
<td>5.4841</td>
</tr>
<tr>
<td>9</td>
<td>65.9610</td>
<td>4.7124</td>
</tr>
<tr>
<td>10</td>
<td>66.0690</td>
<td>5.1652</td>
</tr>
<tr>
<td>11</td>
<td>65.9347</td>
<td>4.7966</td>
</tr>
<tr>
<td>12</td>
<td>60.1109</td>
<td>4.3905</td>
</tr>
<tr>
<td>13</td>
<td>72.0980</td>
<td>4.0550</td>
</tr>
<tr>
<td>14</td>
<td>63.6873</td>
<td>4.4583</td>
</tr>
<tr>
<td>15</td>
<td>62.7630</td>
<td>4.3949</td>
</tr>
</tbody>
</table>

Table C-1: List of identified controller parameters for consistent driver group
Appendix D

Fundamentals in Statistics

D-1 The general linear least square problem

Consider an overdetermined system:

\[ \sum_{j=1}^{n} X_{ij}\beta_j = y_i, \quad (i = 1, 2, \ldots, m), \quad (D-1) \]

of \( m \) linear equations in \( n \) unknown coefficients, \( \beta_1, \beta_2, \ldots, \beta_n \), with \( m > n \).

The optimal coefficients \( \beta \) are found solving the quadratic minimization problem:

\[ \hat{\beta} = \arg \min_{\beta} S(\beta) \quad (D-2) \]

where the objective function is given by

\[ S(\beta) = \sum_{i=1}^{m} |y_i - \sum_{j=1}^{n} X_{ij}\beta_j|^2 \quad (D-3) \]

D-2 SSE

In a model with a single explanatory variable, the sum of squared errors of prediction is given by,

\[ SSE = \sum_{i=1}^{n} (y_i - \hat{y})^2 \quad (D-4) \]

where \( y_i \) is the \( i^{th} \) value of the variable to be predicted, \( \hat{y} \) is the predicted value of \( y_i \).
D-3 R-squared

Based on comparing the variability of the estimation errors with the variability of the original values,

\[ R^2 = 1 - \frac{SSE}{SST} \]  \hspace{1cm} (D-5)

In the above definitions,

\[ SST = \sum_{i=1}^{n} (y_i - \bar{y})^2, \quad SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2, \]  \hspace{1cm} (D-6)

where \( y_i, \hat{y}_i \) are the original data values and predicted values. \( SST \) is the total sum of squares.

D-4 RMSE

The root-mean-squared-error (RMSE) of predicted values \( \hat{y}_i \) for the \( i^{th} \) value of a variable \( y \) is computed for \( n \) different predictions as the square root of the mean of the squares of the deviations:

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \] \hspace{1cm} (D-7)

D-5 VAF

VAF computes the percentage Variance Accounted For (VAF) between two signals:

\[ v = (1 - \frac{\text{var}(y - \hat{y})}{\text{var}(y)}) \cdot 100\% \] \hspace{1cm} (D-8)

where \( \text{var} \) is the variance of a signal.

The VAF is often used to verify the correctness of a model, by comparing the real output with the estimated output of the model.


List of Acronyms

3mE   Mechanical, Maritime and Materials Engineering  
DCSC  Delft Center for Systems and Control  
TU Delft Delft University of Technology  
TNO   Netherlands Organization for Applied Scientific Research  
DAVI  Dutch Automated Vehicle Initiative  
FCO   four consecutive overtaking  
PD    proportional-derivative  
TTC   time-to-collision  
VAF   variance accounted for  
SSE   sum-of-square error  
RMSE  root-mean-square error