Online Estimation of Roll Relevant Vehicle Parameters

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Internship Report

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Eindhoven, March 2016

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DAIMLER

TU/e Technische Universiteit Eindhoven University of Technology
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Source cover picture [1]

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Summary

This report describes the results from a three month internship in which the online estimation of roll relevant vehicle parameters was investigated. Especially for Sports Utility Vehicles (SUV) it is of interest to have knowledge on the vehicle loading conditions while driving. Sport Utility Vehicles usually experience more body roll due to a higher center of gravity (CoG), additional load further increases the height of the CoG and therefore body roll. As shown in this report, one possibility to get a measure for vehicle loading is estimating the roll gradient (German: Wankwinkel Gradient: WG) while driving. With this information future vehicles can be equipped with a refined adaptive ESC system. When vehicle load is low and within limits, a sporty setting with less restrictive functionality of the Active Rollover Mitigation (ARM) could be selected. If vehicle loading is high, body roll increases and therefore roll over may occur at lower lateral accelerations. Due to this risk current vehicles are equipped with a conservative ARM setting based on the maximum vehicle load. An adaptive setting will result e.g. in a more agile vehicle and a higher lateral acceleration level, which the driver can reach with an unloaded vehicle.

The Static Stability Factor (SSF) shows that a clear difference between roof loaded and non-roof loaded vehicles can be identified. Since the SSF discribes the roll limit of the vehicle, online estimation was performed of the roll gradient. This gradient discribes the relation between lateral acceleration and body roll. Based on the calculated SSF for different loads, the roll gradient will be significantly larger for vehicle with a roof load. Also in-vehicle loads should be detectable, however the increase of WG is expected to be smaller for in-vehicle loads in comparison to roof loads. The combined CoG of the vehicle and load is key for the final value of WG. The offline calculated benchmarks, based on steady state cornering maneuvers, prove this hypothesis.

Next the online estimation process needs to be developed and improved. Since not all driving situations suit well for estimating the parameter WG, bounds on different signals have been set. This includes general bounds like velocity v_x, steer angle δ and maximal acceleration/deceleration $a_{x_{max}}$. These bounds were set to exclude special, extreme or uncertain driving situations from the estimation process. Since quasi-stationary parameters were estimated, dynamic driving cases, for example slalom maneuvers are excluded by a 3 step estimation protocol. First, estimation is constrained by the roll rate $\dot{\phi}_E$. Second, in order to ensure a stationary driving state, a "switch on" delay was included on this on/off signals. Finally, some roll excitation is needed to obtain reasonable values of the estimated parameters, i.d. the lateral acceleration has to exceed some threshold for a cumulated time dT_{ay} of e.g. 5 seconds.

Based on measurement data, slalom maneuvers are found not to correspond to representative driving behavior on public roads. Especially high frequency steering inputs result in hysteresis due to friction and/or damping within the suspension/tires. This phenomenon was not present at similar lateral acceleration levels in public driving. Driving data sets from tests on public roads result in an accurate estimations using the protocol described before. So a clear difference between cases with and without roof load is visible. Also a trend with increasing in-vehicle loads was observed. Generally WG increases slightly with the addition of in-vehicle loads (about 3 %), a structural increase (about 12 %) is observed when adding a roof load of 100 [kg]. Based on the estimated WG a decision can be made to select the corresponding ESC level being either conservative or sporty.

Finally a reset logic needs to be implemented at every stand still combined with a door opening or an ignition switch. This has not been implemented in the Simulink model, since each

measurement was used in a separate simulation starting with the initial conditions. Therefore the reset logic would not have been triggered in the simulations. A more detailed analyses is needed to conclude about estimation process at bad road conditions. Future research can also focus on maximal vehicle load and limited roof loads (e.g. 20 [kg]). Additionally known vehicle data like fuel levels and passenger sensors could be used in the WG estimation process. For air sprung vehicles the change in WG due to the changed spring stiffness at high loads is also of interest.

Acknowledgement

I would like to specially thank J. Dürnberger M.Sc. for providing the opportunity at Daimler and his support, assistance and guidance during my internship. Furthermore, I would like to thank employees and fellow trainees of the department RD/FFD for the friendly atmosphere, advice and support.

Finally, I would like to thank Dr.ir. I.J.M. Besselink and Prof.dr. H. Nijmeijer for their efforts, which resulted in the internship at Daimler.

Contents

Chapter 1

Introduction

This report is a result of a three month internship, conducted at Daimler AG in Böblingen from September 1st until November 30th 2015. During this period a project related to the estimation of roll over parameters has been performed at the department RD/FFD, which focusses on research in the field of Vehicle Dynamics.

1.1 Problem Statement

Additional weight, vehicle load or passengers, influences the driving dynamics of vehicles due to the change of the location of the center of gravity. This can influence vehicle behavior, e.g. under- and oversteer, pitch, yaw, body roll and many more. For some specific vehicles with a high center of gravity and/or a short wheelbase, adding weight is more critical and can result in roll over at lower lateral accelerations. This mainly holds for SUV's, but also vans and pickup trucks are at risk. These vehicles are more sensitive to roll over, due to the high position of the body. Especially this type of vehicles can experience a roll over at lower lateral accelerations, simply by adding weight in the trunk of the car, transporting passengers or adding a roof load.

Roll over accidents can be prevented with safety systems like ESC, Electronic Stability Control. Within ESC, the ARM function, Active Roll over Mitigation, is used for this purpose. This system intervenes at critical lateral accelerations with brake interventions. SUV's usually have a more conservative setting by default since SUV's are more notorious to roll. Additionally an effective roll over prevention requires brake interventions at an early stage of cornering. Without any load detection, the ARM function is selected for the maximal load case with the highest center of gravity, since this is the most critical situation. However for optimal performance in both loaded and unloaded driving conditions, the ARM-function needs to be adapted according to the loading condition of the vehicle. Therefor an indicator on the vehicle load must be determined. In this research an important parameter will be investigated which is representative for the vehicle loading condition: the roll gradient. Simultaneously also a roll angle offset will be determined. Additionally, the system needs to estimate these parameters with data from existing sensors present in current vehicles, since additional sensors will increase the cost of the total vehicle. The goal of the project is to investigate if the roll gradient can be used to find the vehicle loading condition and determine the setting of the ARM function. Therefore an accurate and reliable relation between WG estimation and vehicle load of the test vehicle should be observable.

1.2 Project Description

The goal of the project is to detect the vehicle loading condition while driving, with use of the estimated roll gradient and roll angle offset. The estimation process will be tested on multiple measurement datasets of a Mercedes-Benz SUV, driven in many different driving situations, both (quasi-)stationary and dynamic. This data is used to estimate parameters and check and/or improve the estimation process.

In order to estimate the roll gradient and offset accurately, first the correct signals and sensor offsets need to be selected, investigated and processed. The selected sensor data will be used in a Recursive Least Squares approach to estimate the gradient. Therefore different bounds and inputs like initial conditions, covariances and forgetting factors need to be observed and compared in order to achieve a reliable and fast estimation process. Daimler already provides a MATLAB script and Simulink model, which were used as a basis for the optimization process. The MATLAB script is mainly used to introduce vehicle parameters and to store measurement data to the Workspace. The Simulink model consists of a complete offline vehicle simulation models which includes the vehicle sensors and systems. The estimation submodels for the roll gradient and roll angle offset were adapted and optimized within this internship project. A more detailed explanation of the relevant submodels are provided in the next chapters.

1.3 Research Questions

The project can be summarized in the following Research Questions:

- Is it possible to determine and distinguish vehicle load from available sensor data?
- Which input signals from vehicle sensors should be used?
- Which method or protocol can be used best for the estimation of the Roll Gradient?

1.4 Report Content

This report first discusses the Static Stability Factor, SSF. This factor gives a measure for the sensitivity of roll over of the vehicle based on vehicle specifications. Next the roll gradient, or in German: Wankwinkel Gradient, WG is introduced and discussed. The estimation process is described in more detail, covering some background information about the used models and measurement equations. The report continues with a description of measurement data and signal selection. Results of offline estimations are shown and offline benchmark values are given. Next a comparison to online estimation and final validation is provided together with the limits of the RLS-algorithm. Finally conclusions, recommendations and future research is discussed.

Chapter 2

Static Stability Factor

A measure for the sensitivity of roll over of a vehicle is the Static Stability Factor, SSF. The SSF is used worldwide by OEM's and governments to indicate roll over stability. Tests relating to the SSF are part of vehicle homologation and applied by programs/institutes like NCAP (New Car Assessment Program) and NHTSA (National Highway Traffic Safety Administration). This chapter gives some background information and values for the SSF.

2.1 SSF introduction

The SSF indicates how much lateral acceleration a_y is needed to roll over the vehicle in a static situation. This factor is a relation between the lateral and vertical force which are present in cornering situations. The formula for the static stability factor are given below:

$$SSF = \frac{F_y}{F_z} = \frac{m \cdot a_y}{m \cdot g} = \frac{a_y}{g} \tag{2.1}$$

For SSF values larger than 1, more than 1 [g] is needed to roll the vehicle, for SSF values smaller than 1, less than 1 [g] is needed. Regarding safety, a higher SSF is preferred since for higher SSF's a higher lateral acceleration is needed to roll over the vehicle. To give a indication of the SSF a graphical interpretations is displayed in figure 2.1.

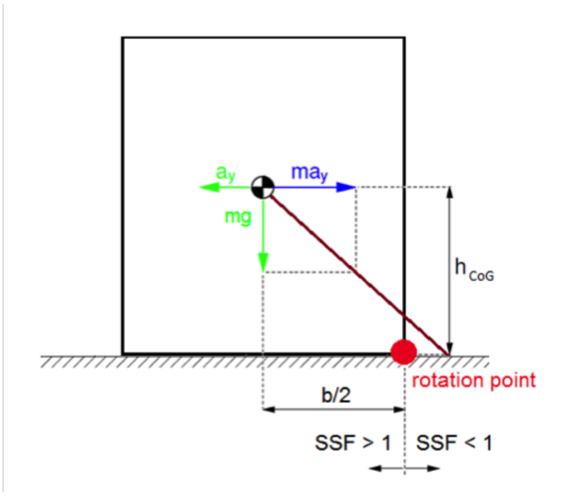

Figure 2.1: Illustration of the SSF

Furthermore, the SSF can also be expressed in relation to vehicle dimensions, track width and height of CoG. Since the total height of the center of gravity is changed when a load is added to the vehicle, also roll behavior and therefore the SSF is changed. This relation is obtained from the rolmoment equation which is rewritten in equation 2.3:

$$m \cdot g \cdot \frac{b}{2} = m \cdot a_y \cdot h_{CoG} \tag{2.2}$$

$$SSF = \frac{a_y}{g} = \frac{b}{2} \div h_{CoG} \tag{2.3}$$

The height of the center of gravity changes, if the vehicle is loaded. The picture below describes the situation and the total center of gravity of the loaded vehicle can be calculated with the following formula:

$$h_{CoG} = \frac{m_{veh} \cdot h_{CoG_{veh}} + m_{load} \cdot h_{CoG_{load}}}{m_{veh} + m_{load}} \tag{2.4}$$

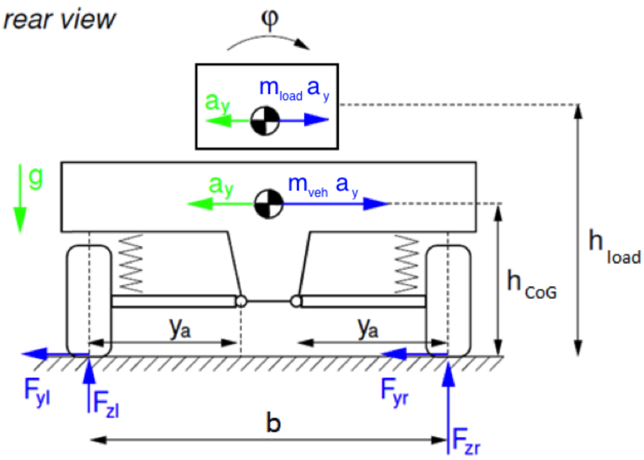

Figure 2.2: Illustration of loaded vehicle [2]

2.2 Calculated SSF values

For this research several measurements were performed with a Mercedes-Benz SUV on test tracks and public roads. Also several vehicle configurations were tested, with different loads at different locations in the vehicle. For these configurations the SSF values were calculated. The vehicle configurations can be divided in two groups, roof- and non-roof loaded vehicles.

2.2.1 Configurations

The different vehicle loads and locations are described below. Note that detailed information on the mass locations and center of gravity are confidential, and are therefore not described in this report:

- Driver - located at driver seat, with a mass of circa 80 [kg]
- Co-Driver - located at passenger seat, with a mass of circa 80 [kg]
- Back seat load - located at the rear seats, with a mass of 100 [kg]
- Trunk load - located in the trunk of the vehicle, with a mass of 100 [kg]
- Roof load - located symmetrically and asymmetrically on the roof, with a mass of 100 [kg]

With use of the mass and coordinates, the center of gravity of the loaded vehicle is calculated in order to determine the SSF for each load case. The SSF values are listed in table 2.1. Due to confidentiality reasons the height of the center of gravity was set to an artificial value in these calculations.

2.2.2 Non-roof loaded vehicle SSF

The static stability factors for non-roof and roof loaded configurations are mentioned below. Note that these values are for indication purposes only.

Table 2.1: Overview, SSF indication

Non-roof loaded vehicles		Roof loaded vehicles	
Driver	1.165	Driver & Roof load	1.101
Driver & Co-driver	1.149	Driver, Co-driver & Roof load	1.088
Driver & Back seat load	1.145	Driver, Back seat & Roof load	1.085
Driver & Trunk load	1.155	Driver, Trunk, Roof load	1.094
Driver, Back seat & Trunk load	1.136	Driver, Back seat, Trunk & Roof load	1.079

2.2.3 Conclusions

Based on the calculated SSF's for the different loading conditions the following conclusions are made:

- A loaded vehicles initiates roll over at lower lateral accelerations a_y since the SSF is lower
- The ARM-function of the ESP should therefore intervene earlier for loaded vehicles
- The addition of roof loads lowers the SSF by circa 5 [%]
- Location, mainly height and weight of the load determine the influence of the added weight on the roll over behavior. E.g. a roof load has a larger influence compared to a trunk load of the same weight due to height difference.

Chapter 3

Roll Gradient

For calculating the SSF the maximum lateral acceleration has to be known, which is usually not available unless you have reached the limit already. Thus the SSF can be used as a measure for the roll criticality, but cannot be estimated online representing the current loading condition. Therefore other parameters, which can differentiate according to the current loading condition, have to be observed in order to create an adaptive ESC setting. The roll gradient, or in German Wankwinkel Gradient (WG), shows such desired behavior and thus it was selected for further investigation. The WG is the slope of the line which describes the behavior of body roll ϕ_E with respect to the lateral acceleration a_y. The roll gradient basically describes the roll stiffness of the vehicle. $WG = [°/(m/s^2)]$, where the unit of the roll stiffness is represented by $c_\phi = [°/Nm]$. The only key difference is that WG is 'normalized' by the mass.

The following equation describes the relation between the roll angle and lateral acceleration, where ϕ_E is the body roll angle and ϕ_{E0} the offset:

$$\phi_E = WG \cdot a_y + \phi_{E0} \tag{3.1}$$

$$WG = \frac{\phi_E - \phi_{E0}}{a_y} \tag{3.2}$$

The equation holds only one unknown, namely WG. The lateral acceleration a_y is measured during driving and body roll angle ϕ_E can be derived from measured wheel travel sensors. In figure 3.1, an example of this relation is given. Here the x-axis represents the lateral acceleration a_y, the y-axis the roll angle ϕ_E with an expected offset at 0 $[m/s^2]$ and the slope equals WG:

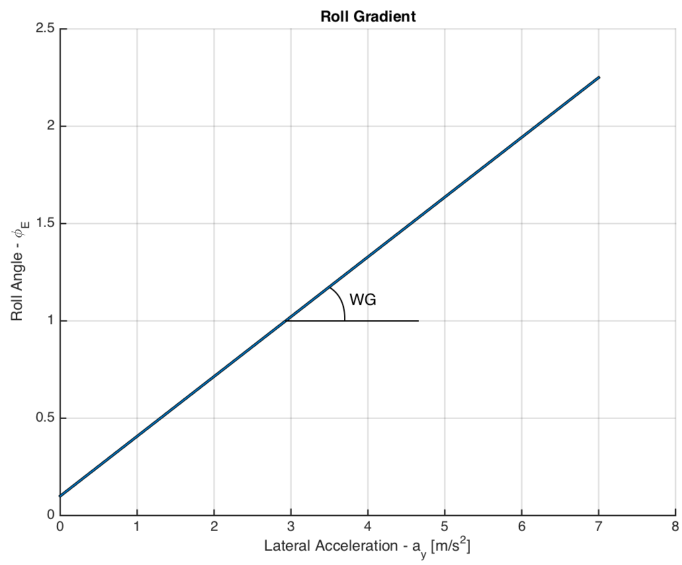

Figure 3.1: Illustration of the roll gradient

3.1 Motivation

WG is expected to be able to differentiate between the different loading conditions since the additional load increases the height of the center of gravity. This will result in higher levels of body roll at the same lateral acceleration. The exact weight and location of the added mass will determine the increase of WG compared to the unloaded vehicle. For in-vehicle loads - like passengers and trunk load - a slight increase of WG is expected. However, for roof loads a significant increase is expected since this type of load increases the height of the center of gravity much more compared to in-vehicle loads due to its location, high of the ground.

Additionally, WG is expected to be different for left and right cornering due to asymmetric vehicle loads. If only a driver is present in the car, a mass is present only on the left side of the vehicle. This would result in a static roll angle ϕ_{E0} for $a_y = 0$ and this can result in varying roll angles at similar lateral accelerations for left and right turns. In order to investigate this hypothesis, the WG need to be estimated individually for left and right corners.

Chapter 4

Roll gradient estimation

The roll-over sensitivity should be obtained from current sensor data, since addition of separate sensors is initially not preferred or possible. To conclude, the roll gradient (WG) needs to be estimated based on wheel travel and lateral acceleration. The roll gradient can not be measured directly since there is no sensor to measure it.

The estimation process is first tested and verified using a framework simulation model provided by Daimler, which has been used for simulations as was well as vehicle prototype-ECU testing. This framework simulation model was used for calculating the vehicle motion, sensor error correction and parameter estimation.

Together with vehicle measurement data, real world driving can be simulated. Changes in the WG estimator model need to be compared to a benchmark in order to validate if modifications improved the process. Therefor a set of benchmarks needs to be determined for the different driving conditions and vehicle loading conditions. By comparing the online calculated WG value to the benchmark, a conclusion can be made about estimat accuracy. This chapter describes the WG estimations and the offset ϕ_{E0} in more detail and explains how the benchmark was obtained from offline processed measurement data. First the simulation model is described briefly.

4.1 Simulation model

At the start of the internship a framework simulation model was provided. This model included a WG estimation block as a base for further improvements of the estimation process. This chapter contains some brief background information concerning this model and provides an overview of its working principles.

4.1.1 Initial Model

The framework simulation model is build up from several individual components. First some unit transformation and general calculations of measurement data are performed and collected in organized busses. Note that both conventional signals, which are available in every production car, and additional measurement signals are used. Daimler test vehicles generally are equipped with additional sensors, which result in more accurate measurements or to include specific signals which are not measured in production vehicles. These signals are not used for the final estimation process, since the estimation should be performed with available sensor data of production vehicles.

After pre-processing the model is divided in multiple blocks. For this research the parameter estimation block is of interest in particular. Within the parameter estimation block, multiple sub blocks were placed for different parameters and purposes. From these estimation blocks the roll gradient block is of main interest.

4.1.2 Roll Gradient estimation model

The estimation block for the roll gradient is used to estimate WG for online simulation. The block consist of the following components:

- First signal preparation is performed:
  - The body roll angle ϕ_E is calculated from the wheel travel signals
  - The vehicle forward velocity is calculated and validated
  - Noisy signals were filtered with a second order low pass filter, all with cut-off frequency 20 $[Hz]$ & $\eta = 0.7$
- Roll gradient WG is estimated with use of the following components:
  - On/off conditions are processed and an on/off signal for the estimation process is created
  - Signals are separated for left and right cornering based on the sign of the lateral acceleration. A separate WG estimator is made for left and right since the test vehicle shows asymmetric roll behavior. More details are provided in the next chapters.
  - RLS algorithm which estimates the WG and offset based on input data and on/off signal

The provided estimator model was modified and extended to improve the estimation process and it is used to investigate and validate several estimation strategies.

4.2 Online- versus offline Estimation

While driving, the on board vehicle sensors will collect data, which will be processed to decide about the actual driving state of the car. This data is currently used for various applications and safety systems within the car. In order to conclude on the vehicle load and roll-over probability of the vehicle, one main parameter is of interest: the roll gradient WG. Since this parameter is not directly measurable, it needs to be estimated while driving (online) from other signals. In order to estimate this parameter, two signals need to be used: the vehicle body roll angle and lateral acceleration. The online estimation process can be reproduced with use of Matlab Simulink and the framework simulation model, described in the previous chapter.

4.2.1 Online Estimation

The online estimation mimics the vehicle data processing in Simulink with measured data as input for the vehicle model. This results in an estimated WG for every stored measurement point, just like in the vehicle while driving. When using measurement data as input, future data is known, however only current values were used in the model. As it would occur in real world driving of the vehicle. For the online estimation of WG, the Recursive Least Squares (RLS) method is applied, using results form previous time steps to obtain a more robust parameter estimator. More details about the online approach will be provided in the next chapters, first the offline approach is discussed in more detail.

4.2.2 Offline Estimation

In contrast to online estimation, offline estimation uses all data points of the measurement to determine actual values that represent the vehicles behavior. Therefore, offline estimation is based on the same measurement data as online estimation, however the complete dataset is used. By fitting a curve on the complete measurement, a model is obtained which represents the vehicle behavior accurately. This model was used further on as benchmark for the online estimation. For offline estimation, the Least Squares (LS) approach is used to estimate parameters, since all data is available and no iterations are required.

Note that for offline estimation only steady state cornering maneuvers are used. This maneuver is performed on a test track for left and right corners individually. Due to the fixed corner radius and increasing vehicle speed, the lateral acceleration increases and an increasing body roll can be observed. Measurements show a linear relation between lateral acceleration and body roll angle, up to high lateral accelerations. These measurements proved to be ideal for determining the benchmark values due to the linear response of the steady state cornering maneuvers. Therefor the slope was constant for the complete range of lateral acceleration.

4.3 Measurement Equation

In this research, the roll gradient WG is calculated by a RLS algorithm using the following inputs: 1) lateral acceleration and 2) roll angle. A linear model, equation 3.1 is applicable as linear behavior was observed in the in measurement data. The measurement equation is given below:

$$y = d_0 \cdot x_0 + d_1 \tag{4.1}$$

Within this relation x_0 is the measured lateral acceleration a_y^M. y is the measured body roll ϕ_E^M, d_0 represents the roll gradient WG and d_1 the offset ϕ_{E0}. Substitution results in:

$$\phi_E^M = WG \cdot a_y^M + \phi_{E0} \tag{4.2}$$

The unit of the measured signal a_y is $[m/s^2]$, the roll angle ϕ_E [°] was calculated from individual measured wheel travels $[mm]$.

4.3.1 Wheel Travel

Body roll is normally not directly measurable on passenger cars. Therefore roll angle needs to be derived from other, available signals. For adaptive ESC the roll angle with respect to the road is of main interest, since the road usually has a slope for drainage of (rain)water. The roll angle of the body in the center of gravity with respect to the road can be derived from wheel travel sensors. Wheel travel is measured individually for each wheel and together with the suspension geometry and the location of the center of gravity, body roll can be calculated.

4.3.2 Roll Angle

The roll angle is calculated based on measurement data of individual spring/wheel travels. The formula compensates for different track widths of the front and rear axle and calculated body roll at the center of gravity. Note that the roll angle calculation is simplified by excluding the tire deflection, therefor the actual body roll will be slightly larger.

Figure 4.1 graphically shows the parameters which are used for the transformation of the average wheel travel of the front and rear axle to the center of gravity. Symbols are introduced on the following page.

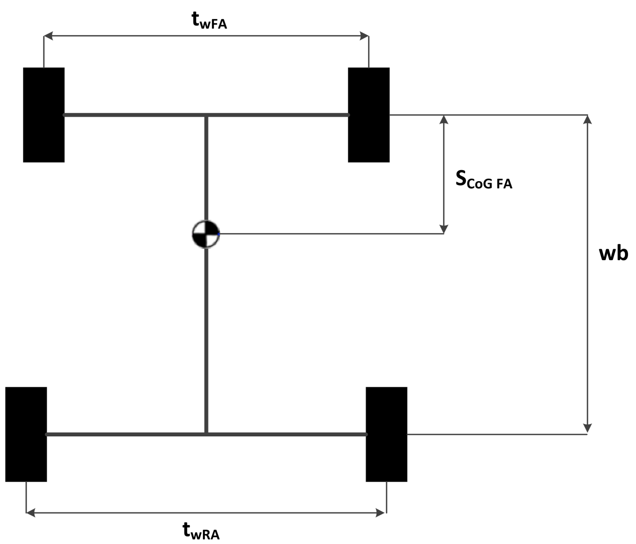

Figure 4.1: Illustration of wheel travel transformation to roll angle in CoG

The following parameters are used for determining the roll angle:

- $s_{FR/L}$ = wheel travel Front Right/Left (measurement data),
- $s_{RR/L}$ = wheel travel Rear Right/Left (measurement data),
- wb = vehicle wheel base (parameter),
- tw_{FA} = track width Front Axle (parameter),
- tw_{RA} = track width Rear Axle (parameter),
- $s_{CoG_{FA}}$ = distance CoG - Front Axle (parameter)

In order to calculate the roll angle in the center of gravity first the imaginary track width needs to be determined in the center of gravity. This value can be found by adding a offset to the front track width, this offset is calculated as follows: $\frac{(tw_{RA}-tw_{FA})}{wb} \cdot s_{CoG_{FA}}$
Next this offset is added to the front track width to calculate the imaginary track width in the center of gravity. When the average wheel travel of the front and rear axles are divided by the imaginary track width, the roll angle is calculated in the center of gravity, like mentioned in equation 4.3:

$$\phi_E\ [rad] = \frac{\frac{1}{2} \cdot (s_{FR} - s_{FL}) + (s_{RR} - s_{RL})}{2 \cdot ((\frac{1}{2} \cdot tw_{FA}) + (\frac{1}{2} \cdot \frac{(tw_{RA}-tw_{FA})}{wb} \cdot s_{CoG_{FA}})} \tag{4.3}$$

Equation 4.3 is further simplified to:

$$\phi_E\ [^\circ] = \frac{180}{\pi} \cdot \frac{1}{2} \cdot \frac{(s_{FR} - s_{FL}) + (s_{RR} - s_{RL})}{2 \cdot ((\frac{1}{2} \cdot tw_{FA}) + (\frac{1}{2} \cdot (tw_{RA} - tw_{FA}) \cdot s_{CoG_{FA}})/wb))} \tag{4.4}$$

Since the vehicle can potentially have different roll gradients for left and right cornering due to asymmetric loading or vehicle configuration, two RLS blocks were applied in the online Simulink model, one for left- and one for right cornering. For the offline calculation two separate calculations were performed for left- and right cornering. The individual RLS blocks are switched on/off based on the sign of a_y (left on, if $a_y >= 0$ and vice versa). Note that RLS inputs like initial conditions and covariances are similar for left and right estimation since similar values and uncertainties are expected when the vehicle load is unknown. Based on measurement input the RLS algorithm then gives the corresponding value for the roll gradient WG. Information about possible asymmetric loading is included in wheel travel data, creating a roll angle offset ϕ_{E0}.

4.4 Initial Conditions

The RLS algorithm is the key component of the estimator model, it finds a linear fit based on current measurement data and previous iterations. It makes an estimate for WG and ϕ_E considering initial conditions and a forgetting factor. The following initial conditions were applied:

- Initial Covariance $d0\_0 = 0.3$
- Initial Covariance $d1\_0 = 0.3$
- Forgetting factor $\lambda = 0.998$
- Reset $rst = 0$ (not used for measurements)
- Initial value WG $th0\_0 = 0.35$
- Initial value offset ϕ_{E0} $th1\_0 = 0$

Both covariances are set to 0.3 since both parameters, WG and offset ϕ_{E0}, have a similar uncertainty and the response of the estimation process is fast enough. A relative high forgetting factor of 0.998 is used since mass can change quickly. For example if some passengers enters the vehicle, additional mass is added to the car and roll behavior changes. Note that the reset function was not used in the simulations since only one measurement data set per simulation is used. Generally the estimation need to be reseted if the vehicle mass could be changed, e.g. if the vehicle is standing still in combination with a door opening.

The Initial value WG is set to 0.35, since for offline estimation of steady state cornering expected roll gradients should be in the range of 0.31 to 0.39 for different load cases. Therefor a value in the middle of the lower and upper bounds has been selected. The initial offset was set to zero because the offline estimation showed very little offset.

4.5 Used Signals

The measurement data used in this report was collected from a Mercedes-Benz SUV during experimental driving on test tracks and public roads. In order to investigate variations of the roll gradient different loading conditions were applied. Furthermore steady-state and dynamic maneuvers were performed. The steady-state measurements, used for benchmark calculation, were both performed for left and right turns since the vehicle is expected to be slightly asymmetric.

4.5.1 Load Cases

Roof load is generally known to negatively influence the roll over probability of a vehicle. Therefor two groups of measurements were performed, without- and with roof load. Additionally a co-driver, loads at the rear seat and trunk were tested. Finally a asymmetric roof load was tested in order to evaluate the roll gradient for asymmetric applications. For this load case a higher WG is expected on the loaded side of the vehicle, since the CoG is shifted laterally towards the added mass. The load cases are given on the following page.
The tested loading conditions are displayed in table 4.1.

Table 4.1: Overview, tested loading conditions

Non-roof loaded	Roof loaded
Driver	Driver & Roof load
Driver & Co-driver	Driver, Back seat & Roof load
Driver & Back seat load	Driver, Trunk, Roof load
Driver & Trunk load	Driver, Back seat, Trunk & Roof load
Driver, Back seat & Trunk load	Driver & Asymmetric roof load

4.5.2 Maneuvers

For the different loading conditions, a set of maneuvers were performed on both test tracks and public roads.

- Steady state cornering, left and right - for offline estimation (Benchmark)
- Slalom, at multiple speeds and frequencies
- Public road driving:
  - Inner city driving
  - Mountain road driving

Both sporty and more conservative driving styles were applied. Also dry and wet road conditions were tested and analyzed.

4.5.3 Test Conditions

Future vehicles should be able to estimate the roll gradient WG and the offset during driving on public roads. Therefore multiple test were performed on test tracks and public driving tests performed on roads in regular traffic. Some public driving measurements were performed in Spain on mountain roads, but also secondary- and intercity roads were tested near Stuttgart, Germany. Both sporty and conservative driving styles were considered to test the estimation process for different driving styles.

In order to visualize the roads, vehicle GPS data was used to plot the trajectory on OpenStreetMaps. In figure 4.2 an example of a test run is given, note that several driving conditions were tested, e.g. low speed-, straight line driving and different corner radius at multiple speeds.

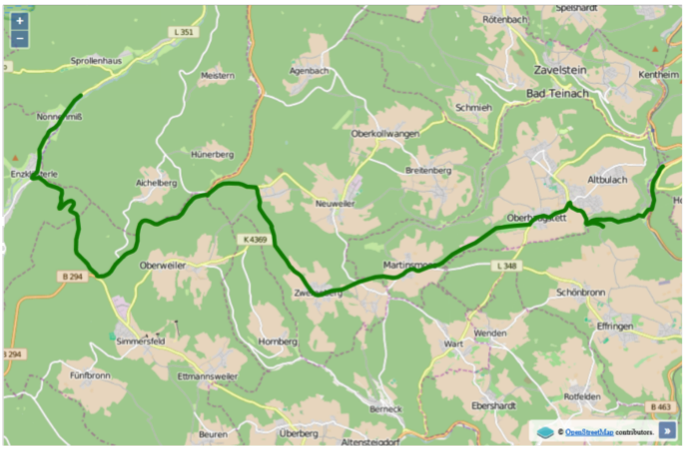

Figure 4.2: Example of public road driving route

For all tests, one vehicle was used to maintain uniform measurement results. Test were performed in dry and wet conditions, which proved not to influence the roll gradient estimation. Fuel levels and other variables were monitored and kept constant as much as possible. Concerning loading, the heaviest tested loading condition consist of a Driver (80 $[kg]$), Roof (100 $[kg]$), Rear seat(100 $[kg]$), & Trunk load (100 $[kg]$) resulting in a combined load of about 380 $[kg]$. Note that the vehicle was not tested with maximal additional load (800 [kg]). Also measurements with small (roof) loads, e.g. a roof load of 20 $[kg]$ are not considered in this report.

4.5.4 Steady State Cornering

For every loading condition tested, left- and right steady state cornering measurements were performed. Since steady state cornering is the perfect maneuver for estimating the roll gradient, this data is used to obtain the benchmark values by offline calculations. The steady state maneuvers are ideal since a constant radius is kept while the vehicle speed is slowly increased. Hereby a slight, constant increase of lateral acceleration and roll angle is measured. Since only one steering direction is applied for each steady state measurement (left or right), hysteresis due to friction and/or damping is excluded which results in a more accurate results.

In figure 4.3, the roll angle - calculated from wheel travel data - is plotted against the lateral acceleration. The linear relation between the roll angle and lateral acceleration is clearly visible. Due to the linear behavior of the body roll a linear model or first order polynomial fit can be used to estimate the vehicle's roll gradient WG.

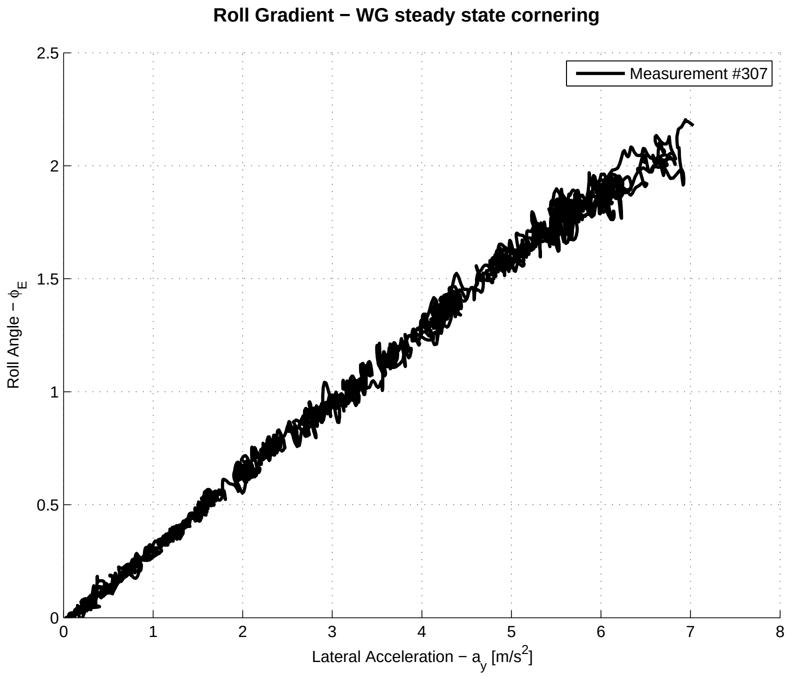

Figure 4.3: Steady state cornering measurement

Since the roll gradient shows a linear relation between the lateral acceleration a_y and roll angle ϕ_E in the measured range, the offline estimation was performed using a polynomial fit on the available data using a Least Squares (LS) approach. The results from offline estimation of steady state corner maneuvers are used as benchmark values. When the online estimated values for WG and ϕ_{E0} correspond to the benchmark values, the proper settings for the estimation process are achieved.

For steady state cornering it can be concluded that no hysteresis is present and the measurements show an almost perfect linear behavior.

4.5.5 Slalom

For a dynamic maneuver (slalom) with a frequency of circa 0.5 Hz the roll angle ϕ_E as a function of lateral acceleration a_y is shown. In figure 4.2, the hysteresis due to the shifting body movement is clearly visible. The hysteresis is caused by friction and/or damping within the suspension and tires. Due to the hysteresis, the stationary parameter WG can not be estimated for these dynamic measurements with the simplified measurement equation 4.4.

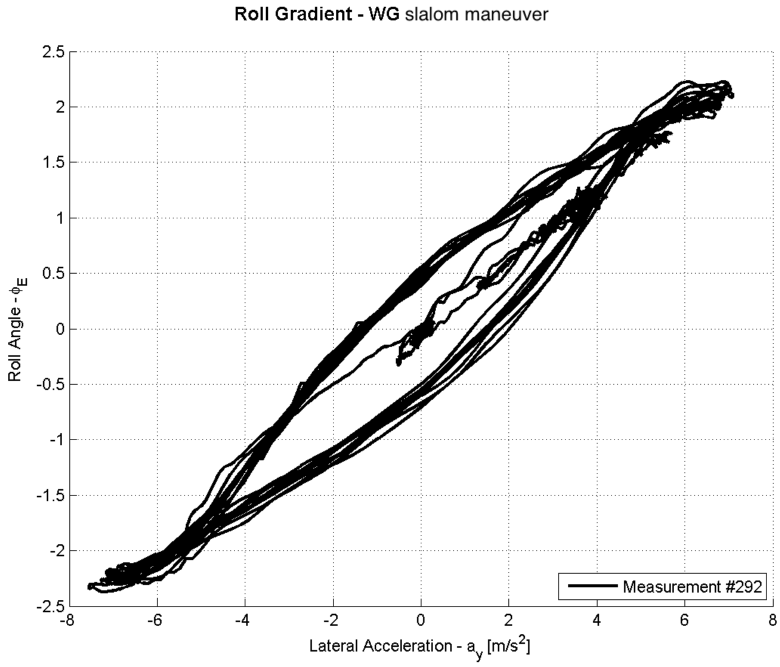

Figure 4.4: Slalom maneuver measurement

From the other measurement data and figure 4.4, the following conclusions can be made for slalom maneuvers:

- It is questionable whetter slalom maneuvers represents dynamic driving states which could occur in real world driving conditions.
- Significant rate dependent hysteresis is present, which also depends on the applied steering frequency.
- For frequencies near the eigen-roll frequency of the vehicle more hysteresis is present due to higher damping forces, for low frequencies (0.2 $[Hz]$) the hysteresis is limited.
- Low frequent slalom maneuvers may be usable for roll gradient estimation due to the limited amount of hysteresis. High frequent slalom maneuvers should be excluded totally from the estimation process.

4.5.6 Public Driving

In figure 4.5 the results of one example public driving measurement is plotted. It represents a typical public drive measurement:

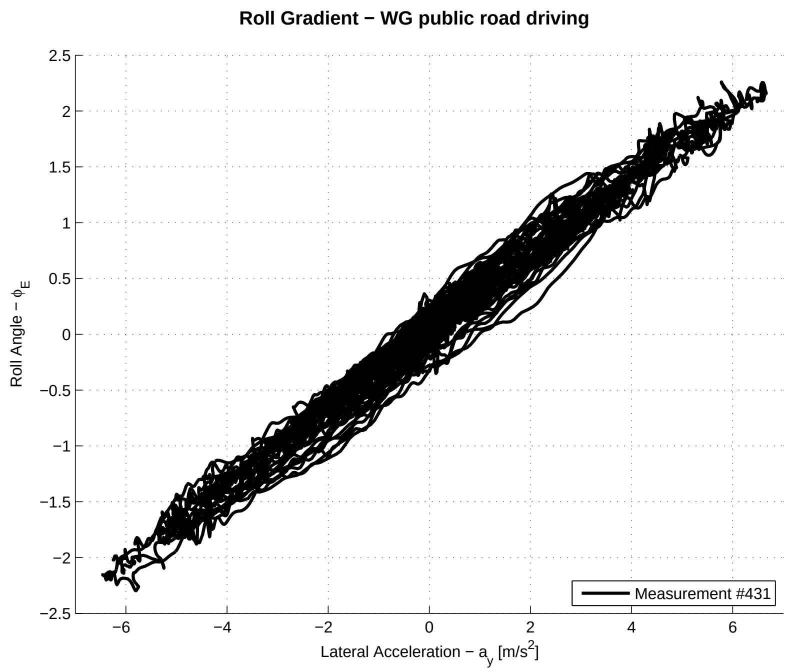

Figure 4.5: Public road driving measurement

From measurement data and figure 4.5, the following conclusions can be made for public driving:

- The driving states are mainly quasi stationary.
- Only little hysteresis is present compared to slalom maneuvers due to lack of dynamic maneuvers, and a low body roll velocity.
- The driving states show a linear roll behavior from zero to maximal lateral acceleration.

Chapter 5

Measurement Data

Most vehicles today process sensor data for built-in safety systems, this data can be stored and used later for offline simulation and validation of new systems or algorithms. In the test vehicle additional signals sources are available, which are more accurate compared to normal production vehicles. There are three sources relevant for this research: raw signals from the sensor cluster which are present in consumer vehicles, processed signals from the Electronic Stability Control (ESC) unit and the additional signals from the Measurement CAN which are only present in test vehicles.

5.1 Measurement Data Check

Before a specific dataset of a measurement is used for simulations, a check is performed to conclude about the measurement quality and driving conditions. A automated MATLAB script is used to plot measured velocity, steering wheel angle and steering wheel angle speed, yaw rate, longitudinal- and lateral acceleration and roll angle. All measurements were checked on data quality and measurements errors and plausibility checks were done. For the offline estimation of the roll angle WG, a more detailed research was done to obtain the most accurate results. For this research the roll angle and lateral acceleration were analyzed in more detail since they are key to estimate the roll gradient WG. In the following sections, more information is provided about the individual signals. First the measurement analysis will be discussed, which was used to check individual measurements.

5.2 Measurement Analysis

In order to analyze the different measurements, an automated MATLAB script was created. This script uses the Simulink framework simulation model to process the sensor data into usable estimator inputs. Next outputs were processed further when needed and selected in order to plot key signals to judge about the estimation process. Also major inputs of the framework simulation model and bound triggering signals e.g. velocity and roll angle were plotted and checked. Bound triggering signals can be used to exclude e.g. low speed maneuvers from the estimator to improve accuracy. Thanks to this automated script changes to the estimation process could be validated quickly since all plots were directly available. For the estimation process of the roll gradient WG the following signals were plotted:

- The roll gradient estimation equation was plotted, with a_y on the x-axis and ϕ_E on the y-axis. In the plot WG can be observed as the inclination and ϕ_{E0} as offset. Note that the data was divided in left and right turns.
- Second, the roll angle was plotted as a function of time.
- Also the roll gradient WG and offset estimation are plotted as a function of time
- The Covariance of the roll gradient WG and offset are added to observe the RLS performance.
- Finally the Estimation time is potted to identify the effective time which is used to estimate parameters considering the bound triggering signals.

In figure 5.1 one example is displayed for a public driving measurement, for each individual measurement similar plots were made.

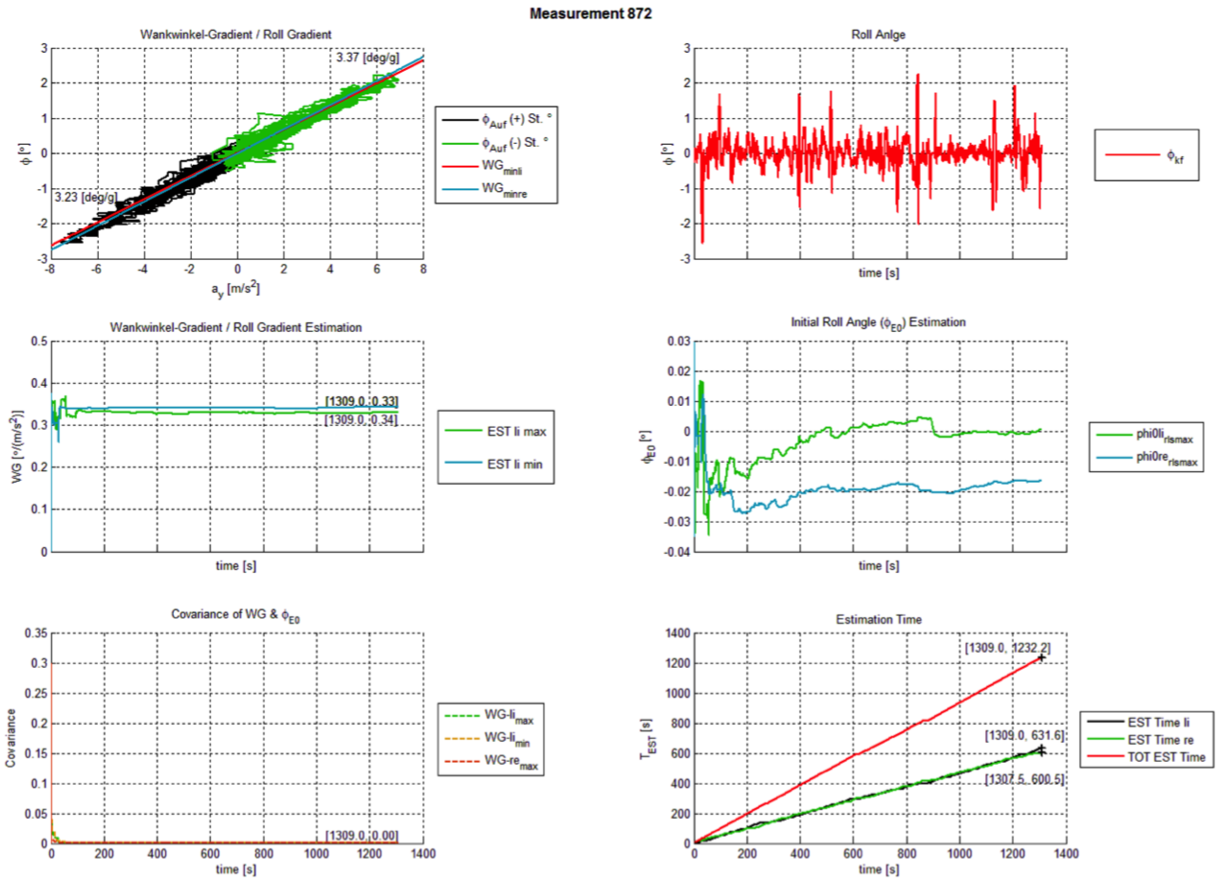

Figure 5.1: Example of measurement analyzing plot

Also input and bound triggering signals were plotted to validate and determine effective bounding values, which were valid for all measurements and corresponding driving states. This plot is not included in this report due to confidentiality reasons since it captures directly measured signals from the vehicle.

Chapter 6

Signal selection

Signals need to be selected for the offline calculation and online estimations. Two measurement signals for lateral acceleration are available and compared, which are named 'DCAN' and 'VEHACCEL_Y' further on. Since bounding of signals is often applied in estimation processes to eliminate non-linear behavior, bounded and unbounded input signals were checked. The bounds were also investigated individually, lower or upper bound only, since an unexpected influence of bounding was found. The following sections describe the available signals and motivation for the selected signals and bounding process.

6.1 Lateral Acceleration - a_y

The lateral acceleration is measured directly by a vehicle sensor during driving, for estimation purposes of the roll gradient WG, two signals were available: 'DCAN' and 'VEHACCEL_Y'. The signals originate from the same sensor, the main difference between the two signals is the processing. 'DCAN' is the raw, unfiltered and unprocessed acceleration signal, 'VEHACCEL_Y' is processed by the ESC unit and therefore slightly delayed. The ESC unit filters the signal and estimates the offset of the lateral acceleration, this offset is subtracted by the ESC unit to obtain a more accurate lateral acceleration. Furthermore the 'VEHACCEL_Y' signal is safety checked by the ESC unit, which result in a more reliable signal. If the signal proves to be an unlikely or impossible value the safety check of the ESC unit notifies and correct the value. In figure 6.1 both 'DCAN' and 'VEHACCEL_Y' are displayed, note that the x-axis represents the time:

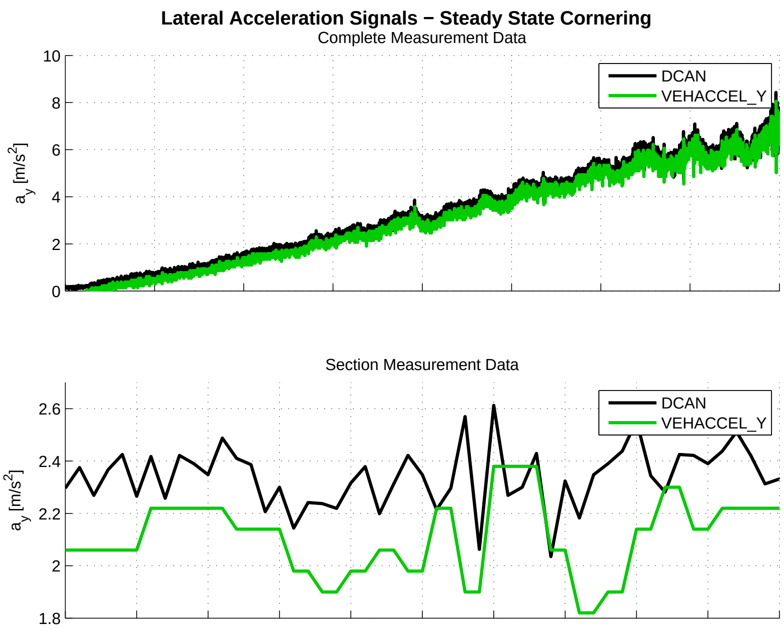

Figure 6.1: Lateral acceleration for steady state cornering

Both signals were considered for offline estimation, further on a comparison is done and 'VEHACCEL_Y' is selected for the estimation of the WG benchmarks and online estimation. From the plot can be concluded that overall the 'VEHACCEL_Y' has a smaller magnitude due to offset calculation of the ESC unit. The applied filtering is clearly visible since 'VEHACCEL_Y' shows a less fluctuated but delayed signal due to filtering by the ESC unit. Note that the offset compensation of a_y is not really necessary, since the a_y-offset would only influence the ϕ_{E0} estimation, but not the inclination of the estimation equation, namely the roll gradient WG.

6.1.1 Bound a_y - Linearity of Coil Springs

For a reliable benchmark of the roll gradient for different loading conditions, data bounds were considered to exclude measurement noise and improve the calculation and estimation process. Normally only data in the lateral acceleration range of 0.5 to 4 m/s^2 are considered in linear estimations, since the test vehicle was equipped with spring coils. These springs tend to have a non-linear behavior above 4 m/s^2. Data up to lateral accelerations of 0.5 m/s^2 are normally not considered since acceleration sensors are very noisy and steady state corner maneuvers, which were used for offline calculation of the benchmark, were only performed in one steer direction at a time. This lower bound is normally applied by default to prevent an estimation based on noise around 0 m/s^2 which corresponds to straight line driving. In figure 6.2 the 'VEHACCEL_Y' input signals for a_y is displayed, both bounded (green) and unbounded (black).

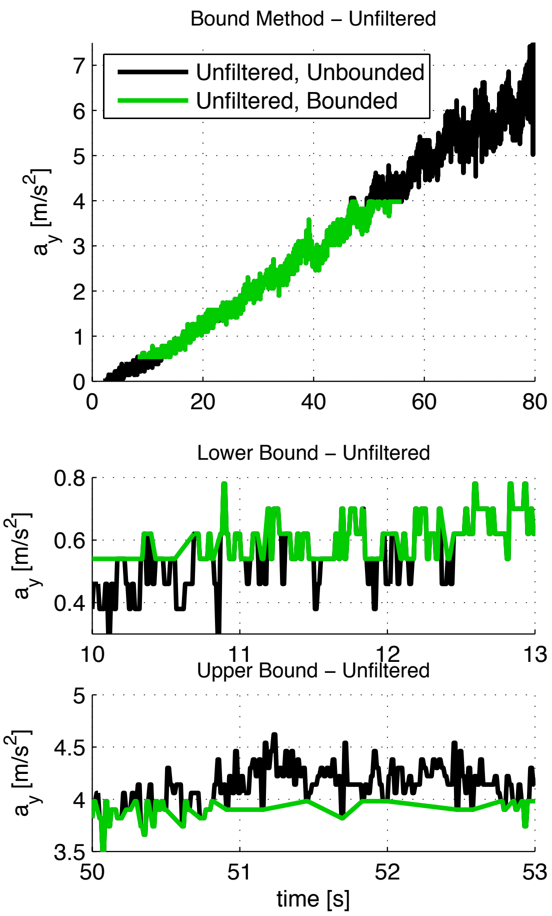

Figure 6.2: Bounded vs unbounded lateral acceleration a_y

However, when bounding was applied not all measurements result in a nice fit. Due to the reduced number of data points the estimate becomes less accurate since it is based on a limited range of data. When for example, the 0 to 0.5 m/s^2 lateral acceleration data is removed, a wrong calculated offset is obtained which also influences the slope of the fit (the roll gradient WG). The Least Squares approach provides a more representative fit if more data points are present. Note that for static (steady state cornering) and quasi-static driving situations, roll behavior appears to be linear up to lateral accelerations of 7 to 8 m/s^2. Therefore no upper bound is required.

6.1.2 Conditions Comparison

The following signals and methods will be compared in order to determine the best signals for the most accurate offline calculation of benchmark values:

- 'DCAN' vs 'VEHACCEL_Y'
- Filtered vs unfiltered data (both a_y and ϕ_E)
- Bounded vs unbounded
  - Minimal- and maximal a_y bound
  - Minimal a_y bound only
  - Maximal $a_y$bound only

6.2 Rating Methods

In order to conclude which combination of signals, conditions and processing need to be applied for the most accurate benchmark calculation of the roll gradient, the following methods were used to determine a final estimation method: standard deviation, correlation coefficient and finally the values of the roll gradient estimates. Both signals for the lateral acceleration a_y ('DCAN' and 'VEHACCEL_Y') and filtered and bounded signals were compared. The results are described in the following sections:

6.2.1 Standard Deviation

The standard deviation of the error between the measured roll angle and the polynomial fit of the roll gradient was considered in order to conclude about the quality of the offline estimation. The results of all conditions for individual steady state measurements are displayed in figure 6.3.

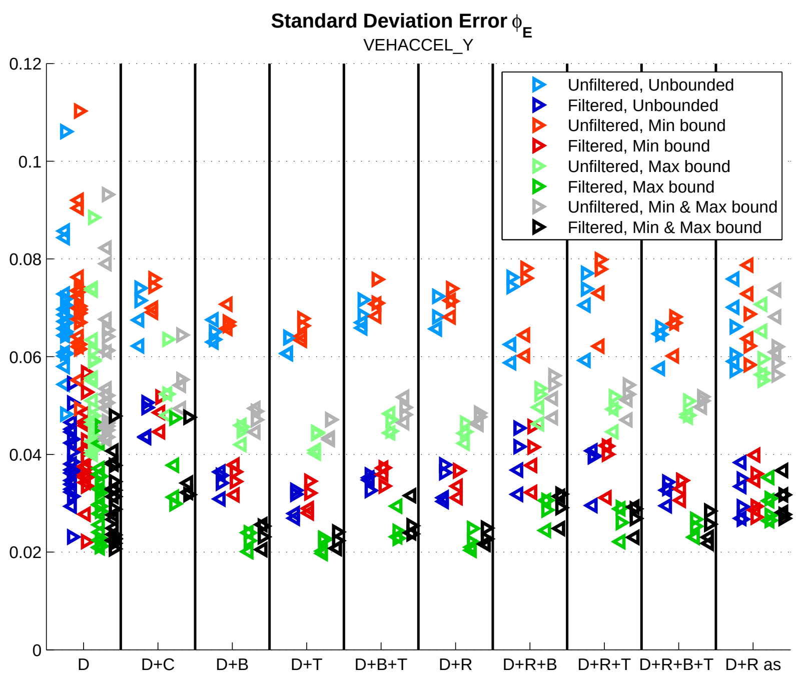

Figure 6.3: Standard deviation of the error between measured roll angle and polynomial fit of WG, y-axis represent the roll gradient WG

Note that left cornering is indicated by a left arrow, and right cornering by a right arrow, the symbols on the x-axis correspond to the load cases described in table 4.1 (D = Driver, C = Co-driver, B = Back Seat-, T = Trunk-, R = Roof- and as = Asymmetric roof load)

The following conclusion can be made from figure 6.3:

- When 'DCAN' and 'VEHACCEL_Y' are compared (only 'VEHACCEL_Y' is shown in this report) the results are identical, however 'DCAN' shown slightly lower standard deviations for filtered signals since the signal is more smooth compared to 'VEHACCEL_Y'. Based on standard deviation no decision on signal choice can be made, since the differences are very small.
- A clear difference in standard deviation between filtered and unfiltered data is shown in the figure. Since filtered data has suppressed influence of noise, the standard deviation of the error is smaller. Therefore, filtered data is preferred.
- When a maximal bound is applied, this holds for both max and min & max bounded data, the lowest standard deviation is found together with the smallest dispersion between individual measurements.

6.2.2 Correlation Coefficient

The correlation between the measured lateral acceleration and roll angle was investigated by considering the correlation coefficient. This coefficient concludes about the relation between these signals. A coefficient of 1 results in perfect linearity of the different signals, since the relation between lateral acceleration and roll angle is expected to be linear, at least within the selected range, a coefficient close to 1 is expected. The lateral acceleration and roll angle could be shifted in time, but only the different filtering and bounding methods are compared. The base signals in the comparison are equal.

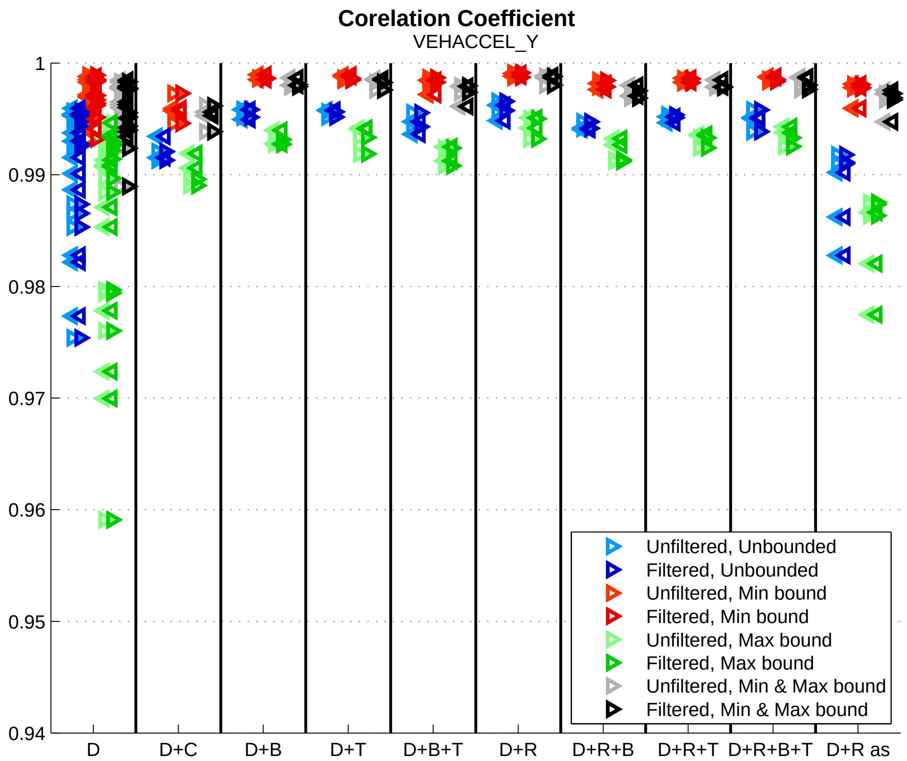

Figure 6.4: Correlation coefficient, y-axis represent the roll gradient WG

Based on the correlation coefficient of the individual steady state measurements the following conclusion can be made:

- Equal to the standard deviation, when 'DCAN' and 'VEHACCEL_Y' are compared the results are identical, however 'DCAN' shown slightly higher correlation coefficients since the signal is more smooth for filtered signals. Based on this differences no decision about signal choice can be made.

- Filtered data shows equal correlation compared to unfiltered signals, since the signal is not structurally changed, only noise is filtered.
- When a minimal bound is present, so for both min and min & max bounded data, the highest correlation is found. Therefore can be concluded that data around the origin influences the model negatively. The minimal bound influences the correlation negatively since it has quite a lot of noise. Therefor the correlation of a lot of points in the range of 0-0.5 m/s^2 is not good. However, for the parameter estimation these data points are of great importance in order to determine an plausible offset ϕ_{E0}.

6.3 Conclusion on offline estimation

In order to conclude about the estimation conditions of WG, the parameter is estimated for the different conditions. The final results are compared and plotted in figure 6.5, note that the marker size refers to the standard deviation (large marker = large std):

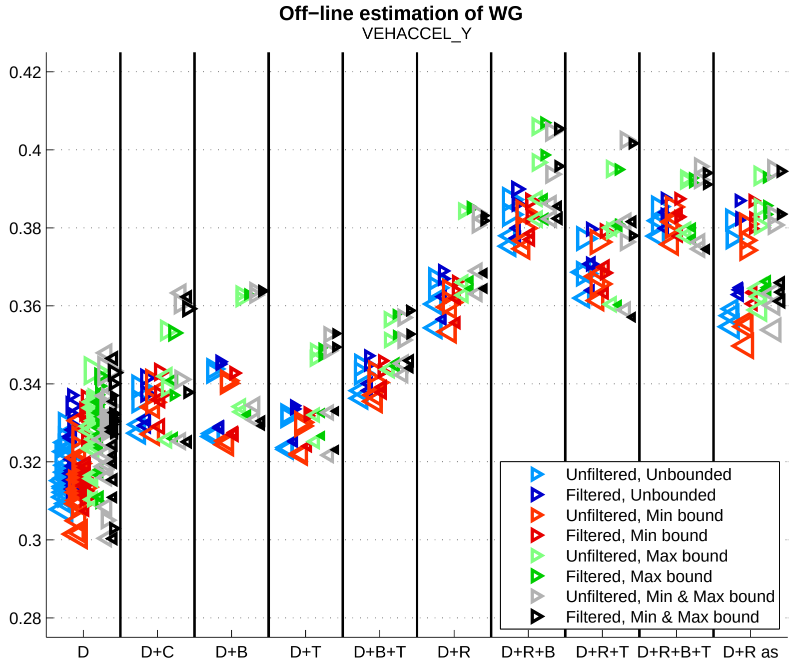

Figure 6.5: Roll gradient estimations, y-axis represent the roll gradient WG

Since all load cases show similar behavior, the results for load case 'driver only' are displayed in figure 6.6 to give a more clear overview. Note that this load case is tested more often compared to other load cases and therefore more estimations could be compared:

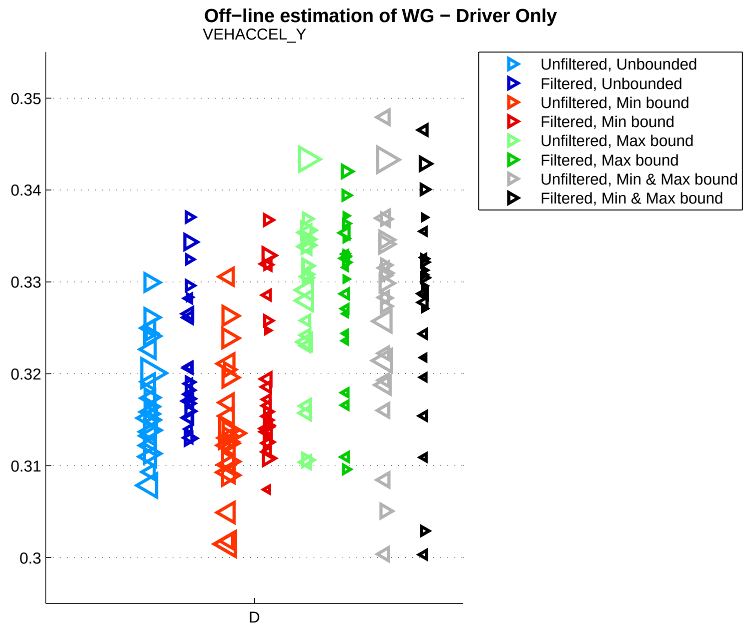

Figure 6.6: Roll gradient estimations Driver only, y-axis represent the roll gradient WG

When the WG estimations are compared, the following conclusions can be made:

- When 'DCAN' and 'VEHACCEL_Y' are compared the results show more dispersion between individual estimations for the 'DCAN' signal. Since only limited measurements are available, the signal with least dispersion is preferred, so 'VEHACCEL_Y' would be preferable.

- Filtered data shows generally higher WG estimations, with less dispersion compared to unfiltered estimations. Filtering will therefor be applied, since filtered data shows less standard deviation.

- The different bounding methods results in mixed conclusions:

  - Adding a bound results in a larger dispersion between individual WG estimations for similar load cases, when both minimal and maximal bounds are applied the largest dispersion is found. Based on this fact, unbounded data would be preferred.

  - Filtered unbounded 'VEHACCEL_Y' data is preferred since this combination results in the best compromise: low dispersion between individual measurements (lowest compared to all other conditions), relative low standard deviation due to filtering and a high correlation coefficient (above 0.975). Finally, 'VEHACCEL_Y' corresponds to the wheel travel data in terms of phase since these signals originates from the same source with similar filtering and delay. This source, the ESC unit, also safety checks the values, therefore it is more reliable.

No bounding of data was applied since the measurement data showed linear behavior over the complete range of measured lateral acceleration and measured roll angle. Therefor the roll gradient could be modeled by a linear polynomial fit for the complete measurement range. The average slope of each loading condition and turning direction is the benchmark value for the roll gradient WG. Furthermore the average offset at zero lateral acceleration is the benchmark ϕ_{E0}. By filtering measurement data a slight improvement of estimation was found, especially the standard deviation was improved by filtering, as expected. Therefor filtered input signals were used.

6.4 Calibration

For online vehicle estimation a calibration should be included once for a ready-to-run configuration. At straight line driving on a flat surface, the roll angle of the vehicle should be stationary and the offset should be used to calibrate the roll angle measurement. Initial roll could be present due to asymmetric loading or vehicle configuration, e.g. different engine and transmissions, and options like a glass roof. This calibration should be done for the vehicle with all liquids filled up and a driver in the car, which is the most likely driving state. For the test data this was checked manually since all measurements were performed with a single vehicle and controlled driving conditions.

The acceleration sensor is not placed in the center of gravity of the vehicle. For the estimation process no transformation was applied for this offset, since the error due to this offset was negligible. Also no transformation of the changed CoG was performed when the test vehicle was loaded.

Note that for validation purposes, measurement data of the wheel travel was recalibrate due to offset problems, but this was only necessary for the available measurements files of the used test vehicle.

6.5 Filtering

Earlier, filtering was discussed. Generally signals are filtered using the same filter to obtain equal phase shifts for signals that were processed together. Next to the input signals for the RLS algorithm, also bounding signals used for the on/off signal are considered. Sensor signals were filtered with use of a second order low pass filter, all with cut-off frequency 20 $[Hz]$ & $\eta = 0.7$. The following signals were filtered: a_y, a_x, ϕ_E, v_x and $\dot{\psi}$.

Chapter 7

Offline Benchmark values

With use of the measurement equations and the selected signals, the offline calculated roll gradient values WG were found for the different load cases. Note that all data points were used in combination with a Least Squares approach to obtain the most reliable fit for steady state cornering measurements. In the table 7.1 the offline estimated values WG and ϕ_{E0} are displayed:

Table 7.1: Overview, offline estimated benchmark

Load Case Vehicle	Abbreviation	Direct.	WG $[\frac{\circ}{g}]$	ϕ_{E0} [°]	Std.	Corr.
Driver	D	Left	3.13	-0.028	0.038	0.990
Driver	D	Right	3.18	-0.087	0.039	0.991
Driver & Co-driver	D+C	Left	3.24	0.076	0.044	0.992
Driver & Co-driver	D+C	Right	3.33	0	0.050	0.992
Driver & Rear seat load	D+B	Left	3.23	-0.015	0.034	0.995
Driver & Rear seat load	D+B	Right	3.39	-0.077	0.035	0.995
Driver & Trunk load	D+T	Left	3.19	-0.045	0.027	0.996
Driver & Trunk load	D+T	Right	3.28	-0.078	0.032	0.995
Driver, Rear seat & Trunk load	D+B+T	Left	3.33	-0.064	0.035	0.994
Driver, Rear seat & Trunk load	D+B+T	Right	3.39	-0.089	0.034	0.995
Driver & Roof load	D+R	Left	3.53	-0.016	0.031	0.996
Driver & Roof load	D+R	Right	3.61	-0.082	0.037	0.996
Driver, Roof & Rear seat load	D+R+B	Left	3.71	-0.035	0.034	0.994
Driver, Roof & Rear seat load	D+R+B	Right	3.81	-0.088	0.043	0.994
Driver, Roof & Trunk load	D+R+T	Left	3.60	-0.054	0.035	0.995
Driver, Roof & Trunk load	D+R+T	Right	3.68	-0.091	0.040	0.995
Driver, Roof, Rear seat & Trunk load	D+R+B+T	Left	3.75	-0.065	0.031	0.995
Driver, Roof, Rear seat & Trunk load	D+R+B+T	Right	3.78	-0.095	0.034	0.995
Driver & Asymmetric roof load	D+R as	Left	3.57	-0.083	0.033	0.986
Driver & Asymmetric roof load	D+R as	Right	3.77	-0.125	0.030	0.991

Based on the results, the following behavior can be concluded:

- For right cornering in all load cases, a higher roll gradient is present compared to left cornering. This effect could be caused by asymmetric vehicle characteristics due to small differences in individual spring stiffness and suspension components like e.g. bushes. Also in most cases, the vehicle is loaded asymmetrically since the driver is located at the left side. This is confirmed by the asymmetric roof load located at the drivers side. In that case the difference between left and right WG is enhanced compared to driver only since more weight is added to the left side of the vehicle. However, since this difference is structural and may change for each individual vehicles, parameter estimation should be split between left and right cornering.

- When the load within the vehicle (so no roof load) is increased, a gentle increase of WG is observable. This effect corresponds with the expectations since adding passengers or trunk load slightly increases the height of the center of gravity. This slight increase in height should indeed result in a gentle increase in body roll and therefor an increase in roll gradient.
- When a roof load is added to the different load cases, a clear and significant difference in WG is observable. This confirms the hypothesis that critical located loads can be identified by estimation of the roll gradient. Since the height of the roof load is drastically larger compared to in-vehicle loads, the roll gradient shows a significant increase.
- When only an asymmetric roof load is applied, a larger difference between left and right WG is found. Since the load was located at the left side of the vehicle, also a larger roll gradient is expected in left corners. This is confirmed by the measurements.

Below, the benchmark values for WG in different load cases are graphically shown in figure 7.1. Note that the abbreviations matches the load cases mentioned in the overview table. Further the size of the marker, left or right arrow, indicates the magnitude of standard deviation. A larger marker corresponds to a larger standard deviation and visa versa.

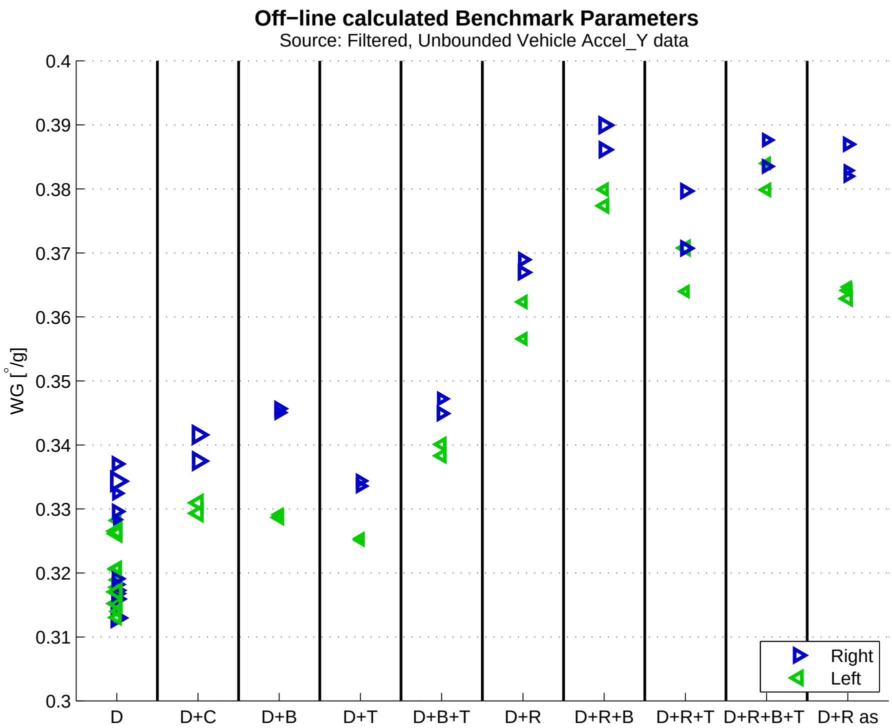

Figure 7.1: Off-line calculated benchmark roll gradient WG

7.1 Road Conditions

Note that for the load case, 'Driver' more measurements were performed in comparison to other loading conditions. The WG estimations for 'Driver' show a significant dispersion. When the individual measurement conditions were checked only one key difference was found. A series of measurements was performed on dry roads, the other on wet roads. However, for both situations similar maximal and minimal WG estimations are found. Therefor humidity conditions of the road are not influencing WG estimation. This can be confirmed by the fact that body roll is directly caused by, and depending on lateral acceleration. If due to road conditions, lateral acceleration is limited (e.g. due to limited friction by wet roads) also body roll is limited.

Chapter 8

Online estimation

After determining the reference roll gradient values using offline calculation, the next phase of the project is focussed on online estimation of dynamic maneuvers and public driving. To accurately estimate the roll gradient and offset bounding was considered to exclude selected situations which could negatively influence estimation. First only general bounds were considered, in order to determine the basic performance of the estimation process.

8.1 General Bounds

In order to exclude some extreme, uncertain or uncommon situations which would reduce the accuracy of the WG estimation, general bounds were applied to the measurement data. The following bounds were applied:

- If there was an ESP intervention or a brake intervention by an ADAS, advanced driver assistance system, WG is not estimated

Due to active single wheel brake interventions like they are performed by the ESP or ADAS, the vehicle behavior is changed and thus the estimation results may be less accurate.

- Only estimate if the vehicle velocity exceeds 20 km/h

The velocity of the vehicle v_x was bounded to exclude data at low speeds. This would not negatively affect the estimations since generally the body does not roll significant at low speeds since limited lateral acceleration a_y is present. The measurement signals are generally noisy for these conditions and in combination with little excitation makes it reasonable to bound v_x.

- Only estimate if the steering wheel angle is below 10°

The wheel steer angle δ is bounded to exclude parking maneuvers with very large steer angles. Note that for normal driving δ will not exceed 10°. Limiting the wheel steer angle is useful, since due to large caster angles the wheel travels at high wheel steering angles are changed by the suspension kinematics. Since the roll angle ϕ_E is calculated by the wheel travel, this effect may influence the WG estimation in an undesired way.

- Only estimate if vehicle longitudinal acceleration $|a_x| < \pm\ 3\ [m/s^2]$

Finally also the acceleration a_x is bounded to exclude medium and high acceleration and deceleration from the estimation process. Above the proposed limit, nonlinearities could occur in e.g. springs and other suspension components. Since this level of acceleration is not very common, it will not drastically decrease the number of measurement points.

After finishing the online Simulink simulation for each measurement considering general bounds, the online estimated values for the roll gradient WG are stored. The estimation accuracy was determined by comparing the online estimated values for WG to the offline calculated benchmark values. For each corresponding loading condition: Driver, Co-driver, Back Seat, Trunk and Roof load. An estimation is regarded bad if the online estimation varies more than 5 % compared to the benchmark. This value was chosen arbitrary however proved to be correct when estimations were analyzed.

Applying only general bounds, v_x, δ and a_x resulted in the following results where green icons represent a final online estimation within the 5 % range. Red icons vary more compared to the benchmark and are considered wrongly estimated:

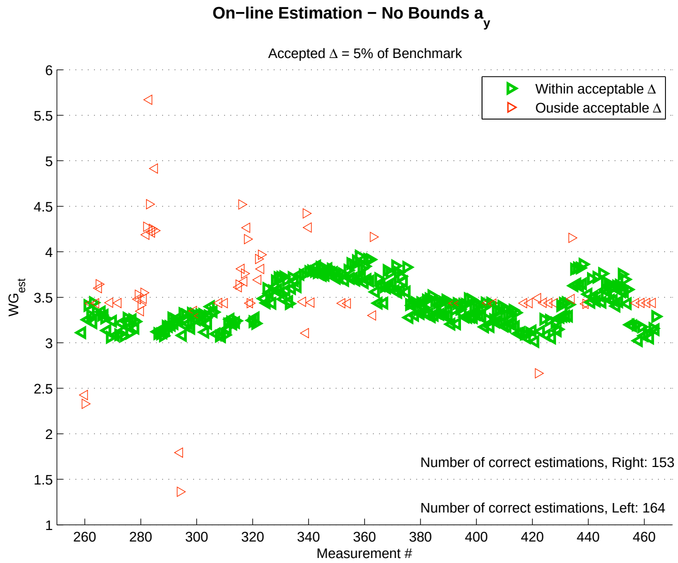

Figure 8.1: Online estimation results

Within an arbitrary selected estimation error bound of 5%, many WG estimations already match the offline calculated benchmark with only applying general bounds, marked in green in figure 8.1. Next, the number of bad estimations needs to be reduced and excluded from the estimation process. When the estimation process was checked for the incorrect estimated measurements, plotted in red, the following causes were found:

- Wrong estimations were based on measurements with too small lateral acceleration excitation, straight line driving, which can be observed as noise around $a_y = 0\ m/s^2$
- For high frequency maneuvers hysteresis is present since the roll behavior is non-linear like mentioned in section 4.5.5.

8.2 No general bounds applied

As a check also an unbounded simulation was performed, without applying the general bounds. These bounds resulted in more accurate estimations for left WG (157 to 164), but less for right WG (165 to 153) compared to the unbounded simulations. Therefor the total accurate estimations dropped from 322 to 317 by including the bounding process. However all general bounds are important for extreme conditions and not excluding this data points from the estimation could result in significant deviations for these conditions. Note that low speed maneuvers with high steering wheel angles influenced the simulations and resulted in large errors for the unbounded process. For the available measurement data, general bounds did not improved the number of correct estimations however, as for some specific driving conditions major errors are prevented. Also using general bounds proved to increase accuracy since present errors were smaller. The general bounds therefore will be applied in further simulations.

8.3 Bound on the lateral acceleration a_y

In order to reduce the noisy data around $a_y = 0$ and to minimize a possible influence of nonlinear spring behavior a_y bounding was considered. A minimal bound of $|a_y| = 0.5$ $[m/s^2]$ and a maximum bound of $|a_y| = 4$ $[m/s^2]$ was set, since the spring behavior is known to be rather linear in this range. Bounding the measurement data for the estimation process resulting in the following plots:

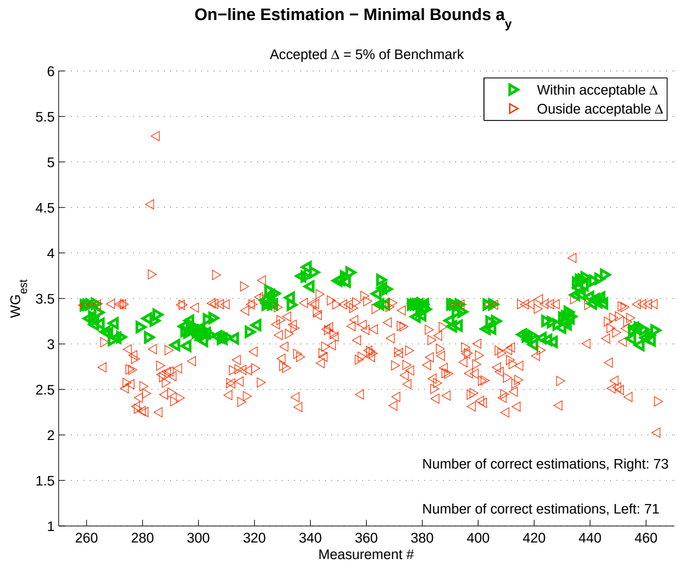

Figure 8.2: Online estimation results, minimal a_y bound

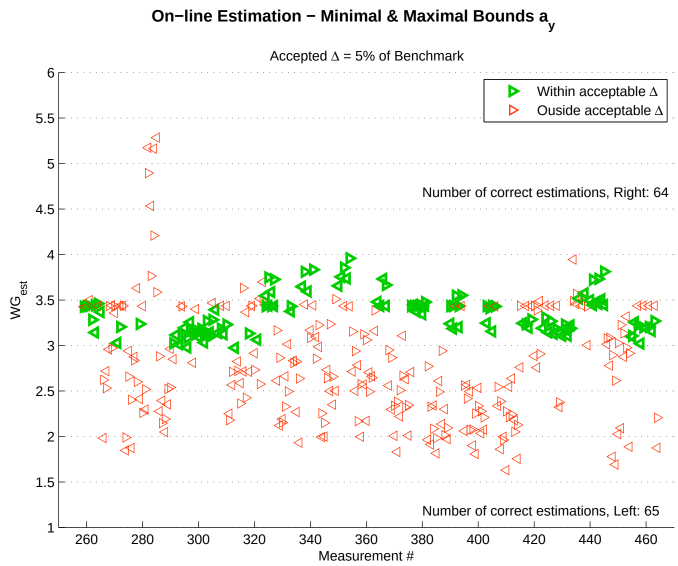

Figure 8.3: Online estimation results, minimal and maximal a_y bound

Both minimal as combined minimal and maximal bound of a_y did not result in more correct estimations, compared to figure 8.1 much more red icons are present which represent a bad WG estimation. In contrast, the loss of data resulted in more incorrect estimation and therefor bounding of a_y should not be considered for online estimation of WG. This conclusion was earlier also made for offline calculations, and proved to have similar response on online estimation. Note that the estimated values have a significant larger dispersion, when measurement data is excluded. Many values were estimated too low if data was removed, this is critical since for lower values a less conservative ESC setting will be allowed. Unjustified too low estimation of the roll gradient is therefor undesirable. However, if the value is estimated too high, a more safe ESC setting is chosen which would not result in critical situations. Therefor it is desired that if there is an estimation error, the roll gradient WG is accurate or estimated too high.

8.4 Exclude Hysteresis from Estimation

Since hysteresis was observed in the plot of the roll gradient for offline evaluation of dynamic maneuvers, the simple linear estimation equation is not valid for these conditions. Dynamic - especially slalom - maneuvers result in hysteresis, which makes an accurate WG estimation impossible. The behavior is simply not linear for these driving states and therefore the used estimation equations will not be valid any more. Therefore a non-linear equation could be applied, but this will result in a more complex estimation process. However dynamic driving states can also be excluded from the estimation process when a linear equation is considered, this last method is preferred and will be used in this research.

In order to exclude such dynamic driving states, they have to be identified. Generally, this could be done by any available dynamic signal. The derivative of such dynamic signal should be constant while driving steady state maneuvers. Since the task is to estimate a parameter related with the lateral and roll dynamics, bounding of the following signals is considered:

- The roll angle speed $\dot{\phi_E}$
- The yaw acceleration $\ddot{\psi}$
- The steering wheel angle speed $\dot{\delta}$

These signals could be used for this specific purpose since they all indicate changes in body roll. In this chapter a comparison of the signals is given and a selection is made.

Roll rate
The roll angle velocity or roll rate $\dot{\phi_E}$ is very closely related to the roll gradient estimation since the roll angle is used in the calculation of the estimation. Bounding on the derivative of this signal would therefor be an intuitive solution. However $\dot{\phi_E}$ is based on the derivative of ϕ_E which is calculated from wheel travel data, this signal therefore is processed most compared to the yaw acceleration and steering wheel angle speed. Processing like calculations and filtering needs some time which could delay the signal.

The use of a raw or less filtered signals could therefore improve estimation accuracy. Within the available signals two other signal could be used to identify the dynamic maneuvers and to overcome the shortcomings: yaw acceleration $\ddot{\psi}$ and steering wheel angle speed $\dot{\delta}$.

Yaw acceleration
The yaw acceleration $\ddot{\psi}$ is differentiated from measurement data of the yaw rate sensor. Note that this signal is filtered in the differentiation process since unfiltered differentiations are very noisy. The original measured signal $\dot{\psi}$ is already noisy and differentiating only increases the noise level. However this signal is considered since it behaves similar to the roll angle derivative. And since body roll is a result of the rotation of the vehicle around the z-axis, the yaw acceleration is expected to be less delayed compared to the roll angle derivative.

Steering wheel angle speed
The steering wheel is the input for the maneuvers performed. Therefore it would be the initial signal with the least amount of delay. However, the vehicle needs some time to settle and adapt to the steering inputs. Additionally this factor is speed dependent, a certain steering wheel angle speed could be dynamic for high velocities but not for low speeds.

The final WG estimation needs to be checked and validated in order to check which of the above signals can be used. There can also be other inputs that influence body roll, which are not present in the steering angle speed.

8.4.1 Comparison

The bound signals, roll angle speed $\dot{\phi_E}$, the yaw acceleration $\ddot{\psi}$ and steering wheel angle speed $\dot{\delta}$ are compared and results are showed below. Note that the signals are normalized since amplitudes vary due to different units and the steering wheel ratio. However not the amplitude, but the signals shape and behavior in time quantifies whether it could be selected or not. First the results for a slalom maneuver is given in figure 8.4, note that other slalom measurements with different speeds v_x and frequencies f show similar behavior:

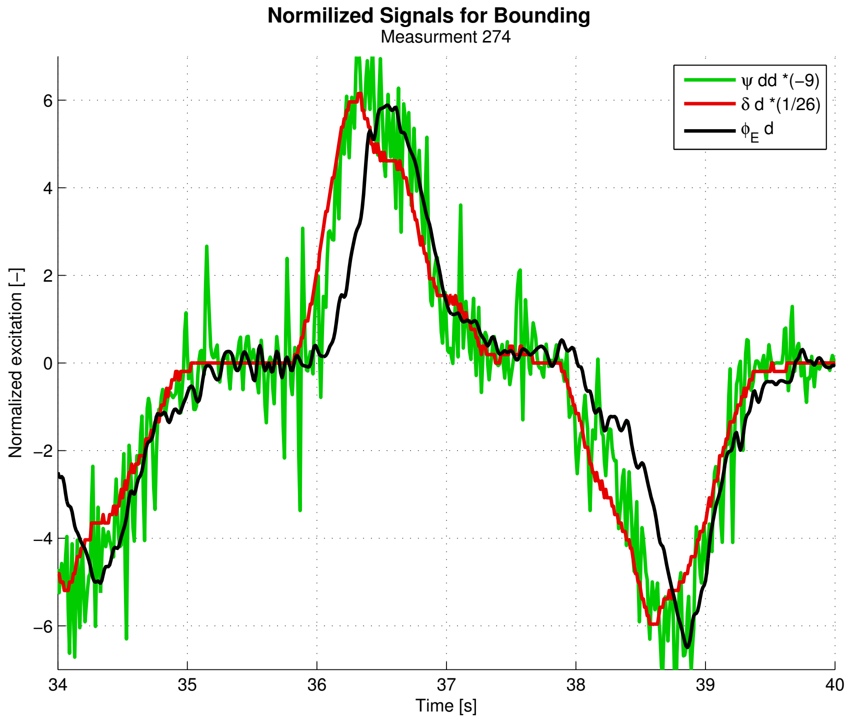

Figure 8.4: Normalized signals for bounding.

Note that the normalization factors used in figure 8.4 are mentioned in the legend.

For slalom maneuvers the following conclusion can be made: the three selected signals do show similar behavior and as expected a slight phase difference is present due to the different origins of the signals, calculations and filtering. The steering wheel angle speed is a raw signal directly measured in the vehicle. This signal shows the first change since it is the input of the driver, followed by the yaw acceleration and finally the roll angle speed. The body roll is caused by the lateral acceleration and thus this order is plausible.

Note that the yaw acceleration and roll angle speed, despite filtering still shows a relative noisy response. Further behavior which is present in the roll angle speed, is not visible in the steering wheel angle speed. E.g. the body of the vehicle can also roll due to other inputs from outside the vehicle. Effects like road slope, road surface and side wind are not directly represented in the steering wheel angle. These effects should be taken into account and are present in the roll angle speed since it is derived from wheel travel data. Therefor the final comparison of the online calculated roll gradient estimations need to determine, which signal is best for this estimated parameter.

8.4.2 Comparison of dynamic bounds

Bounds were selected based on measurement data in order to exclude high frequent behavior by momentarily switching off the estimator. The bounding values for the yaw rate, roll rate and steer angle speed are set at different individual values, such that the triggering moment is similar for each bounding signal. For the following bounds, online estimation is simulated in Simulink and final WG estimations are compared:

- Yaw rate $\ddot{\psi} < 0.25\ [\frac{rad}{s^2}]\ (\approx 14.3\ [\frac{\circ}{s^2}])$
- Roll rate $\dot{\phi_E} < 2.5\ [\frac{\circ}{s}]$
- Steer angle speed $\dot{\delta} < 50\ [\frac{\circ}{s}]$

Below, the results of the roll rate bound are displayed:

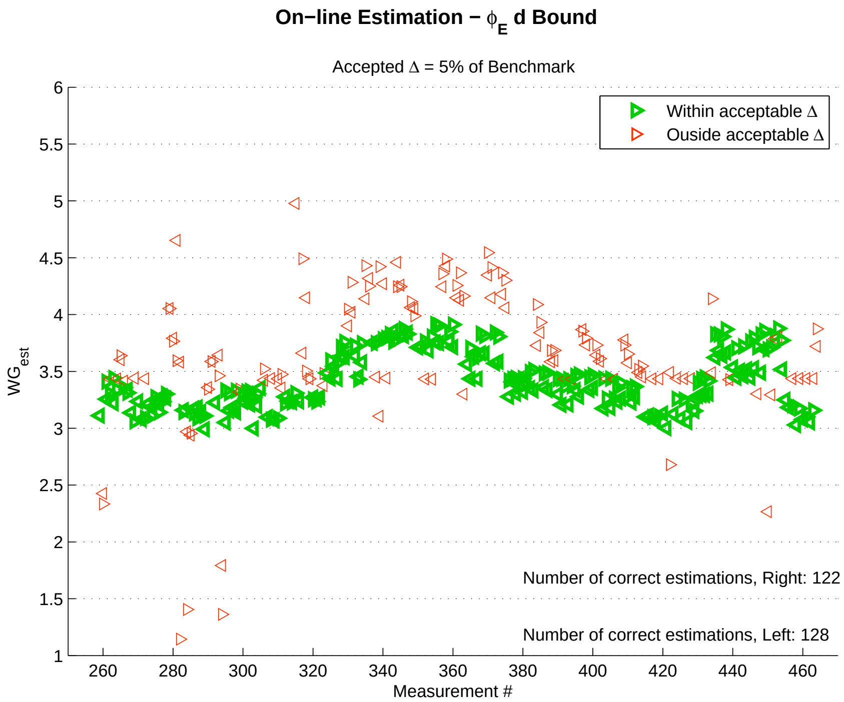

Figure 8.5: Online estimation results, roll rate bound

Analyzing the WG estimations for the three frequency bounds resulted in the following conclusions:

- All three additional dynamic bounds did not result in significant improved number of estimations compared to the estimation process with only general bounds.
- From the considered bounds, bounding $\dot{\phi_E}$ is preferred due to its close relation to the estimated parameters and included side affects e.g. road slope, road surface and side wind
- But if the process is bounded on $\dot{\phi_E}$, wrong estimations have a bigger error compared to the general bounded process.
- Highly dynamic, high frequency maneuvers are still estimated incorrectly.

The estimation process should be further limited to a certain range of driving states, especially high frequency maneuvers should be excluded completely. In the following chapter a more detailed approach is described which should result in a good working estimation protocol.

Analyzing the dynamic bounds and wrongly estimated measurements proved that further limitations are required. The following conclusions can be made:

- The RLS-algorithm needs a certain amount of measurement points to estimate WG correctly. If there is not enough data available, estimated WG should not be used as a reference for the ESC setting. Therefor, a method should be found to determine the amount of available measurement data.
- Due to non-linear behavior at slalom maneuvers, no linear estimation of WG is possible for high steering frequency states. The dynamic bound, bounds most of the dynamic data, however still some data is used for estimation between the bounding limits. A method need to be found to reduce this data in the estimation, especially at high frequent slalom maneuvers.

Chapter 9

Final validation & constraints of the estimator

In the previous chapter, two issues have been shown that influenced the final results. This chapter contains the final solutions, starting with the problem of too little data samples and/or excitation.

9.1 Data Samples and Excitation

If in a measurement set, only small excitations are present for the lateral acceleration, the vehicle is generally driving in a straight line. Since acceleration sensors are generally relative noisy, for most straight line measurements a bad estimation is made. Secondly, the roll angle is noisy as well for straight line driving since ϕ_E is calculated form the measured single wheel travels. The roll angle is also affected by road noise since one wheel can experience a rough road surface, e.g. a pothole. In this situation generally some real roll angle of the body is present which is calculated correctly. But since the wheel will be excited it will experience rebound, therefor the calculated body roll angle will be affected due to e.g. one wheel traveling through a pothole.

In order to address this problem the estimation will only be trusted if a significant amount of measurement points exceeds a selected limit for a_y. A stable value for ϕ_{E0} can be obtained only if enough measurement data with significant excitation is available. In order to address the problem of too little data samples, a minimal time is required where a_y exceeds this limit. This was realized by introducing a_y time or dT_{ay}.

When estimating the WG, a counter in the Simulink estimation block registers the estimation time. This is the time where the RLS algorithm is actively estimating WG, while all bound signals are within range. By using function 9.1, the estimation time where a_y is larger than a selected bound is registered, this is referred as the a_y time. The a_y time is determined as follows:

$$dT_{ay_{li/re_k}} = \begin{cases} dT_{ay_{li/re_{k-1}}} + T_s; & if\ |a_y| > a_{y_{min}}\ (a_{y_{min}} = 1\ [m/s^2]) \\ dT_{ay_{li/re_{k-1}}}; & else \end{cases} \tag{9.1}$$

Note that T_s is the sample time.

There should be significant excitation to accurately estimate WG whit in this selected time. The a_y time, time where $|a_y| > a_{y_{min}}$ $[m/s^2]$, should be larger than circa 5 $[s]$, or in other words, $a_y > a_{y_{min}}$ for at least 5 cumulated seconds. So if $dT_{ay} > 5$ $[s]$ the final estimation will be approved and used for the ESC setting of the vehicle, if the constraint does not hold, the WG estimation should not be used. The time bound of 5 seconds was chosen arbitrary but proved to be a good value to keep as much estimations as possible valid, while still removing the bad estimations. More information about the results is provided in section 9.4. On the following page, the Simulink implementation is shown.

Below the Simulink implementation of 9.1 is displayed, note that the threshold inside of the switch is: $a_{y_{min}} = 1$ $[m/s^2]$. Furthermore ay_re is multiplied with a gain of -1 since for right cornering negative lateral accelerations are present and the switch block only works for $>$ or $>=$ statements.

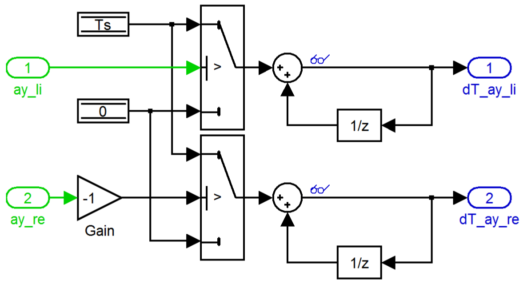

Figure 9.1: Simulink dT_{ay} counter

Implementation of the dT_{ay} time solved the problem of limited data samples and excitation of lateral acceleration. However data of the high steering frequencies still needed to be excluded from the estimation process. Section 9.2 describes the final changes to the bounding conditions.

9.2 Delay

Bounding on the steering input is required to exclude hysteresis from the estimation process. Previous, three signals were checked, but dynamic bounding did not result in more correct estimations. When the results and more specific, individual measurements are observed the following problem can be found. When a bound for high frequent maneuvers was set, still measurement data was used when the bound signal was below the bound limit while zero-crossing of the slalom maneuvers. When the vehicle switched from left- to right corners during the slalom, still an estimation was performed. This resulted in good results for low frequent slaloms. However for higher frequencies bad estimated WG's were found. To solve this issue a delay is introduced to the on-switch of the RLS-algorithm based on the roll rate bound value.

Note that the roll rate was chosen to bound the system since it is closely related to the WG estimation, derivative of the roll angle. Additionally this signal also contains information which is not present in the steer angle speed, body roll due to external components, and compared to the yaw acceleration, this signal is less noisy. For dynamic maneuvers the solution, based on a roll rate bound in combination with a switch on delay and dT_{ay} time, resulted in the following behavior described in section 9.2.1 to 9.2.3.

9.2.1 Slalom maneuvers with 0.2 $[Hz]$ steering frequency

Measurements for different slalom frequencies and loads were investigated based on the previously described protocol. All similar measurements of equal frequencies showed comparable behavior. Summarized, low frequent performed slaloms resulted in acceptable WG estimations, so therefore this data still needs to be used in the estimation. However, higher frequencies should be excluded from the estimation process. On the following page the results for measurement 274 are displayed, note that this measurement represents all 0.2 $[Hz]$ slalom maneuvers.

The plot of figure 9.2 contains the following information: The black line represents the roll rate, the red and green dotted lines are the off- and on triggering values. The separated on- and off conditions are added to prevent affects of fast switching due to measurement noise. In orange the 'normal' on/off signal based on the roll angle speed bound is given, if the roll rate is below the limit, the signal is 1. The blue dotted line represents the delayed signal, note that only the on-switch is delayed, the off-switch corresponds to the 'normal' signal. Finally the estimator is only active if the delayed switched on signal is 1.

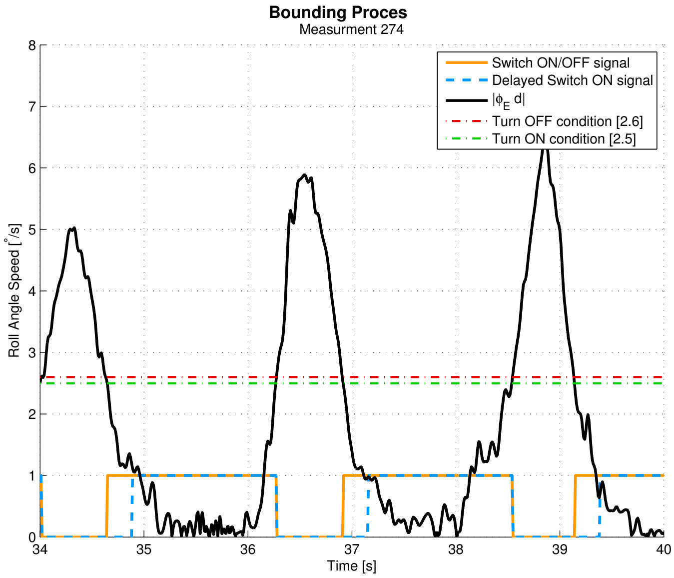

Figure 9.2: Bounding process at 0.2 Hz

Above the roll angle speed for the slalom of 0.2 $[Hz]$ is displayed. The delay of the on/off switch only removes some of the measurement points. Since 0.2 Hz is a low frequency, the estimator is excluded for only short periods of time. Still significant data is available for estimation. Final results for the roll gradient WG did not change using this protocol for 0.2 $[Hz]$ slalom maneuvers.

9.2.2 Slalom maneuvers with 0.5 $[Hz]$ steering frequency

Next, the 0.5 $[Hz]$ slalom was analyzed and a similar plot was made:

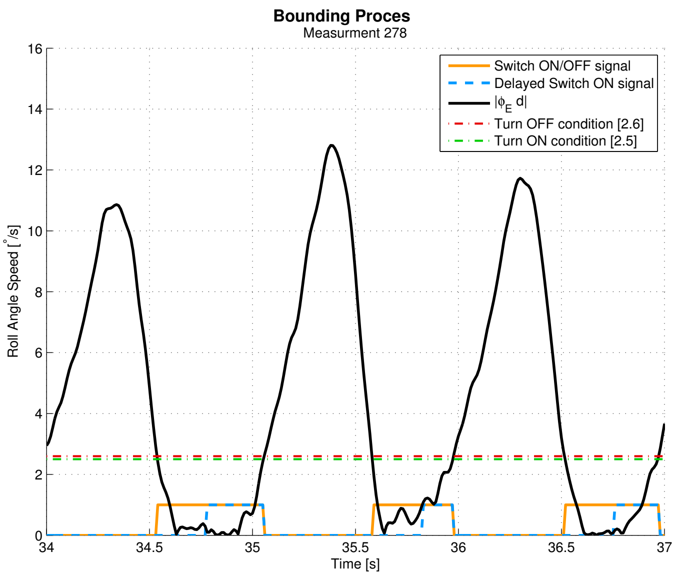

Figure 9.3: Bounding process at 0.5 Hz

For 0.5 $[Hz]$ slalom maneuvers only a little amount of the measurement data is used by applying the delay in combination with the roll angle speed bound. The majority of the data is excluded by the bound and the on-switch delay. Therefor in combination with the dT_{ay} time limit, for short slalom maneuvers, the estimator is effectively switched off. Therefor the protocol of combined bound, delay and dT_{ay} time proved to be successful to exclude high frequent slalom maneuvers from WG estimation.

9.2.3 Slalom maneuvers with 1 $[Hz]$ steering frequency

Finally also 1 $[Hz]$ slalom maneuvers were checked. Below the result is displayed:

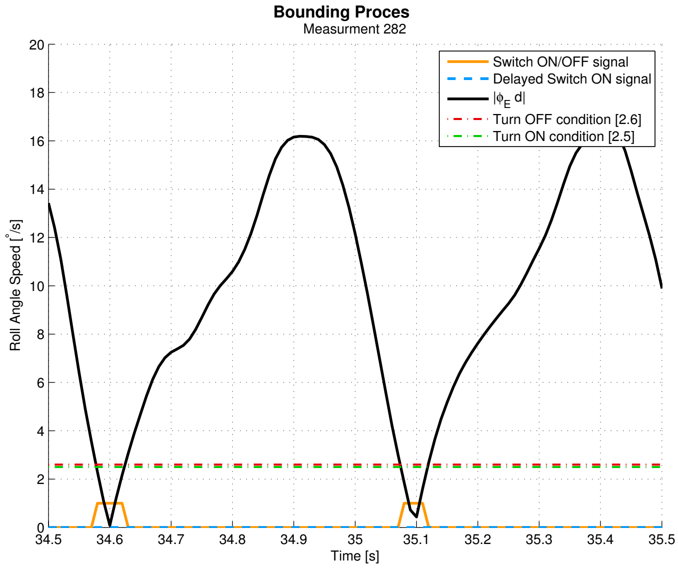

Figure 9.4: Bounding process at 1 Hz

For 1 $[Hz]$ slalom maneuvers no estimation will be made, since all the data is present outside the roll angle speed bound or is canceled by the delay. This area of with hysteresis will therefore not be estimated, since also the dT_{ay} time requirement is not met since the estimation time is zero.

9.2.4 Public driving

Pure slalom driving like displayed before is not likely to occur in real life, therefor also the public road test were analyzed and checked using the new protocol. Usually only limited dynamic maneuvers are present in public driving, for some short measurement periods dynamic behavior was found. The results are displayed below for one of these dynamic moments during public driving:

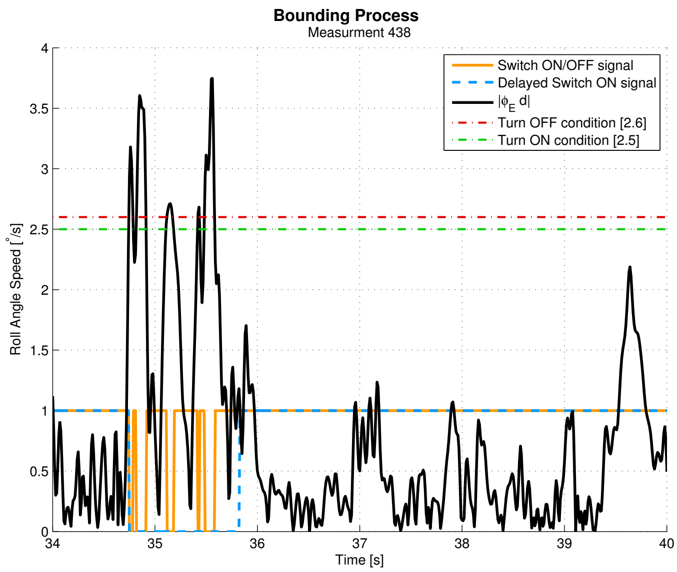

Figure 9.5: Bounding process at public driving

For public road driving the bound of the roll angle speed and the delay generally does almost not influence the estimation. High frequency maneuvers will take place like displayed above, in only very limited time frames. In these high frequency maneuvers no estimation is made based on this data, however most of the measurements are within all bounds for public driving. However extreme conditions could occur and therefor, slalom maneuvers proved the working principle of the protocol.

9.3 RLS constrains

Finally, in addition to the bound, delay and dT_{ay} time requirement, some additional limits are given which should always be valid for the final WG estimation:

- Estimated values for WG must be in a plausible range: $0.30 < WG < 0.40$ $\left[\frac{\circ}{m/s^2}\right]$ since offline estimation of steady state maneuvers show results between these values for different loads ($0.31 < WG < 0.39$ $\left[\frac{\circ}{m/s^2}\right]$). This limit is vehicle model specific.
- Second, the Covariance of the estimated value should be low. The exact acceptable value need to be determined in future research. Note that the covariance is also an output of the RLS-algorithm and is needed in the estimation process for the following iteration.

9.4 Final Results

Considering 1) the general bounds, 2) the bound of the roll rate, 3) the delay of the on-switch, 4) dT_{ay} time and finally 5) the RLS-constrains the following results were found:

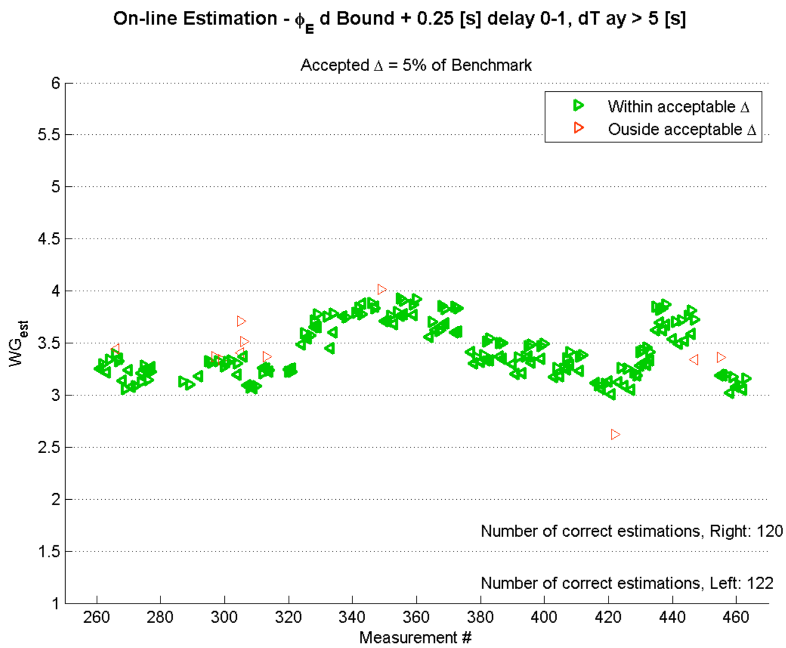

Figure 9.6: Final results online estimations

Like displayed in the plot above, almost all estimations were found to be correct within the selected error range. A few estimations were incorrect, therefor an analysis was performed on these exceptions:

Measurement 297 & 299: Very little error was present, therefor the estimation was very close to the required value. No principal estimation problem was detected.

Measurement 305 & 306: Very rough road conditions influenced the measurement, more detailed analyses is needed to conclude about the precise cause for the deviation in WG and the estimation process in general at bad road conditions. However, the WG is estimated too high which would only trigger a more conservative ESC setting. Therefor this result is not alarming.

Measurement 422: This measurement started in a corner, therefore the offset ϕ_E was estimated too high, since data was missing for low a_y. This results in a too low slope: WG. This case will not occur in real life, since in practice the estimator will not be started while driving in a corner. When the system is implemented, the vehicle will start estimation when the ignition is turned on at still stand. **Measurement 266 (Slalom @ 0.2 [Hz]), 313 (Slalom @ 0.35 [Hz]), 349 (Slalom @ 0.5 [Hz]) and 447 (Slalom @ 0.2 [Hz])**

If a slalom maneuver was wrongly estimated, the following conditions hold:

- The a_y time was very close (circa 6 $[s]$) to dT_{ay} bound (= 5 $[s]$)
- For all cases WG was estimated slightly too high, therefor in the worst case resulting in a more conservative ESC setting

Summarizing all results, it can be concluded that the protocol works when all components are considered:

- 1) the general bounds,
- 2) the bound of the roll angle speed,
- 3) the delay of the on-switch,
- 4) dT_{ay} time and
- 5) the RLS-constrains.

However the final bound values for the allowable error and dT_{ay} time needs further consideration and could be tuned based on future research. Note that in practice it is not likely for slalom maneuvers to occur like tested in this research. If shorter slalom maneuvers are considered, all measurements were estimated correctly since dT_{ay} time was very close to the selected bound of 5 seconds.

9.5 Reset Logic

The estimation process and stored values need to be reseted in future usage. For every moment in time where the vehicle could be loaded the RLS-algorithm needs to continue with new initial conditions in order to obtain the most reliable results. Therefor a reset logic needs to be considered at every stand still combined with a door opening or an ignition switch by the driver.

Chapter 10

Conclusions

In this report a working protocol was found for the estimation of the roll gradient. In order to estimate this parameter online, two signals are required. The lateral acceleration was measured within the vehicle by an acceleration sensor and the roll angle was derived from individual wheel travel sensors. This data is used as an input for the estimator and the estimation protocol determines when the estimator need to be active. The protocol results in an accurate roll gradient estimate, which can be used for an adaptive ESC system. Based on the project research, the following conclusions can be drawn:

- Vehicle load can be distinguished by estimation of WG, especially roof loads are clearly noticeable.
- Lateral acceleration a_y should not be bound when estimating WG, since it decreases estimation accuracy.
- Steady state cornering maneuvers proved to result in trustworthy benchmark values for different load cases.
- Based on measurements, slalom maneuvers do not represent real world driving states very accurate. Especially high frequency steering inputs result in hysteresis, which is not present at similar levels in public driving measurements.
- For 'normal' driving on public roads, estimations are accurate. A clear difference between cases with and without roof load is visible. Also a trend between increasing in-vehicle loads can be observed. Generally WG increases slightly with addition of in-vehicle loads (+ 0.05-0.10 $[\frac{\circ}{m/s^2}]$) and a structural increase of circa 0.4 $[\frac{\circ}{m/s^2}]$ is observed for adding a roof load of 100 $[kg]$.
- General bounds (v_x, δ and $a_{x_{max}}$) should be considered to exclude extreme, uncertain or uncommon driving situations from estimation
- Bounding on frequency related signals ($\dot{\phi_E}$, $\ddot{\psi}$ and $\dot{\delta}$) only, does not lead to significantly improved estimations
- a_y must have significant excitation for some time. This research shows that at least 5 $[s]$ is necessary to obtain accurate estimation, therefore estimations should be bounded on dT_{ay} time.
- A good working protocol was found which includes the following components:
  - 1) The general bounds (v_x, δ and $a_{x_{max}}$)
  - 2) The bound of the roll rate,
  - 3) The delay of the on-switch of the roll rate bound,
  - 4) dT_{ay} time must be larger than 5 $[s]$,
  - 5) The RLS-constrains
    - Estimated WG should be in the range of: $0.3 < WG < 0.4$ $[\frac{\circ}{m/s^2}]$ for the tested vehicle model range

  - The Covariance of the estimated WG should be low, the exact value need to be determined in future research.

- More detailed analyses is needed to conclude about estimation process at bad road conditions
- A reset logic needs to be implemented at every stand still combined with a door opening or an ignition switch

Chapter 11

Recommendations and future research

Suggestions for future research based on the results of this research are listed below:

- Determine exact allowed value for the covariance.
- Test maximum allowed vehicle load.
- Test limited roof load (e.g. 20 $[kg]$ in stead of 100 $[kg]$).
- Include known vehicle information:
  - Fuel level.
  - Seat sensors (passengers information).

Furthermore the WG of air sprung vehicles could be of interest, since in this research only a vehicle with steel springs was observed. Especially change in WG due changed spring stiffness at higher loads is of interest.

Bibliography

[1] 2016 Mercedes-Benz ML350 Bluetec, *www.newbestcars2016.com*, 2015.

[2] Dr.ir. I.J.M. Besselink, *Advanced Vehicle Dynamics slides, 4J570*, TU/e, Eindhoven, 2015.