Detection of driver unawareness based on long- and short-term analysis of driver lane keeping

Master's thesis
performed in **Vehicular Systems**

by
Fredrik Wigh

Reg nr: LiTH-ISY-EX -- 07/3912 -- SE

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Supervisor: **Dr. Wolfgang Stolzmann**
DaimlerChrysler AG
Anders Fröberg, PhD student
Linköpings Universitet

Examiner: **Assistant Professor Jan Åslund**
Linköpings Universitet

Linköping, March 13, 2007

Abstract

Many traffic accidents are caused by driver unawareness. This includes fatigue, drowsiness and distraction. In this thesis two systems are described that could be used to decrease the number of accidents. In the first part of this thesis a system using long-term information to warn drivers suffering from fatigue is developed. Three different versions with different criteria are evaluated. The systems are shown to handle more then 60% of the cases correctly.

The second part of this thesis examines the possibilities of developing a warning system based on the predicted time-to-lane crossing, TLC. A basic TLC model is implemented and evaluated. For short time periods before lane crossing this may offer adequate accuracy. However the accuracy is not good enough for the model to be used in a TLC based warning system to warn the driver of imminent lane departure.

Keywords: driver lane keeping, detecting driver fatigue, time-to-lane crossing

Preface

This thesis completes my studies at Linköpings University for a Master of Science in Applied Physics and Electrical Engineering. Combining theory and practice at DaimlerChrysler AG in Stuttgart has been both interesting and challenging. Most of all working for a legendary mark in the automotive industry has been a great adventure.

Thesis outline

In chapter 1 a short introduction to this thesis is given. Readers interested in the warning system based on long-term information of driver lane keeping can find this in chapters 2 to 5. System functionality is explained in chapter 2. Test data, input signals and parameters are given in chapter 3. Validation of the models used and robustness for the LAA system is presented in chapter 4. Results can be found in chapter 5.

Readers interested in the warning system using short-term information of the drivers lane keeping should focus on chapters 6 to 8. System functionality is explained in chapter 6. Test data and input signals for the TLC system are presented in chapter 7. Simulation, evaluation and results can be found in chapter 8.

Acknowledgment

Many heartfelt thanks to Dr. Wolfgang Stolzmann, without whom this thesis would have capsized before it even left the harbor. Many thanks also to the team Dr. Klaus-Peter Kuhn who all helped me feel welcome and at home during my time in Stuttgart. Furthermore, thanks to Hr. Rothe for the lesson in Autobahn driving.

To my family and to J, your loving support made it all possible.

Contents

Chapter 1

Introduction

Every year thousands of people die in traffic accidents caused by unintended lane departure. Statistics from ADAC [11] show that roughly 66 000 or 15% of single vehicle accidents in Germany occur because of unintended lane departure. In the USA the numbers are as high as 24% [5]. The reasons for the driver to unintentionally depart the lane can be many, for example activities such as eating and drinking but also physical reasons such as drowsiness and fatigue. These numbers would definitley be smaller if there was a system in vehicles that warn the driver before the lane departure occurs. In this master thesis two different warning systems for driver unawereness are examined and evaluated. The first system evaluates the drivers lane keeping over a longer time period in the past to detect driver fatigue. The second system uses current lane keeping information to calculate a Time-to-Lane Crossing, TLC, value to predict future lane departure. TLC is defined as the time available for the driver before any part of the vehicle crosses a lane border. While the first system warns drivers suffering from fatigue, the second system could be used to warn drivers of general unawereness.

Lane drifting is the usual manifestation of sleepy driving [8]. To detect lane drifting information over the actual lane width and vehicle position within the lane has to be obtained. This is done via a lane detection system, LDS. The LDS is made up of a forward looking camera within the vehicle and a processing unit. Via image processing on images from the camera the lane edges are recognized, thus enabling the system to calculate vehicle position. The LDS delivers, among other signals, the actual lane width and the lateral offset of the vehicle center from the middle of the lane. LDS systems are readily available in cars today which means that one can easily obtain the wanted information.

One way to discover lane drifting is to consider the lane edges and the vehicles closeness to these. The problem is to decide what closeness to the lane edge means. Virtual edge zones, VEZs, are defined by the left and right lane edge respectively. Within the VEZs a weight function is used to grade

the vehicles closeness to the lane edge. This is then used by the system to decide whether to generate a warning or not.

Another way to detect lane drifting is to consider the drivers over run area, ORA. The ORA is the area that forms between the optimal path and the actual path of the vehicle. The problem here is to define the optimal path. A simple way to find the optimal path is to use the center of the lane. This is however not an efficient measurement, while dependent on for example traffic situation and visibility drivers tend to drive with more or less offset to the center of the lane. Therefore a running mean over the lateral offset is used as the optimal path in the calculation of the ORA. The size of the ORA is then used to decide whether to generate a warning or not.

A third way to detect lane drifting is to use Time-To-Lane Crossing. The Time-To-Lane Crossing, TLC, value was first introduced by Godthelp et.al. (1984) (as cited in [13]). It represents the time available for the driver before any part of the vehicle crosses a lane edge. The TLC is a prediction of future vehicle movement calculated using short term information of the drivers current lane keeping. This TLC value is in a way a measurement of vehicle position in the lane and can therefore be used to discover lane drifting. A minimum limit for the TLC value is set. The system registers if the driver reaches a TLC value lower than the limit. This information is then used to decide whether the system should generate a warning or not.

Since the TLC value is a prediction in the future it can also be used to warn drivers before the actual lane departure. If such a warning is to be effective it needs to be given in such a time that the driver can respond and avoid the lane departure. In order to establish if such a system could be introduced with existing in-car sensors TLC models found in [13] and [10] are implemented. The system is then evaluated to see if the accuracy of the available test data is sufficient for the development of a TLC based warning system.

1.1   Objective

The objective of this thesis is to develop two systems to detect driver unawareness based on driver lane keeping. The first system shall use long-term information of the drivers lane keeping to warn drivers suffering from fatigue. The second system shall use short-term information and TLC to predict lane departure and warn the driver.

1.2   Method

The systems are developed with a possible implementation in a vehicle in mind, which means that calculations and memory usage must be kept at a minimum. Calculations that would demand large amounts of data buffering are approximated with incremental functions. Implementation in a vehicle

also means that the calculation parts of the models have to run in real-time. To allow for this during development the systems are simulated offline in Matlab Simulink. All blocks are implemented discrete since only sampled signals are used. All signals are seen as constant between samples. As equation solver a discrete fixed step method is used.

All collected test data is available offline. In addition to signals logged from the vehicle the LAA test data also include an external criterion evaluating drivers current state of fatigue. Development of the LAA systems is done on part of the test data while evaluation is done over all test data.

Simulation and evaluation of the TLC system is done over the TLC test data. Although both TLC model 1 and TLC model 2 are implemented in Simulink, only TLC model 1 is simulated and evaluated due to signal availability.

Chapter 2

LAA - Lane-based attention assistant

A lane-based attention assistant, LAA, system to detect driver fatigue is developed. The system uses three different methods to detect driver fatigue. One method based on vehicle closeness to lane edge, one method based on time-to-lane crossing, TLC, and one method based on vehicle over run area, ORA. In the development of the LAA system the two first methods showed more potential then the calculation of ORA. As ORA was developed within another thesis [4] parallel to this one it was decided to concentrate efforts to closeness to lane edge and TLC. For the sake of completeness the calculation of ORA is also included.

To filter the input signals for the LAA systems a filter is also developed. The filter generates a system activity signal that controls LAA system activity and allows the system to be active only when input signals are usable.

2.1 Closeness to lane edge

A good indication of sleepy driving is lane drifting [8]. One way of detecting this is to calculate the distance between the vehicles outer edge and the lane edge. The minimum distance to lane edge, for the right and left side of the vehicle, is then delivered every ten seconds. These distances are used to describe the drivers lane keeping. To decide whether the distance given is close to the lane edge or not virtual lane edge zones, VEZs, are established. In the VEZs a weight function is used to grade the vehicles closeness to lane edge. These weights are then summed and compared to a warning level in order to decide whether to warn the driver or not. The warning level is individualized to allow for drivers different driving behavior.

It is important for the system to separate drifting close to the lane edge from normal driving close to the lane edge. If a driver drives close to the lane

edge for a longer time period this is no sign of fatigue. Examples of this can be during highway driving in dense traffic where drivers drive with an offset to the car in front to increase forward visibility. Other cases where the driver is close to the lane edge or passes over the lane edge is during overtaking. These crossings of the lane edge are intentional and should not result in a warning from the system. In the same way it is also important to let the driver pass narrow sections of road, for example road construction sites, without the system warning him.

2.1.1   Distance to lane edge

In order to calculate the distance between the vehicle and the lane edge it is necessary to first decide the vehicles position within the lane. A model for this can be found in [10]. The vehicle is assumed to be parallel to the lane edge. With the lateral offset, y_0, and the lane width, b, given from the LDS and the vehicle width, b_c, known it is easy to calculate the distance of the outermost part of the vehicle relative to the lane edge. This distance can be calculated as

$$y_l = \frac{b}{2} - \left(y_0 + \frac{b_c}{2} \right) \tag{2.1}$$

$$y_r = \frac{b}{2} + \left(y_0 - \frac{b_c}{2} \right) \tag{2.2}$$

where y_r and y_l denotes the distance between the right and the left hand side of the vehicle and the right and left lane edge respectively. The lateral offset, y_0, is defined positive to the left and negative to the right. The smallest calculated distances to lane edge for the right and left hand side of the vehicle are given every 10 seconds. Driving close to the lane edge is generally not to be considered as a sign of driver fatigue. To handle this the system monitors if the driver drives within a certain distance from the lane edge over a certain amount of time. If this is the case, the driver is said to be driving close to the lane edge intentionally and the distance measurement is switched off.

2.1.2   Calculation of virtual lane borders

To register and evaluate the drivers lane keeping virtual lane edge zones, VEZs, are established at the left and right lane edge. The zones are defined by an inner and an outer border, both parallel to the lane edge. Driving within one of these zones is classified as being close to the lane edge. The VEZs can be seen in figure 2.1.

In a first version of the system fixed distances were used to establish the VEZs. This delivered poor results. Analysis of the data from the test drives showed big differences between drivers lane keeping behavior. Some drivers tended to use the full road width while others stayed in the center of the lane.
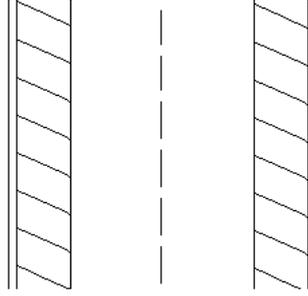
Figure 2.1: Lane with VEZs. Broken line designates lane center. [Observe that the VEZs are not drawn in scale.]

A closer examination of the minimum distances to the lane edges showed that they are normally distributed.

A normally distributed variable X is given as $X \sim N\left(\mu, \sigma^2\right)$, where μ is the mean value of X and σ^2 is the variance. Equivalently, σ is the standard deviation. Notable for X is that approximately 68% of the values lies within ± 1 standard deviation of the mean value. Only 5% of the values of X lies outside ± 2 standard deviations. The idea is that the closeness to lane edge increases as fatigue progresses. This would mean that the smaller distances become more and more common as drivers level of fatigue increases. To capture this behaviour a combination of mean and standard deviation , $\mu - f \cdot \sigma$, where f is a constant, is used to calculate the VEZ borders individually for every driver. By using different values for f the inner and outer borders for the VEZs are generated.

The mean value and standard deviation over the distance to lane edge are individual for each driver and each test drive. Therefore an approximation of these values must be calculated in real time. This is done via an incremental calculation. The mean value over the distance to lane edge is calculated as

$$\mu_{\text{n}} = \frac{(\mu_{\text{n-1}} \cdot (\text{n-1})) + y_{\text{n}}}{n} \tag{2.3}$$

where μ_{n} is the mean value at time n, $\mu_{\text{n-1}}$ is the mean value at time n-1 and y_{n} is the distance to lane edge at time n. The calculation of the standard deviation over the distance to lane edge is also straight forward. According to the maximum likelihood method the standard deviation can be written as

$$\hat{\sigma}_{\text{ml}} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_{\text{i}} - \mu_{\text{n}}\right)^2} \tag{2.4}$$

where μ_n is the mean value of y_i over all n. Denote the sum in equation (2.4) with s_n. Then let s_{n-1} represent the sum at time n-1.

$$s_{n-1} = \sum_{i=1}^{n-1} (y_i - \mu_{n-1})^2 \qquad (2.5)$$

Now s_n can be approximated as

$$\tilde{s}_n = \tilde{s}_{n-1} + (y_n - \mu_n)^2 \qquad (2.6)$$

This means that the standard deviation can be approximated at every time step as

$$\tilde{\sigma}_n = \sqrt{\frac{1}{n}\tilde{s}_n} \qquad (2.7)$$

The mean value and standard deviation are calculated separately for the left and the right side of the lane. The approximation in equation (2.6) holds for big n since the distance to lane edge is normally distributed. To show that the approximation is also valid for the n which occurs in the model an empirical validation is done in chapter 4.

The calculation of the VEZ borders are then done as

$$D0_{l/r} = \mu_{l/r} - (d0_{l/r} \cdot \tilde{\sigma}_{l/r}) \qquad (2.8)$$

$$D1_{l/r} = \mu_{l/r} - ((d0_{l/r} + d1_{l/r}) \cdot \tilde{\sigma}_{l/r}) \qquad (2.9)$$

where $D0_{l/r}$ is the distance from lane edge where the weight function is zero and $D1_{l/r}$ is the distance from lane edge where the weight function is one. The parameters $d0_{l/r}$ and $d1_{l/r}$ are used to tune the VEZ borders. Calculating the borders in this manor means that the VEZs are individualized, not only for drivers and test drives, but also for the left and the right hand side of the lane.

2.1.3 Weight function

As mentioned before, driving within the VEZs are considered as being close to the lane edge. To grade the drivers closeness to lane edge a weight function is defined within the VEZs. The weight function, Δw, is linear and can be expressed as

$$\Delta w = \begin{cases} 0 & \text{if } y_{l/r} \leq D0_{l/r} \\ \frac{y_{l/r} - D0_{l/r}}{D1_{l/r} - D0_{l/r}} & \text{if } D1_{l/r} < y_{l/r} < D0_{l/r} \\ 1 & \text{if } y_{l/r} \leq D1_{l/r} \end{cases}$$

where $y_{l/r}$ denotes the distance to lane edge and $D0_{l/r}$ and $D1_{l/r}$ denotes inner and outer borders of the VEZs on the left and right side of the lane respectively. With the distances to lane edge given every 10 seconds, the weight

function also gives weight peaks every 10 seconds. The peaks generated from each side of the vehicle is added together to form a total weight peak. As a measurement of drivers lane keeping during the test drive a running sum over the weight peaks several minutes back in time is calculated. The running sum is defined as

$$\Delta w_{running}(t) = \sum_{i=t-t_0}^{t} \Delta \mathrm{w}(i) \qquad (2.10)$$

where $\Delta \mathrm{w}(i)$ is the value of the weight function. The exact calculation of this running sum over values several minutes back in time would require buffering of large amounts of data. With consideration taken to future implementation in a vehicle, the running sum is approximated. This is done in two steps. First the mean value over the weight peaks, $\Delta \mathrm{wsum}_t$, are calculated using a delta function. This function resembles an incremental mean, the difference being that the delta function considers a constant number of samples whereas the incremental mean considers an ever increasing number of samples. The delta function used is defined as

$$\Delta \mathrm{wsum}_t = (1 - \alpha) \, \Delta \mathrm{wsum}_{t\text{-}1} + \alpha \Delta \mathrm{w}_t \qquad (2.11)$$

where $\Delta \mathrm{wsum}_{t\text{-}1}$ is the value of the delta function at sample t-1 and $\Delta \mathrm{w}_t$ is the current value of the weight function. The constant α is used to weight the importance of older weight function values against the current weight function value. In this case $\alpha = \frac{1}{t_0}$, where t_0 is the number of samples over which to calculate the running sum. By multiplying $\Delta \mathrm{wsum}_t$ with the number of samples considered the approximation of the weight sum is calculated.

$$\mathrm{wsum}_t = \Delta \mathrm{wsum}_t \cdot \mathrm{t}_0 \qquad (2.12)$$

By approximating the running sum in equation (2.10) with a delta function only two values, $\Delta \mathrm{wsum}_{t\text{-}1}$ and $\Delta \mathrm{w}_t$, are needed to calculate the next value of the sum which minimizes memory usage. The difference between the approximated weight sum and the running sum is that the approximation considers all values in the past, the older ones weighted to minimize their influence.

2.1.4   Baseline

By comparing the weight sum, wsum_t, from equation (2.11) with a warning level the system decides whether to give the driver a warning or not. The warning level is generated individually for every driver and is made up of a baseline value and a baseline factor. The first part of every test drive is used to establish a baseline for the driver, i.e a value to describe the drivers normal closeness to lane edge when not suffering from fatigue. The baseline is generated as

$$\text{wsum}_{\text{max}} = max_{t \in [0, t_{\text{baseline}}]} \text{wsum}_t \qquad (2.13)$$

where the parameter t_{baseline} gives the time limit within which the maximum value of the weight function sum is to be found. This value is then used as a baseline. The baseline is multiplied with a baseline factor, ξ, bigger then one to form the warning level. This factor gives a value of how much drivers can diverge from their normal behavior before a warning is generated. The warning level, $\rho_{\text{warning level}}$, is given by

$$\rho_{\text{warning level}} = \text{wsum}_{\text{max}} \cdot \xi \qquad (2.14)$$

To generate a warning a comparison is done between the current value of the weight function sum and the warning level as shown below

$$warning = \begin{cases} 0 & \text{if wsum}_t < \rho_{\text{warning level}} \\ 1 & \text{if wsum}_t \geq \rho_{\text{warning level}} \end{cases}$$

where $warning = 0$ means no warning and $warning = 1$ means warning given. The baseline time, t_{baseline}, and the time over which the weight function sum is calculated, t_0, are equal to enable a comparison between the warning level and the weight function sum value. Results of the system evaluated over the nightly test drives and over all test drives can be found in section 5.3.

The use of a baseline is based on the assumption that drivers are not suffering from fatigue as they start driving. This is also the case in all test data. If however a driver suffers from fatigue as he starts driving, the baseline and thus the warning level generated will be to high, causing the system not to warn the driver. This problem could be solved by setting a maximum value for the baseline, thus setting a maximum value for the warning level. This value can not be constant for all drivers and must also allow for different drivers to use the same vehicle without being warned. How to calculate and set this maximum value is a question that needs to be investigated further.

2.2 TLC

First introduced by Godthelp et.al. (1984) (as cited in [13]) the Time-To-Lane Crossing, TLC, value represents the time available for the driver before any part of the vehicle crosses a lane edge. Throughout the years different models for the calculation of TLC have been suggested. The most basic model in [13] defines TLC as the lateral distance to lane edge divided by the vehicles lateral velocity. This is also the model used here. A closer description of TLC and the exact calculation of the TLC value can be found in sections 6.1 and 6.2.

The TLC value represents the predicted time before the vehicle crosses the lane edge and is therefore in a way a measurement of vehicle position. This measurement can be used as a criterion in the LAA system to detect

lane drifting. By setting a TLC minimum limit and comparing this with the predicted TLC value peaks are generated. Peak generation is according to

$$peak = \left\{ \begin{array}{ll} 1 & \text{if } TLC_{\text{pred}} < TLC_{\text{limit}} \\ 0 & \text{else} \end{array} \right.$$

where TLC_{pred} is the predicted value and TLC_{limit} is the threshold value. Peaks are calculated for both the left and the right side of the vehicle. As for the closeness to lane edge the comparison runs over 10 seconds and peaks are given in the same interval. Just as for closeness to lane edge the peaks are then summed via a delta function, a baseline is used to generate a warning level and finally the value of the peak sum is compared with the warning level to decide whether to generate a warning or not. More information about the delta function, baseline generation and warning level can be found in sections 2.1.3 and 2.1.4. The results of the system simulated over all nightly test drives and over all test drives can be found in section 5.4.

2.3   Over Run Area

Another way to detect lane drifting and thus sleepy driving [8] is to calculate the drivers over run area, ORA. While driving in a straight line drivers tend to sway a little back and forth. This is also the case in more regular, everyday driving. The idea is to calculate the area between the optimal path and the actual path of the vehicle. Choosing the optimal path is the problem. One could argue that the lane center should be the optimal path. However in certain traffic situations, for example highway driving in dense traffic, drivers may choose to drive with an offset to the lane center, thus increasing forward visibility. Another case would be when drivers cut corners. If this is the optimal path or generally safe can be discussed, it is however not a sign of fatigue.

Therefore a running mean of the lateral offset signal over t_{mean} seconds back in time is used to calculate the optimal path. The running mean is calculated as

$$y_{\text{mean}}(t) = \frac{1}{t_{\text{mean}}} \sum_{i=t-t_{\text{mean}}}^{t} y_0(i) \qquad (2.15)$$

The ORA is then given as

$$A_{\text{ora}}(t) = \frac{1}{t_{\text{ora}}} \sum_{i=t-t_{\text{ora}}}^{t} |y_0(i) - y_{\text{mean}}(t)| \qquad (2.16)$$

where t_{ora} is the length of the window over which the ORA is calculated. Equation (2.16) yields the area normalized with time and are therefore in meters. Since the over run area is dependent of the vehicle speed, equation (2.16) must be multiplied with the vehicle reference speed, v_{ref}, in order to give the

physically over run area. In the data used for evaluating the LAA system information over vehicle speed was unavailable. Even without information about the vehicle speed the ORA calculated in equation (2.16) can be used to evaluate the system. Just as for the two versions of the LAA system mentioned above, a baseline and a baseline factor is used to generate a warning level. The ORA is then compared to the warning level to decide whether a warning should be given or not. Results of the evaluation can be seen in section 5.5.

2.4   System Activity Signal, SAS

The input signals to the model contain measurement errors and situations where the measurement values cannot be used. Examples of these situations are lane changes which are intended lane departures. Therefore all input data are filtered before use. The filter generates a binary system activity signal, SAS, where one indicates that input data is usable and zero indicates that input data is unusable. The LAA system is only active when the SAS is one.

This has consequences for the calculation of the weight function sum in the LAA system based on vehicle closeness to lane edge. Two possible system solutions have to be separated, one with a calculation of weight sum dependent on the SAS, the other with a calculation of weight sum independent of the SAS. The first system uses an active weight sum, i.e. a weight sum that is calculated over the past twenty minutes where SAS=1. The second system uses a general weight sum, i.e. a weight sum calculated over the past twenty minutes regardless of SAS value. Closer descriptions of the functionality of these systems are found in sections 5.1.1 and 5.1.2. Both systems are tuned and simulated and the results are given in section 5.3.

For the LAA system based on TLC an active weight sum is used to sum the peaks. For the ORA system the area is only calculated when SAS=1 else the area is kept constant at its last active value.

2.4.1   Properties of the SAS

Three signals, lateral offset, describing the vehicles offset from the center of the lane, error, describing whether the LDS is working properly or not and lane width, giving the actual width of the lane, are used to generate the SAS.

The lateral offset signal contains lane changes. These crossings of the lane edge are intended by the driver and must therefore be filtered out. A typical lane change can be seen in figure 2.2. The lateral offset value is referenced from the center of the lane, positive values meaning offset to the left and negative values offset to the right. The increasing lateral offset in figure 2.2 indicates that the vehicle moves to the left. Halfway through the lane change the LDS identifies the left lane and changes reference point to the left
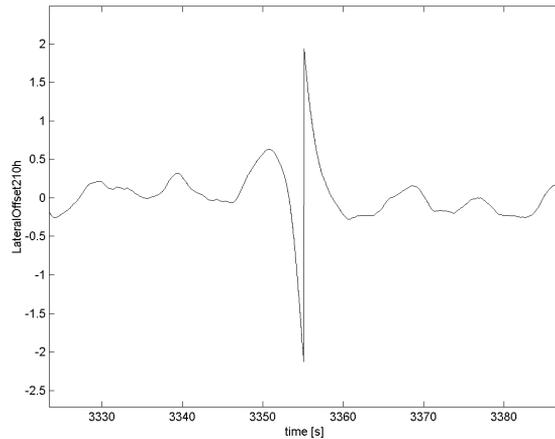
Figure 2.2: Lateral offset signal from the LDS. Typical lane change to the right. [Offset in meters]

lane center, causing the lateral offset to jump from roughly two meters positive offset to two meters negative offset. This jump is made between samples. By comparing the values of adjacent lateral offset signal samples these jumps, and with them the lane changes, can be detected. When a lane change is detected the SAS is set to zero. 50 randomly chosen lane changes are examined in the 125 test drives. The worst lane changes found start ten seconds before the change or end up until ten seconds after the change. To cover both these cases the time when the SAS is set to zero is extended to ten seconds before and ten seconds after the lane change. By choosing this time conservatively the chances of lane change effects filtering through decrease.

The error signal is handled in a similar fashion. When the system performance of the LDS is low, i.e. when signals delivered are unusable, the LDS sets the error signal to one. When the error signal is one the SAS is set to zero. To safeguard against any problems the time where SAS is set to zero is set to one second before and one second after error.

A typical segment of the lane width signal can be seen in figure 2.3. The sudden decrease in lane width occurs during the passing of a road construction site. Passing these sections the driver automatically drives close to the lane edges, regardless of if he is tired or not. Therefore these sudden decreases have to be filtered out while the driver has to be able to pass narrow sections on the road without the system warning him. The minimum lane width is chosen to three meters to allow for the vehicle width plus margins. Since the lanes of a new German Autobahn are 367,5 cm wide and the lanes of an old German Autobahn are 342,5 cm wide it seemed reasonable to allow lane
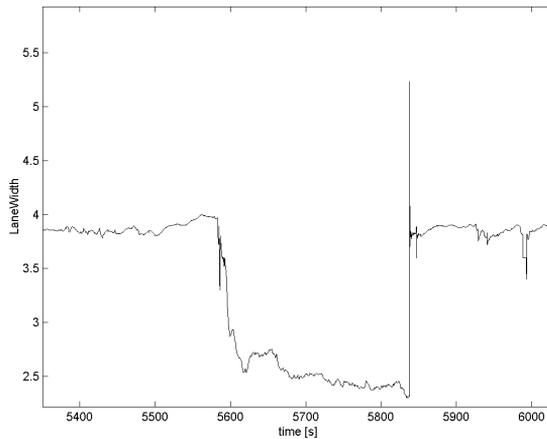
Figure 2.3: Lane width signal from LDS. Lane width while passing a construction site. [Lane width in meters]

widths of up to four meters. Any widths above four meters are considered an error from the LDS and are therefore filtered out.

2.4.2 Consequences of the SAS

The filter delays all signals with half the SAS zero time from the lane changes. This means that all signals are delayed ten seconds in comparison with the SAS. The time delay is no problem for the system functionality since it is in the region of seconds and the LAA uses data up to twenty minutes back in time to issue a warning.

Chapter 3

LAA - Signals and parameters

Test data used for the development of the LAA system is described. A short description of the input signals and parameters for the LAA system is given.

3.1   Test data

All simulations of the LAA system are performed on data previously collected during test drives in and around Stuttgart. A total of 125 test drives were performed, day and night in lengths between 1 and 5 hours. Data was collected on Autobahns and Schnellstrassen, which means roads with multiple lanes in each direction with separation from oncoming traffic. During the test drives the drivers were instructed to drive in a speed interval ranging from 80 km/h to 140 km/h. Only these parts of the test data are considered.

The vehicles used during the test drives were equipped with a lane detection system, LDS, used to recognize the road and to calculate the vehicle position. The LDS delivers, among other signals, the actual lane width and the lateral offset of the vehicle. The system performance of the LDS is dependent on driving conditions, for example weather, unclear lane edges and heavy traffic. Therefore a error signal is delivered to indicate system performance. Further reading on lane detection systems can be found in [9] and in [12].

During the test drives the drivers were also instructed to give a rating of their own sleepiness on the Karolinska Sleepiness Scale (KSS).

Karolinska Sleepiness Scale

The Karolinska Sleepiness Scale (KSS) was introduced by Åkerstedt el.al.(1990) (as cited in [3]). The scale has nine levels, which can be seen in table 3.1, and

is commonly used as a method to measure sleepiness. The scale has been used with good results in studies of shift work among train drivers and controllers [2] and in studies of driving home after night shifts [1]. Kaida et.al [3] found a strong relation between KSS and EEG and behavioral variables. This indicates that KSS has a high validity in measuring sleepiness. Nevertheless one should be aware of the problems with the KSS. The scale is subjective since the drivers estimate their own level of sleepiness. This makes it difficult to exactly compare levels of sleepiness between different drivers.

KSS-level	Description
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very sleepy, great effort to keep alert

Table 3.1: Karoliska Sleepiness Scale

3.2   Input signals

Input signals are given with name and definitions. If nothing else is said the signals originate from the LDS and are sampled at a rate of 50Hz.

Lateral Offset

The signal gives the lateral offset of the vehicles longitudinal axis in comparison with the center of the lane. Positive values represent offset to the left and negative values offset to the right. A typical lateral offset signal can be seen in figure 3.1. The lateral offset is given in meters.

Lane Width

The signal gives a measurement of the current lane width. A typical lane width signal can be seen in figure 3.2. The lane width is given in meters.

Error Code

The signal is binary and gives an indication of the performance of the LDS. By zero the system delivers reliable measurements, by one measurements are
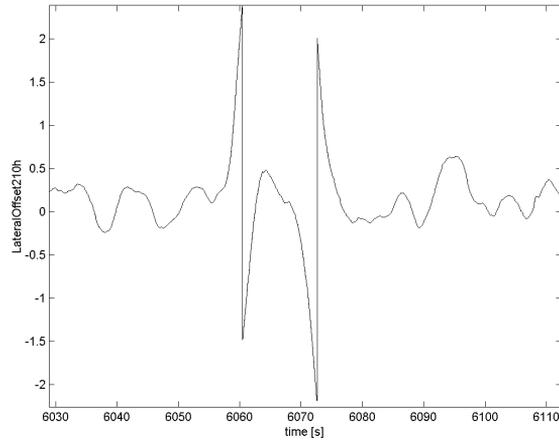
Figure 3.1: Lateral offset signal from the LDS. Typical signal characteristics when overtaking. Lane change to the left are followed by lane change to the right. [Offset in meters]
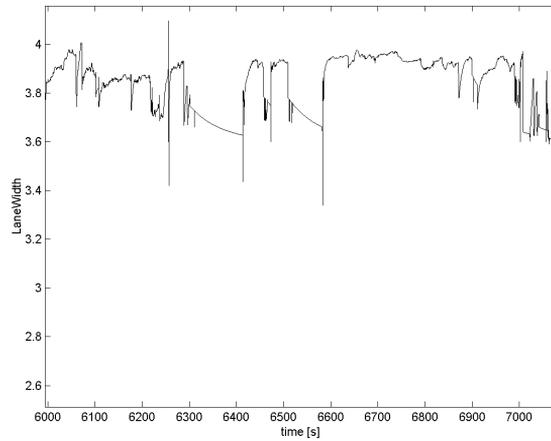

Figure 3.2: Lane width signal from the LDS. [Lane width in meters]

unreliable. A typical error code signal can be seen in figure 3.3. Lateral offset and lane width signals are shown to give an idea of how unreliable signals from the LDS look.
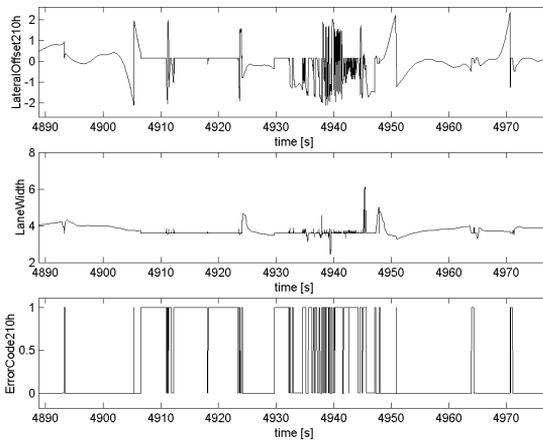

Figure 3.3: Signals from the LDS. Typical signal characteristics when error signal is 1. [Offset and lane width in meters]

Active

The signal is binary and generated from observations done during the test drives. It is set to zero when the measurements is of no use for the test. This includes for example dense traffic, bad weather conditions, speeds lower than 80 km/h or higher then 140 km/h and malfunctioning measurement equipment.

KSS

The signal gives the evaluation of the drivers sleepiness according to the Karolinska Sleepiness Scale. During the test drives the driver is asked to estimate his or hers sleepiness on the KSS every twenty minutes. The estimation is noted with a time reference. This is then compiled into a signal and used as an outer criterion to compare drivers level of sleepiness with warnings given by the system. More about KSS can be found in section 3.1.

Lateral velocity

The TLC value is calculated as lateral distance to lane edge divided by lateral velocity. Therefore the lateral velocity of the vehicle must be found. This

signal is not measured and must therefore be calculated. The simplest way to do this is to derive the lateral offset signal. How this is done can be found in section 7.2.

3.3 Parameters

A short description of the parameters for the system is given. System parameters are divided into two groups, one containing physical parameters with given values and one containing parameters that are used to tune the system. The tuning parameters are used in the LAA system based on closeness to lane edge since this is the only LAA system version that is tuned.

3.3.1 Physical parameters

The physical parameters for the system, some of which can be seen in table 3.2, are given values dependent of signal characteristics and physical conditions. These values are constant and hence not used for tuning of the system. They are used in all LAA system versions.

Parameter	Description
$L_{\text{lane change}}$	Level to compare with difference between adjacent samples in lateral offset to discover lane change.
$LaneWidth_{\text{max}}$	Maximum allowed lane width.
$LaneWidth_{\text{min}}$	Minimum allowed lane width.

Table 3.2: Examples of physical parameters used in model LAA.

3.3.2 Tuning parameters

Tuning parameters are used to adjust the LAA system based on vehicle closeness to lane edge in the tuning phase of the development. Examples of tuning parameters can be seen in table 3.3.

Parameter	Description
$d0_{\text{l/r}}$	Parameters adjusting virtual edge zone inner borders.
$d1_{\text{l/r}}$	Parameters adjusting virtual edge zone outer borders.

Table 3.3: Examples of tuning parameters used in model LAA.

Chapter 4

LAA - Validation and robustness

Validation of models used for calculation of mean and standard deviation, used in the LAA system based on closeness to lane edge, are presented. All calculations of mean and standard deviation is over the distance to lane edge on the right and left side of the vehicle respectively. Parts of the LAA system versions are shown to be offset neutral, i.e. the system is shown to be robust against constant errors in the lateral offset signal from the LDS.

4.1 Mean and standard deviation

Validation of the mean and standard deviation can be seen in figures 4.1 and 4.2. The full line shows the approximations from the model and the broken line shows the value calculated over all samples in one test drive. As can be seen in the figures the approximated values end the calculated values are in the same range.

At the start of the calculation the mean value is quite separated from the true value. Over time the approximation converges toward the real mean value. The calculation of standard deviation also displays this big difference at the start. During the drive the value of the approximation and the real value close in on each other but they end up with a difference. To get an estimation of how good the approximations are the relative error between the final value of the approximation and the correct value is calculated over all test drives. Results are presented in table 4.1.

In both cases displayed in figures 4.1 and 4.2 the approximation of standard deviation is bigger then the correct value, i.e. the error is positive. This could indicate a constant error in the calculation of the standard deviation. However, an examination over all cases shows that errors in the standard deviation approximation are both negative and positive.

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Figure 4.1: Comparison between real and approximated mean value and standard deviation. Calculated over distances to left lane edge. The broken line shows the values calculated over all samples in the test drive.
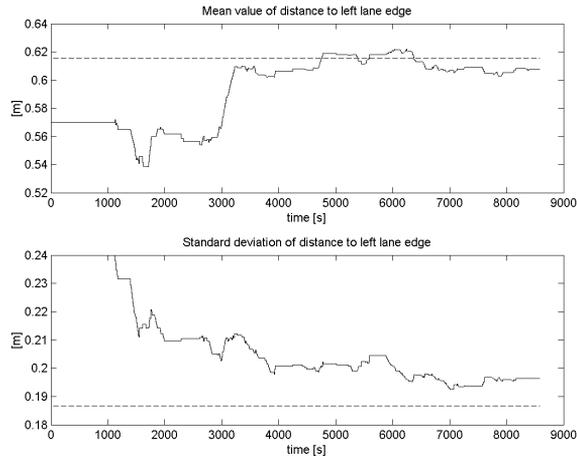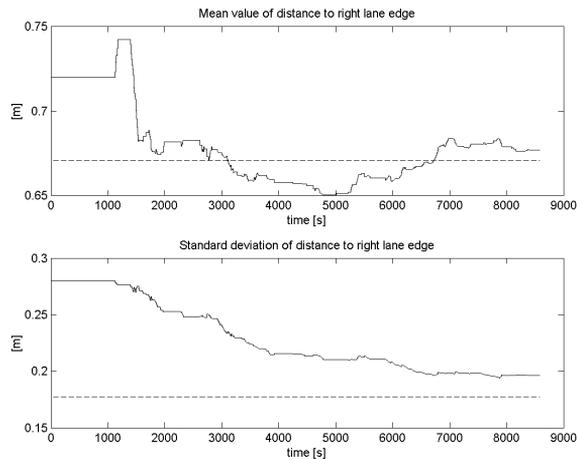

Figure 4.2: Comparison between real and approximated mean value and standard deviation. Calculated over distances to right lane edge. The broken line shows the values calculated over all samples in the test drive.

Error estimation		
	Error Left (in %)	Error Right (in %)
Mean value	4,3	4,2
Standard deviation	8,6	6,2

Table 4.1: Relative error between approximated end values and real values of mean and standard deviation over all test drives. [Error in %]

The main problem with the incremental calculation of mean and standard deviation is that it is very dependent of given start values. In its current form the system uses start values found by calculating mean and standard deviation over all test data. This can be done while all test data is available and all simulations are done offline. For the same reason start values could be calculated separately for every single test drive, something that would probably increase system performance. The problem with this is then that the system would be tailored to fit these test data, something that should be avoided.

When run in a vehicle these types of start value calculations could of course not be performed. Another way of generating start values for the approximation could be to use the approximated mean and standard deviation values from the last time the car was used. Problems with this are that different drivers use the same car, thus possibly causing large differences between the mean and standard deviation between drives.

4.2   Offset neutral

As said in section 2.1.2 the distances to lane edge are examined and found normally distributed. During the gathering of test data for the LAA system two different vehicles were used. Data collected from these two different vehicles are compared. They display a significant difference in mean value and standard deviation. This is most likely an error caused by incorrect camera alignment in the LDS. Since these offset errors exist it became important to test the robustness of the LAA system against constant errors in the lateral offset signal.

4.2.1   Closeness to lane edge

This is first done for the LAA system based on vehicle closeness to lane edge. To test this a 0.1 m constant offset is added to the lateral offset signal. The part of the system that monitors if the driver is intentionally driving close to the lane edge is shut off, while this part of the system includes a comparison that is offset dependent.

The system is then run over all nightly test drives with and without the constant offset. As mentioned in section 4.1, the system is sensitive to start values for the approximations of mean and standard deviation. Therefore start

values are generated by calculating the mean and standard deviation over the
nightly test drives with and without constant offset. These start values are
then used accordingly. The weight peaks from one test drive with and without
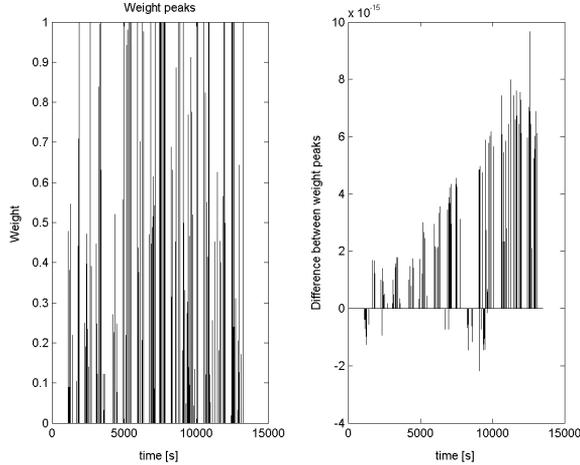constant offset can be seen in figure 4.3.

Figure 4.3: Weight peaks generated during system simulation with and without constant offset. Left: Weight peaks plotted in the same figure. Right: Difference between the plotted weight peaks.

As can be seen the weight peaks generated are equal in both systems. The
difference between the delivered weight peaks is in the range of 10^{-15} which
is the smallest values used by Matlab. Furthermore warnings given by the
system with and without constant offset are compared and found to be equal.
These both results are strong indications that the basic LAA system using
closeness to lane edge is offset neutral, i.e independent of a constant error
in the lateral offset signal. A mathematical proof that the basic algorithm is
offset neutral is given in appendix A.

4.2.2   TLC

The LAA system using TLC as criterion to detect lane drifting is not offset
neutral. The TLC value is calculated by dividing lateral distance to lane edge
with lateral velocity. Lateral distance to lane edge is calculated as described
in equations (2.1) and (2.2). Adding a constant offset to the lateral offset
signal will increase the lateral distance to lane edge on one side of the vehicle
and decrease it on the other side. The lateral velocity is found by derivation
of the lateral offset signal. The value of the derived signal will be the same
regardless of if a constant value is added to the lateral offset signal or not.

Since the distance to lane edge changes with an addition of constant offset but the lateral velocity remains the same, the TLC values for the systems with and without a constant offset will not be equal. Since the TLC values are compared to a constant TLC limit the different systems will give different results. The peaks given from the system with and without constant offset can be seen in figure 4.4.
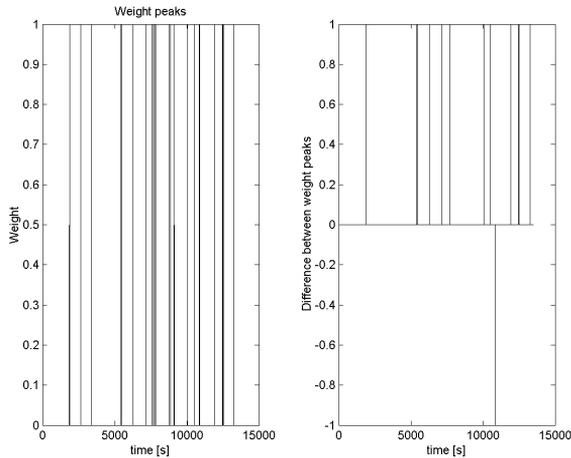
Figure 4.4: Weight peaks generated during system simulation with and without constant offset. Left: Weight peaks plotted in the same figure. Right: Difference between the plotted weight peaks.

As can be seen the generated peaks are not equal. Thus the system is not offset neutral. Mathematical reasoning to support this can be found in appendix B.

4.2.3 ORA

To test if the LAA system using ORA as criterion is offset neutral a constant offset of 0.1 meters is added to the lateral offset signal. The system is then run over all nightly test drives with and without constant offset. The calculated ORA from each system can be seen in figure 4.5.

As can be seen the areas are equal in both systems. The difference between them is in the range of 10^{-15} which is the smallest values used by Matlab. Mathematical evidence that the ORA system is offset neutral can be found in appendix C.
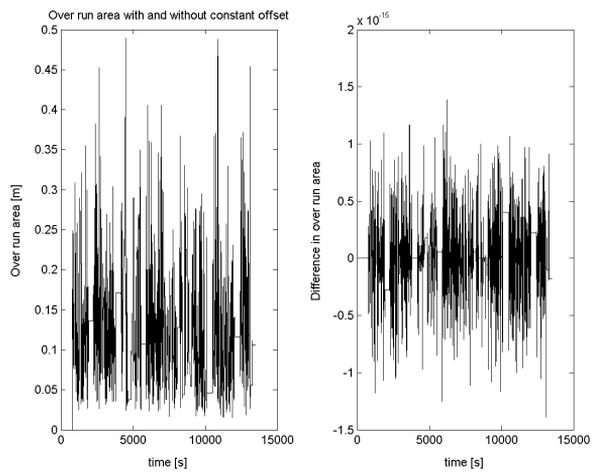
Figure 4.5: Over run area from system simulation with and without constant offset. Left: ORAs plotted in the same figure. Right: Difference between the plotted ORAs.

Chapter 5

LAA - Simulation, tuning and results

Two different versions of the LAA system based on vehicle closeness to lane edge, active weight sum and general weight sum, are explained. Model tuning for these systems are described. Results of these different versions run over the available test data are presented. Results of the LAA system based on TLC run over the available test data are also given. Results of the system based on ORA are presented for completeness. The systems mentioned below refers to the systems which uses the vehicles closeness to lane edge to issue a warning. Active time mentioned below is the time where SAS=1.

5.1 Simulated system versions

As mentioned in section 2.4 two different versions of the LAA system based on closeness to lane edge are created. The first one is called active weight sum and uses information from twenty minutes of active time in the past to calculate the weight sum. The other system version is called general weight sum and uses information from the past twenty minutes, regardless of SAS value, to calculate the weight sum.

5.1.1 Active weight sum

The first system uses an active calculation of the weight sum. This means that the weight function sum is calculated over the past twenty minutes of active time. The past twenty minutes active time is of course not the same as the past twenty minutes. A consequence of this is that information older then twenty minutes may affect the system to give the driver a warning or not. At the same time it guarantees that calculations are only done over values generated when the system is active, i.e. when input data is usable.

Interesting is of course to see how big the difference between twenty minutes of active time and twenty minutes of real time is. Two pointers are set, one pointing at the first active time value, the second pointing at the value twenty minutes of active time later. Thus the pointers point to the first and last value used to calculate the active weight sum. Both pointers also have a real time reference thus making it possible to compare the two pointers and calculate the difference in real time between them. By increasing both pointers one second in active time a new value of the real time between them is found. This is done for all active time values in all test drives. The results are plotted in a histogram which can be seen in figure 5.1. The x-axis shows the real time difference during twenty minutes of active time. The y-axis shows the number of times this specific time difference occurs.
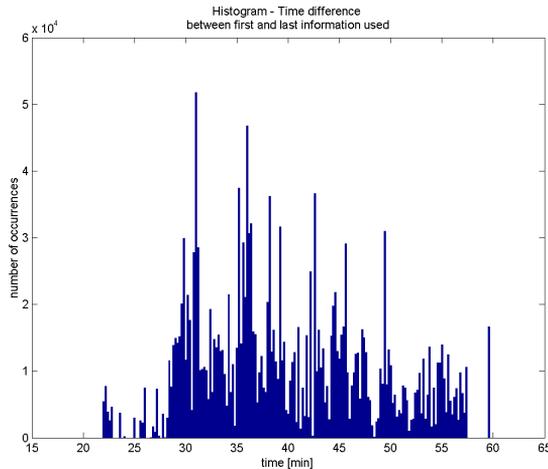
Figure 5.1: Length of twenty minutes of active time in real time.

As can be seen of course no values are lower then twenty minutes. A large amount of the values lies between thirty and fifty minutes but values can be found as far back in time as sixty minutes. It is clear that driver lane keeping data from an hour ago has very little to do with if the system should deliver a warning or not at the present time. It can also be seen that the system never is active for twenty minutes without interruption. With the best test data the system needs approximately twenty three minutes in real time to gather twenty minutes of active time information.

5.1.2   General weight sum

The second system uses a general calculation of the weight function sum. This means that the weight function is calculated over the past twenty minutes regardless of SAS value. When SAS=1 the weight sum is calculated as

normal. When SAS=0 only zeros are added to the weight sum. This means that the value of the weight sum decreases rapidly as soon as the SAS is zero over a longer time period. During test drives where SAS is often zero this of course keeps the system from generating a warning. If the traffic is dense and the driver active, i.e. when there are many lane changes and the SAS therefore is zero, this is correct. If however the SAS is zero because of unusable input data it is faulty.

5.2 Model tuning

Both systems are tuned via a parameter study. The study is run over all nightly test drives as these all display an increasing level of driver fatigue. The results of the system versions run with different parameter settings are evaluated with a system effectiveness measurement. More about this measurement is given below. With help of the effectiveness measurement optimal parameter settings for the two system versions are found. The system versions are then run with these parameter settings over all test drives. Results can be seen in section 5.3.

Model effectiveness measurement

All drives are sorted in to an evaluation matrix. The matrix is made up of different fields categorizing the warnings given or not given. If a warning is correctly or falsely given is dependent on the KSS value of the driver. The evaluation matrix can be seen in table 5.1.

Evaluation Matrix					
	KSS 1-3	KSS 4-6	KSS 7	KSS 8	KSS 9
Warning given	False (-2)	False (-1)	- (0)	Correct (+1)	Correct (+1)
Warning not given	Correct (+1)	Correct (+1)	- (0)	Faulty (-1)	Faulty (-2)

Table 5.1: Functionality of evaluation matrix. Effectiveness measurement value within parenthesis

The effectiveness measurement is calculated in a straight forward way. All correct warnings are given the value +1. All false warnings are given negative values, their size depending on how far from correct they are. This means that warnings given for KSS levels 1-3 and no warnings given for KSS level 9 are valuated to -2. In the same fashion warnings given for KSS levels 4-6 and no warning given for KSS level 8 gets a value of -1. KSS level 7 is considered to be the change over point of the KSS scale. Thus both warnings

and no warnings are excepted and the value of KSS level 7 is therefore set to 0. These values are then simply added to form the effectiveness measurement.

5.3   Results - Closeness to lane edge

The best results of the system version with active weight sum calculation can be seen in table 5.2.

Results - Active weight sum			
	False	Correct	Faulty
Nightly test drives	15	57,5	27,5
All test drives	26,4	62,4	11,2

Table 5.2: Results of system with active weight sum run over the test drives. [Results given in %]

The best results of the system version with general weight sum calculation can be seen in table 5.3.

Results - General weight sum			
	False	Correct	Faulty
Nightly test drives	27,5	47,5	25
All test drives	22,4	68	9,6

Table 5.3: Results of system with general weight sum run over the test drives. [Results given in %]

During the nightly test drives all drivers reached a KSS level high enough for the system to warn them. Run over all nightly test drives 57,5% of the drivers are warned at the right time by the system with active weight sum. A further 27,5% of the cases render no warnings, these are known as faulty warnings. The last 15% of the drivers are warned to early, these are known as false warnings. All false warnings can be found between KSS levels 4-6 with half of them given at KSS level 6. The same numbers for the system with general weight sum is 47,5% correct warnings, 25% faulty warnings and 27,5% false warnings. All false warnings can be found within KSS level 4-6 with the majority (64%) at KSS level 6. The system with active weight sum is better during the night drives. It handles more cases correctly and gives the driver far fewer false warnings.

System performance over all test drives gives a somewhat different view. A bit over 60% of all cases are handled correctly by the system with active weight sum. The percentage of faulty warnings, 11,2%, decrease which is expected since only a few test drives during the day include KSS values of seven or more. The problem is the large percentage of false warnings given.

In more then 25% of all cases warnings are given to soon, some at a KSS level as low as 1. The results for the system with general weight sum is 68% correct warnings, 22,4% false warnings and 9,6% faulty warnings. Here the system with general weight sum outperforms the other system. This is due to the fact that during test drives at day time traffic is denser and the driver is more active, causing the SAS to be set to zero more often. This in turn causes the weight function value to decrease therefore it is harder for the system to reach the set warning level. This is good during day time driving as only few of the test drives in day time reach a KSS value high enough for the system to give a warning.

Both systems suffer from a too high percentage of false warnings. If the system continually warns the driver too early and in situations where he or she does not suffer from fatigue it will only cause driver annoyance. This can also serve to enhance a feeling of being "watched" and "falsely corrected" by the vehicle. Both false and faulty warnings given to often decreases driver confidence in the system. Further possibilities to improve the system are discussed in chapter 9.

5.4   Results - TLC

The best results of the LAA system with TLC as criterion for discovering lane drifting can be found in table 5.4

Results - LAA with TLC			
	False	Correct	Faulty
Nightly test drives	20	52,5	27,5
All test drives	28	62,4	9,6

Table 5.4: Results of LAA system with TLC as criterion. [Results in %]

As mentioned before all drivers reached a KSS level high enough for the system to warn them during the nightly test drives. In the case of the LAA system with TLC as criterion 52,5% of the drivers are warned correctly. In some 20% of the cases drivers are falsly warned. All false warnings can be found within KSS level 5-6, with as many as 75% at KSS level 6. No warnings are given in 27,5% of the cases. During all test drives the system performance is 62,4% correct warnings, 28% false and 9,6% faulty. Here the false warnings can be found at KSS level as low as 2.

Since this LAA system uses an active sum to sum the peaks it is interesting to compare it to the LAA system with active weight sum described in section 5.1.1. The results of both the systems can be seen in tables 5.2 and 5.4. The system with TLC is just barely outperformed by the system with active weight sum. Over nightly test drives the difference is 5% less false warnings and 5% more correct warnings for the system with active weight

sum. Over all test drives the system with TLC as criterion delivers the same amount of correct warnings. The number of faulty warnings are lower on the cost of more false warnings. An intresting aspect is that although the system with TLC as criterion gives more false warnings the false warnigs are given for higher KSS levels. The earliest false warning given by the system with active weight sum lies at KSS level 1 wheras the earliest false warning given by the system with the TLC criterion lies at KSS level 2.

The system with TLC as criterion can also be compared with the system using a general weight sum described in section 5.1.2. The results of the systems can be seen in tables 5.3 and 5.4. During the nightly test drives it is clear that the system with TLC criterion outperforms the system with general weight sum. The false warnings are 7,5% fewer and the correct warnings are 5% higher. This at a cost of 2,5% more faulty warnings. Over all test drives the system with a general weight sum is better. It gives more correct values and fewer false warnings.

As for the systems above the system using TLC as criterion must be further developed, important issues being to decrease the number of false and faulty warnings. Although the system delivers false warnings they are all found at high KSS levels. The question is also where to put the TLC limit. If the limit is too low, the TLC is more like a closeness to lane edge criterion and then that alone is enough. If the TLC limit is too high the calculation of TLC is too inaccurate and the system is rendered ineffective. These questions are shortly addressed in chapter 9.

5.5   Results - ORA

The best results of the system based on ORA can be seen in table 5.5.

ORA - Results			
	False	Correct	Faulty
Nightly test drives	20	35	45
All test drives	24,8	59,2	16

Table 5.5: Results of ORA-system [in %]

During the nightly test drives all drivers reached a KSS level high enough for the system to warn them. Run over all nightly test drives the ORA system gives the driver a correct warning in only 35% of the cases. Almost half of the drivers, 45%, are not warned at all. Finally 20% of the drivers are given false warning, some (25%) for a KSS level as low as 3. Over all test drives 59,2% of the cases are handled correctly. The fact that the system is built to warn drivers suffering from fatigue makes the high number of faulty warnings unacceptable.

Chapter 6

TLC - System

A short introduction to Time-to-lane crossing, TLC, is given. Two different mathematical models for calculating TLC are presented. To filter the input signals for the TLC models a filter is developed. The filter generates a system activity signal that controls TLC model activity and allows the system to be active only when input data is usable.

6.1 Calculation of TLC

The Time-To-Lane Crossing, TLC, value was first introduced by Godthelp et.al. (1984) (as cited in [13]). It represents the time available for the driver before any part of the vehicle crosses a lane edge. For a number of years the TLC value has been discussed as a possible measurement of driver awareness, for example in [10] or [13]. Throughout the years different models for the calculation of TLC have been suggested.

   The most basic model given in [13] defines TLC as the lateral distance to lane edge divided with the lateral velocity of the vehicle. This is also the model used in the LAA system based on TLC. In [13] it is found that this simple estimation of TLC may be reliable enough for driver warning systems, but that the reliability of the approximated TLC value is satisfactory for only a very short time before actual lane crossing occurs.

   Slightly more advanced models for calculating TLC are developed in [10]. These models use mathematical descriptions of the lane edges and the vehicle path to calculate the distance to future intersection between vehicle and lane edge. This distance is then divided with the vehicle speed to form a TLC value.

6.2 TLC model 1

A model used to calculate TLC can be found in [13] and is given as

$$TLC_1 = \frac{y_{l/r}}{\dot{y}} \tag{6.1}$$

where $y_{l/r}$ is the distance to left and right lane edge respectivley and $\dot{y}$ is the lateral speed of the vehicle. Depending on the vehicles lateral speed the model has three different versions. If the vehicle moves to the left the lateral speed, $\dot{y}$, is positive, and the distance to left lane edge is the relevant distance. If the vehicle moves to the right $\dot{y}$ is negative and the distance to the right lane edge is the relevant distance. If the lateral speed is zero, TLC is infinite. Undefined TLC values and TLC values bigger then three seconds are not considered.

$$TLC_{1.\text{left}} = \begin{cases} \frac{y_l}{\dot{y}} & \text{if } \dot{y} > 0 \\ 3 & \text{if } \dot{y} \leq 0 \text{ or if } \frac{y_l}{\dot{y}} \geq 3 \end{cases}$$

$$TLC_{1.\text{right}} = \begin{cases} \frac{y_r}{|\dot{y}|} & \text{if } \dot{y} < 0 \\ 3 & \text{if } \dot{y} \geq 0 \text{ or if } \frac{y_r}{|\dot{y}|} \geq 3 \end{cases}$$

6.3   TLC model 2

The model developed in [10] uses clothoids to describe the road in front of the vehicle and to describe the future path of the vehicle. By finding the point where the lane edge and the vehicle path intersect a distance to lane crossing, DLC, can be calculated. The DLC is defined as the distance, in the direction of the vehicle, before any part of the vehicle crosses the lane edge. Since the DLC is calculated based on the direction of the car it only needs to be divided with the vehicle speed to give a TLC value.

6.3.1   Road model

In order to compute the distance to lane edge first a model of the lane edge is needed. In [10] the lane edges are modeled as clothoids. A clothoid is a spiral curve in the plane, defined by its curvature κ, that changes with constant rate

$$\kappa(\tau) = \frac{1}{R(\tau)} = c_0 + c_1\tau \tag{6.2}$$

where τ is the coordinate along the curve, $R(\tau)$ is the radius of curvature, c_0 is the curvature at $\tau = 0$ and c_1 is the constant curvature change rate. This of course means that when $c_0 = c_1 = 0$ the curve is a straight line, and when $c_0 \neq 0$ and $c_1 = 0$ the curve is an arc of a circle. This fact has been used for many years in road and railroad construction to achieve a smooth transition from a straight to a curve.

The clothoid is defined by its parametric formula found in [7]

$$\left(\int_0^\tau \cos\left(\frac{x^2}{2} \right) dx, \int_0^\tau \sin\left(\frac{x^2}{2} \right) dx \right) \tag{6.3}$$

The length, dl, of an infinitesimal piece of a curve in the plane can be written as

$$dl = dx\hat{x} + dy\hat{y} \tag{6.4}$$

which with use of the chain rule yields

$$dl = \frac{dx}{d\tau}d\tau\hat{x} + \frac{dy}{d\tau}d\tau\hat{y} \tag{6.5}$$

The total arclength, $s\,(t)$, between $[0, t]$ is then given by

$$s\,(t) = \int_0^t |dl|\,d\tau = \int_0^t \sqrt{\left(\frac{dx}{d\tau} \right)^2 + \left(\frac{dy}{d\tau} \right)^2}\,d\tau \tag{6.6}$$

which with the use of the parametric formula (6.3) and basic trigonometry yields

$$s\,(t) = \int_0^t 1\,d\tau = t \tag{6.7}$$

and thus the arc length of a clothoid is exactly the same as the value of the coordinate along the curve. For a plane curve the curvature, κ, is defined by

$$\kappa\,(\tau) = \frac{d\Phi}{ds} \tag{6.8}$$

where $d\Phi$ is the change in angle and ds is the change in distance along the curve. Using the chain rule and results from equation (6.7) in equation (6.8) yields

$$\kappa\,(\tau) = \frac{\frac{d\Phi}{d\tau}}{\frac{ds}{d\tau}} = \Phi' \tag{6.9}$$

since $\frac{ds}{d\tau} = 1$. The reference system used is a right handed cartesian coordinate system with origin at the center of the road in accordance with the DIN 70000 standard [6]. The x-axis is in the direction of the tangent of the road, the y-axis points to the left and the z-axis points upwards. The calculation of the angular variation, $\Delta\Phi$, of the curve tangent to the x-axis can be done with use of (6.9) and (6.2). The x-axis is parallel to the road meaning that $\Phi_0 = 0$.

$$\Delta\Phi = \Phi\,(\tau) - \Phi_0 = \int_0^\tau \Phi'\,(\tau)\,d\tau = \int_0^\tau (c_0 + c_1\tau)\,d\tau = c_0\tau + \frac{1}{2}c_1\tau^2 \tag{6.10}$$

Adding a starting point (x_0, y_0) where $\tau = 0$ gives

$$\begin{cases} x\left(l\right) = x_0 + \int_0^l \cos \Phi(\tau) d\tau \\ y\left(l\right) = y_0 + \int_0^l \sin \Phi(\tau) d\tau \end{cases}$$

Assuming that the angle, $\Phi\left(\tau\right)$, is small $\cos \Phi(\tau)$ and $\sin \Phi(\tau)$ can be approximated with Taylor series to the first degree. Combining this with equation (6.10) yields

$$\begin{cases} x\left(l\right) = x_0 + l \\ y\left(l\right) = y_0 + \frac{1}{2}c_0 l^2 + \frac{1}{6}c_1 l^3 \end{cases}$$

Finally adopting a reference system with origin at the start of the clothoid, where $x_0 = 0$ and $y_0 = 0$, one arrives at

$$\begin{cases} x\left(l\right) = l \\ y\left(l\right) = \frac{1}{2}c_0 l^2 + \frac{1}{6}c_1 l^3 \end{cases}$$

The equations above describe the road center. To describe the lane edge one needs to take into account the width of the lane. In [10] the constant c_1 is found to be small and is therefore omitted to simplify calculations. This gives an easier to handle second order equation

$$y\left(l\right) = \pm\frac{b}{2} + \frac{1}{2}c_0 l^2 \tag{6.11}$$

where $\pm$ are for the left and right lane edge respectively, b is the lane width, c_0 is the curvature of the road, defined positive to the left and negative to the right, and l is the distance along the x-axis.

6.3.2   Vehicle path model

In [10] two different models for the future motion of the car are presented. The first model is based on the assumption that the vehicle keeps its current direction. The second model is based on the assumption that the driver almost keeps his current direction. The two models are described by

$$y\left(l\right) = y_0 + \theta l \tag{6.12}$$

$$y\left(l\right) = y_0 + \theta l + \frac{1}{2}c_c l^2 \tag{6.13}$$

where θ is the angle between road and vehicle defined positive counter clock wise, CCW, l is the distance along the x-axis and c_c is the curvature of the curve of the vehicle, defined positive to the left. The curvature of the curve of the vehicle is defined as $c_c = 1/r_c$ where r_c is the radius of the curve of the vehicle. This radius can be calculated via the steering angle, δ. The steering angle is not measured but can be calculated from the steering

wheel angle. One problem here is the ratio between steering wheel angle and steering angle. This ratio is progressive to increase vehicle stability at high speeds. Since a specific speed interval is considered it seems viable to use a linear relation to calculate steering angle from steering wheel angle.

The equations (6.12) and (6.13) describe the future path of the vehicle center. To describe the path for the wheels one needs to take the vehicle width into account. This yields

$$y(l) = \pm \frac{b_c}{2} + y_0 + \theta l \tag{6.14}$$

$$y(l) = \pm \frac{b_c}{2} + y_0 + \theta l + \frac{1}{2} c_c l^2 \tag{6.15}$$

where the $\pm$ is for the left and right side of the vehicle respectively.

The distance-to-lane crossing, DLC, can now be calculated as the distance l when the models intersect. Care must be taken in the calculation of DLC when $\theta = 0$, $c_0 = 0$ or $c_c = 0$. The TLC value is then calculated as

$$TLC = \frac{DLC}{v_{\text{ref}}} \tag{6.16}$$

where v_{ref} is the vehicle speed in m/s.

6.4 System Activity Signal, SAS TLC

The input signals for the TLC system contain measurement errors and parts where the measurements cannot be used. Examples of this is vehicle speeds below 80 km/h or above 140 km/h. Therefore the input signals are filtered before use. The filter is made up of a system activity signal, SAS_{TLC}. The TLC system is active only when the $SAS_{\text{TLC}} = 1$.

The SAS_{TLC} is dependent on four different signals. The lane width signal, given from the LDS, gives the actual lane width. During the passing of road construction sites the lane width is small. To avoid that the system warns the driver of imminent lane departure because of small lane width, only lane widths bigger than 3 meters are considered. Lane width of an old German Autobahn is 342,5 cm, for a new German Autobahn it the lanes are 367,5 cm wide. No data has been found for Schnellstrassen, and therefore it seems reasonable to use the data for German Autobahns here. The maximum allowed lane width is set to four meters.

The system is aimed for use at highway driving. Therefor only parts of the test data when the vehicle speed is between 80 km/h and 140 km/h are considered. Limiting the speeds allowed means that the start and end of the test drive is filtered out. Maximum lane curvature must be between $\pm$ 1/500 1/meter. This is while no curves on Schnellstassen have a radius smaller then 500 meters, meaning that values outside of this interval is faulty. Steering

wheel angle must also be within reasonable limits. After a closer look at the input signals it is found that the steering wheel angle normally lies within $\pm$ 15 degrees.

Chapter 7

TLC - Input signals

Test data used for evaluation of the TLC system is described. A short description of the input signals for the system is given.

7.1   Test data

All simulations of the TLC system were preformed on data previously collected during expert trials in and around Stuttgart. Twenty four test drives were done on Schnellstrassen, roads with multiple lanes in each direction with separation from oncoming traffic. Each test drive was between one and two hours long.

   The vehicle used during the expert trials was equipped with a LDS used to recognize the lane edges and to calculate the vehicle position in the lane. The LDS delivers, among other signals, the actual lane width and the lateral offset of the vehicle. Further reading on lane detection systems can be found in [9] and in [12]. More information over the expert trials can be found in [4].

7.2   Input signals

Input signals are given with name and definition. If nothing else is said the signals are sampled from the LDS at a rate of 50 Hz. Signals explained earlier in this thesis are only given with reference.

Lateral Offset

See section 3.2 on page 15.

Lane Width

See section 3.2 on page 15.

Curve of the road

The signal gives a measurement of the curve of the road at the camera position. The curve is given in 1/m.

Steering Wheel Angle

Signal logged from vehicle CAN-bus. The signal gives the actual steering wheel angle measured positive to the left. Steering wheel angle is given in degrees.

Vehicle speed

The signal is taken from the speedometer and gives the speed of the vehicle. The speed is given in km/h.

Lateral velocity

To use TLC model 1 the lateral speed of the vehicle is needed. This speed is not measured and must therefore be calculated. The simplest way to do this is to derive the lateral offset signal.

$$\dot{y}(t) = \frac{dy}{dt} \approx \frac{\Delta y}{\Delta t} \tag{7.1}$$

where $\dot{y}(t)$ is the lateral velocity. Given (7.1) the derivation of the lateral offset signal in the model is done as

$$\dot{y}_{\text{lat}}(t) = \frac{mean(y_{\text{lat}}(t, t + win)) - mean(y_{\text{lat}}(t - win, t))}{\delta t \cdot win} \tag{7.2}$$

where $mean(y_{\text{lat}}(t, t + win))$ is the mean value of the signal between sample t and $t + win$ defined as

$$mean(y_{\text{lat}}(t, t + win)) = \frac{1}{1 + win} \sum_{i=t}^{t+win} y_{\text{lat}}(i) \tag{7.3}$$

The definition (7.3) can also be used for $mean(y_{\text{lat}}(t - win, t))$ with $t = t - win$. The parameter win designates how many samples before and after time t that shall be considered and δt is the sample time. Total number of samples used are $(2 \cdot win + 1)$. Lateral offset and lateral velocity of the vehicle as used in the simulation can be seen in figure 7.1

The fact that values in the future have been used makes it impossible to run the TLC calculation in real time. If for example, if five samples before and after time t are used, $win = 5$, this means a time delay of 5 samples. The sample frequency is 50 Hz and thus the sample time is 0.02 seconds. With
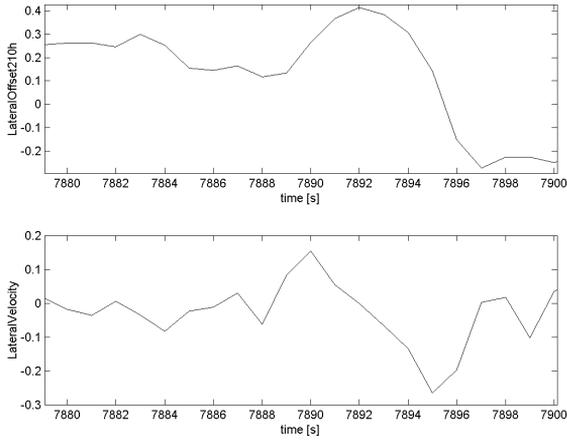
Figure 7.1: Above: Lateral offset of the vehicle. [Offset in meters] Below: Lateral velocity of the vehicle derived from lateral offset. [Velocity in meters/second]

$win = 5$ this gives a time delay of 0.1 seconds. This is a problem as the TLC system needs to give the driver a warning of imminent lane departure at least half a second before the lane departure occurs.

Chapter 8

TLC - Simulation, evaluation tool and results

Simulation of the TLC system is described. A tool to evaluate the effectiveness of the TLC system is developed. The results of the system run over available test data is presented.

8.1   Simulation

As mentioned in section 7.1 the test data used to evaluate the TLC system was collected during expert trials in and around Stuttgart. These trials were not made with the sole purpose of collecting test data for a TLC system, and therefore not all signals needed for the TLC system were logged. Signals needed for the calculation of TLC model 1 are all available. For calculation of TLC Model 2 the vehicle direction angle θ is unavailable. For this reason only TLC model 1 is simulated although both TLC model 1 and TLC model 2 are implemented in Simulink. The terms TLC system and TLC model used below refers to TLC model 1. The TLC system is simulated and evaluated over all twenty four expert trials.

8.2   Evaluation tool

To evaluate the results of the TLC system an evaluation tool is developed. The objective of the evaluation tool is to create a standardized evaluation of the quality of TLC systems. Important things are that the system is automated and that the evaluation results are presented in a sensible way.

The evaluation is done by first finding all samples in the data where the distance to the left or right lane edge is zero, i.e. all the samples where the

lane edge is crossed either to the left or to the right. There are some criteria that must be fulfilled for the lane crossings to be valid. The TLC system must have been active for the last two seconds before the lane crossing. This means that the first two seconds of data in every expert trial are discarded. Furthermore the time between lane crossings must be more then two seconds. At set times before the lane crossing the predicted TLC value is examined to see how effective the system is. Since the system is sampled at 50 Hz the time difference between two samples are 0.02 seconds. This means that once a sample where the lane is crossed has been found the real TLC value can be found by calculating the number of samples back in time. For example, say that the lane crossing occurs at time t. Then the real TLC is 0.1 seconds five samples before t, real TLC is 0.2 seconds at ten samples before t etc. Therefore the predicted values from the TLC system can noted at t-0.1 seconds, t-0.2 seconds, t-0.4 seconds etc.

As the evaluation tool is run over all expert trials these values are noted for all lane crossings. The found values are then plotted in histograms, one for each time value before lane crossing. The results of this can be seen in 8.3.

8.3   Results

As mentioned in section 6.1 the TLC model 1 is found in [13]. In [13] it is also found that this simple estimation is only reliable a very short time before actual lane crossing occurs. The results from the evaluation of the TLC system support this. In figure 8.1 and 8.2 the predicted TLC values for 0.1 and 0.2 seconds before lane crossing are plotted.

The cases where the predicted TLC value is three, i.e. where the predicted TLC value is undefined, are not plotted in the figures for visibility reasons. Undefined values are 1.3% of the cases where real TLC = 0.1 seconds and 3% in the case of real TLC = 0.2 seconds. As can be seen in figures 8.1 and 8.2 the values are approximately normal distributed. The mean value of both TLC values are close to the correct value. The standard deviation is big but still manageble. For example, in the case where it is 0.2 seconds to lane crossing the system would tell the driver there is a lane crossing within 0.22 seconds or less in 50% of the cases.

If a warning of imminent lane departure is to be effective it must come in such a time that the driver has a chance to respond to it. How long before lane crossing that are needed is individual for drivers and driving situations. It is however most likely so that a warning of lane departure given 0.2 seconds before the actual lane departure is too late. It seems more reasonable that a warning must be given about half a second before actual lane departure to be effective. Between the warning and the actual lane departure the driver must first get his orientations and then respond by turning the steering wheel. If the inattentiveness is caused by other tasks in the vehicle the driver may also have to move one hand back to the steering wheel before he can steer to avoid the

Figure 8.1: TLC predicted by the TLC system. Real TLC is 0.1 seconds.
[Cases where TLC prediction is 3 seconds, i.e. cases where predicted TLC is
undefined, are not shown. They are 1.3% of the cases]

Figure 8.2: TLC predicted by the TLC system. Real TLC is 0.2 seconds.
[Cases where TLC prediction is 3 seconds, i.e. cases where predicted TLC is
undefined, are not shown. They are 3% of the cases]

lane departure. TLC system performance in a longer time span can be seen in figure 8.3
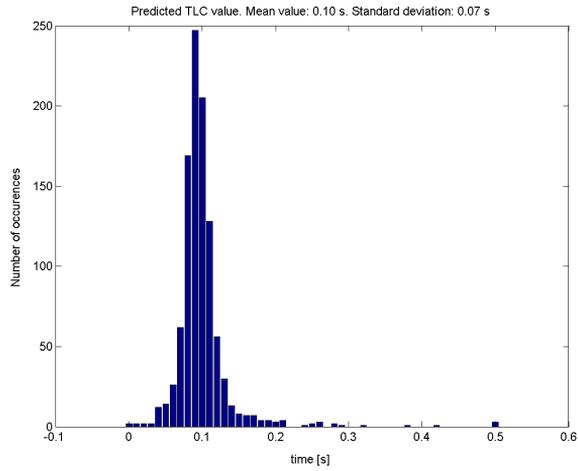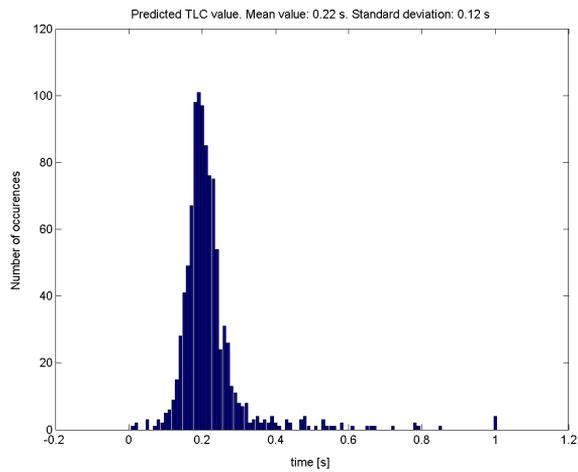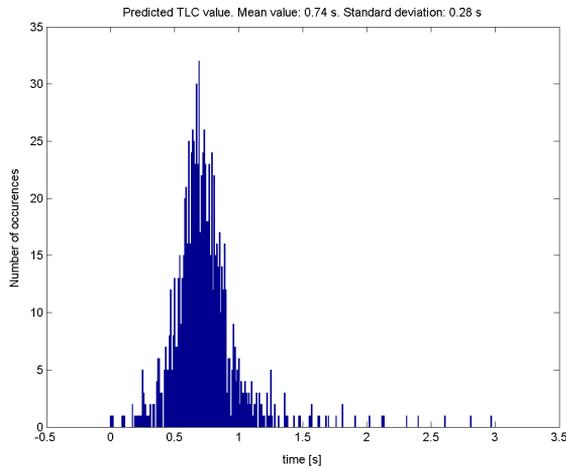

Figure 8.3: TLC predicted by the TLC system. Real TLC is 0.6 seconds. [Cases where TLC prediction is 3 seconds, i.e. cases where predicted TLC is undefined, are not shown. They are 4% of the cases]

Again, the cases where the predicted TLC value is three, i.e. where the predicted TLC value is undefined, are not plotted in the figures for visibility reasons. Undefined values are 4% of the values in the case of real TLC = 0.6 seconds. In this case the TLC system is to inexact too be used. The mean value of the TLC is 25% off from the real value. This means that if there is 0.6 seconds to a lane departure the system would warn that there is 0.74 seconds or less in 50% of the cases. This shows that the performance of TLC model 1 is inadequate to be used as a criterion for a TLC based warning system. For this purpose a more accurate model of TLC, and a model independant of future offset values, must be used.

The most important result is that the evaluation tool developed is working correctly. In an automated way TLC systems can now be evaluated. The results are also presented in a reasonable fashion. The evaluation for this TLC system is done by using actual lane crossings in the form of lane changes as references. Most likely there is a difference in driver behavior between an intended and an unintended lane change. Furthermore unintended lane crossings also have to be separated from intended lane crossings before a TLC based warning system can be built. To solve these questions more data has to be gathered, logging all signal needed for the TLC models suggested in this thesis. Then the second TLC model, TLC model 2, could also be used to improve accuracy in the TLC calculation. This is not done in this thesis.

Future work for the TLC system are discussed in chapter 9.

Chapter 9

Conclusions and further work

The objective with this thesis has been to develop and evaluate two different systems to warn drivers of unawareness. The first system, LAA, uses long-term information over the drivers lane keeping to issue a warning to drivers suffering from fatigue. Three different versions of the system are developed, all of them with a more or less satisfactory capacity to warn drivers suffering from fatigue. The second system, TLC, uses short-term information over driver lane keeping to calculate a time-to-lane crossing, TLC, value for the driver. This TLC value gives the time left before any part of the vehicle crosses a lane edge. Due to signal availability only a very basic TLC model has been evaluated and the results are not accurate enough to be used for a TLC based warning system. The same basic TLC model is however successfully used in one of the LAA system versions as a criteria for detecting lane drifting.

An important question is the offset neutrality of all the LAA system versions. If the systems can be made offset neutral this decreases demands of LDS mounting and camera alignment, making the system more robust. In chapter 4.2 two of the three different LAA systems are shown to be partly offset neutral. For the LAA system based on vehicle closeness to lane edge the problem that needs to be solved is the monitoring of if the driver intentionally drives close to the lane edge. This is now regulated by a constant distance from the lane edge that is deemed to be close to the lane edge. An idea to solve this problem would be to replace the constant value with a value calculated via the mean and standard deviation which both are available. Solving this problem would make two out of three LAA systems truly offset neutral. This would definitely increase the robustness of the LAA system. Since the test data from different vehicles does show some offset differences it is reasonable to think that the LAA system using closeness to lane edge as criterion

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mentioned above would display better results were it completely offset neutral.

As said in section 4.2.2 the LAA system with TLC as criterion is not offset neutral. Some work is needed here to individualize the TLC limit and to make it offset neutral. The TLC limit is used as a measurement of vehicle position in the lane. If this value is made to small, the TLC criterion resembles the closeness to lane edge criterion. If however the TLC limit is made to big, with the TLC model used, the calculated TLC value is too inaccurate to deliver usable information. This needs to be taken into consideration when developing an individualization of the TLC limit for the LAA system. As well as for the other versions of the LAA system it is reasonable to think that the results of the LAA system with TLC as criterion would display better results if it was developed to become offset neutral.

For the TLC system there are also questions left to address. Due to signal availability only a very basic TLC model is implemented in this thesis. The results of this model are accurate enough for predicting the TLC value a short time before lane departure but inaccuracy increases with the time to lane departure. As a criterion for the LAA system the accuracy is good enough since the TLC value is used to gather information of the drivers lane keeping over a longer time period. For use in a TLC based warning system that should warn the driver before lane departure the TLC model implemented is not accurate enough.

A second problem with the TLC value calculated in this thesis is the calculation of vehicle lateral velocity. This velocity is not available as a measured signal. Therefore it has been derived from the lateral offset. The derivation of measured signals is always uncertain and the results must be thoroughly examined before they are used. In this case the derivation is done over both past and future values of the lateral offset signal which makes it impossible to run the system in real time. This is no problem for the LAA system using TLC. For one, all signals in the LAA system are delayed with half the SAS zero time, in this case 10 seconds, secondly the LAA system uses information from the last twenty minutes to generate a warning for the driver. For a warning system only based on TLC this issue must be solved. Since the TLC model evaluated in this thesis is too inaccurate to be used for a TLC warning system the solution could be to evaluate the second TLC model. One advantage then is that there is no need for the vehicles lateral velocity, only the velocity of the vehicle is needed. How accurate the second TLC model could be is impossible to say, but it is reasonable to assume that is has a better accuracy then that of TLC model 1.

If a TLC based warning system is to be effective there is also a need to separate intended and unintended lane departures. In the LAA system all intend lane departures, i.e. lane changes, are filtered out at the cost of a ten second time delay in the system. As said before the LAA system uses information of the last twenty minutes of driver lane keeping, making a 10

second time delay unimportant. This could not be done for a TLC system since the system is intended to give warnings to the driver between a half and one second before lane departure. Therefore other methods must be found to detect intended lane departure.

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[1]IVI
[2]IVI
[3]IITB
[4]IVI
[5]IITB

Notation

Abbreviations and symbols used in the report.

Abbreviations

TLC	Time-to-Lane Cross-ing	The time available for the driver before the vehicle crosses a lane edge. See chapter 6 on page 31.
DLC	Distance-to-Lane Crossing	The distance available before the vehicle crosses a lane edge. See chapter 6.3 on page 32.
LDS	Lane Detection System	Gives information of lane width and vehicle position. See section 1 on page 1.
VEZ	Virtual Edge Zone	A zone created between two virtual lane borders. See section 2.1.2 on page 5.
LAA	Lane-based Attention Assistant	System to warn drivers suffering from fatigue. See chapter 2 on page 4
ORA	Over Run Area	The area generated between the optimal path and the actual path of the vehicle. See section 2.3 on page 10.
SAS	System activity signal LAA system	Binary signal generated by the signal filter, based on when input data is usable. See section 2.4 on page 11.
SAS_{TLC}	System activity signal TLC system	Binary signal generated by the signal filter, based on when input data is usable. See section 6.4 on page 35.
CCW	Counter Clock Wise	Used to define angles. See section 6.3.2 on page 34.

Variables and constants

y_l	distance between the vehicle and lane edge, left
y_r	distance between the vehicle and lane edge, right
b	lane width
y_0	lateral offset
b_c	vehicle width
μ	mean value
σ	standard deviation
$D0_{l/r}$	the distance from lane edge where the weight function is zero (left/right)
$D1_{l/r}$	the distance from lane edge where the weight function is one (left/right)
$\Delta\mathrm{wsum}_t$	approximation of mean over weight peaks at time t
$\Delta\mathrm{wsum}_{t-1}$	approximation of mean over weight peaks at time t-1
$\Delta\mathrm{w}_t$	value of the weight function at time t
α	$1/t_0$. Parameter to weight $\Delta\mathrm{w}_t$ and $\Delta\mathrm{wsum}_{t-1}$ in $\Delta\mathrm{wsum}_t$
t_0	number of samples considered in the delta function
$wsum_t$	approximation of weight sum at time t
t_{baseline}	time limit to chose baseline
$wsum_{\mathrm{max}}$	maximum value of $wsum_t$ when $t \in [0, t_{\mathrm{baseline}}]$
ξ	baseline constant
$\rho_{\mathrm{warning\ level}}$	warning level for the system
θ	The angle between road and vehicle
l	The distance forward along the x-axis
c_0	The curvature of the road
c_c	The curvature of the curve of the vehicle
r_c	The radius of the curve of the vehicle
δt	sample time

Appendix A

LAA - Closeness to lane edge, offset neutral

Here follows a mathematical evidence to prove that the LAA system based on vehicle closeness to lane edge is offset neutral. The evidence is done for distance to right lane edge. It is also valid for the distance to left lane edge, since both distances are generated in the same manor. Furthermore only the inner borders of the VEZs are used. The evidence is valid also for the outer borders of the VEZs, since inner and outer borders are generated in the same way.

Let y_r denote the distances to the right lane edge. The mean value of y_r is denoted μ while the standard deviation is denoted σ.

Then let $\tilde{y}_r = (y_r - y_{const})$ where y_{const} is a constant offset. In the same way as above the mean and standard deviation are denoted $\tilde{\mu}$ and $\tilde{\sigma}$.

Since the distances to lane edge are normally distributed and y_{const} is constant

$$\tilde{\mu} = (\mu - y_{const}) \tag{A.1}$$

$$\tilde{\sigma} = \sigma \tag{A.2}$$

In the LAA system the mean value and standard deviation are used to generate borders for the VEZs. This is done as

$$D_0 = \mu - (f \cdot \sigma) \tag{A.3}$$

where D_0 is the inner border of the VEZ and f is a constant. For the LAA system with a constant offset added the border can be written as

$$\tilde{D}_0 = \tilde{\mu} - (f \cdot \tilde{\sigma}) \tag{A.4}$$

Using (A.1) and (A.2) in (A.4) yields

$$\tilde{D}_0 = \mu - y_{\text{const}} - (f \cdot \sigma) \tag{A.5}$$

Using (A.3) in (A.5) gives

$$\tilde{D}_0 = D_0 - y_{\text{const}} \tag{A.6}$$

The system generates weight peaks when the distance to lane edge, y_{r}, is within the VEZ. Hence if

$$y_{\text{r}} < D_0 \tag{A.7}$$

a weight peak is generated. In the same way for the system with an offset

$$\tilde{y}_{\text{r}} < \tilde{D}_0 \tag{A.8}$$

Using the definition $\tilde{y}_{\text{r}} = (y_{\text{r}} - y_{\text{const}})$ from above together with (A.6) in (A.8) yields

$$y_{\text{r}} - y_{\text{const}} < D_0 - y_{\text{const}} \tag{A.9}$$

which is equal to the results form (A.7). Hence the system is offset neutral.

Appendix B

LAA - TLC, offset neutral

Here follows mathematical reasoning to show that the LAA system based on
TLC is not offset neutral. The evidence is done for distance to right lane edge.
It is also valid for the distance to left lane edge, since both distances are gen-
erated in the same manor.

Let y_0 denote the lateral offset and let $\tilde{y}_0 = (y_0 + y_{\text{const}})$ denote the lateral
offset with a constant offset, y_{const}, added. The TLC value is defined as lateral
distance to lane edge divided by lateral velocity of the vehicle.

$$TLC = \frac{y_{\text{r}}}{\dot{y}} \tag{B.1}$$

where y_{r} denotes the distances to the right lane edge and $\dot{y}$ is the lateral
velocity of the vehicle. In the same way for $\tilde{y}_0$

$$\widetilde{TLC} = \frac{\tilde{y}_{\text{r}}}{\dot{\tilde{y}}} \tag{B.2}$$

where $\tilde{y}_{\text{r}}$ denotes the distances to the right lane edge and $\dot{\tilde{y}}$ is the lateral ve-
locity of the vehicle.

The distance to lane edge, y_{r} is given as

$$y_{\text{r}} = \frac{b}{2} + \left(y_0 - \frac{b_{\text{c}}}{2} \right) \tag{B.3}$$

where b is the lane width and b_{c} is the vehicle width. In the same way for
the distance with constant offset

$$\tilde{y}_{\text{r}} = \frac{b}{2} + \left(\tilde{y}_0 - \frac{b_{\text{c}}}{2} \right) = \frac{b}{2} + \left(y_0 - \frac{b_{\text{c}}}{2} \right) + y_{\text{const}} \tag{B.4}$$

Using (B.3) in (B.4) gives

$$\tilde{y}_r = y_r + y_{const} \tag{B.5}$$

The lateral velocity $\dot{y}$ is calculated as

$$\dot{y} = \frac{d(y_0)}{dt} = \dot{y}_0 \tag{B.6}$$

In the same way for the system with constant offset added

$$\dot{\tilde{y}} = \frac{d(\tilde{y}_0)}{dt} \tag{B.7}$$

Using the definition $\tilde{y}_0 = (y_0 + y_{const})$ in (B.7) yields

$$\dot{\tilde{y}} = \frac{d(y_0 + y_{const})}{dt} = \frac{d(y_0)}{dt} + \frac{d(y_{const})}{dt} \tag{B.8}$$

With the help of (B.6) and the fact that y_{const} is a constant

$$\dot{\tilde{y}} = \frac{d(y_0)}{dt} = \dot{y}_0 = \dot{y} \tag{B.9}$$

With the results from (B.5) and (B.9) inserted in (B.2) it can be seen that $TLC \neq \widetilde{TLC}$. Since both TLC values would be compared to the same TLC limit in the system, the system is not offset neutral.

Appendix C

LAA - ORA, offset neutral

Here follows a mathematical evidence to prove that the LAA system based on ORA lane edge is offset neutral.

The ORA is defined as

$$A_{\mathrm{ora}}(t) = \frac{1}{T} \sum_{i=t-t_{\mathrm{ora}}}^{t} |y_0(i) - y_{\mathrm{mean}}(t)| \, \Delta t \qquad \text{(C.1)}$$

where y_0 is the lateral offset and y_{mean} is a running mean of the lateral offset over several samples back in time. The running mean is defined as

$$y_{\mathrm{mean}}(t) = \frac{1}{t_{\mathrm{mean}}} \sum_{i=t-t_{\mathrm{mean}}}^{t} y_0(i) \qquad \text{(C.2)}$$

Now let $\tilde{y}_0$ denote the lateral offset with a constant offset added. This can be written as $\tilde{y}_0 = (y_0 + y_{\mathrm{const}})$, where y_{const} is a constant value. The over run area for the system with a constant offset added can now be written as

$$\tilde{A}_{\mathrm{ora}}(t) = \frac{1}{T} \sum_{i=t-t_0}^{t} |\tilde{y}_0(i) - \tilde{y}_{\mathrm{mean}}(t)| \, \Delta t \qquad \text{(C.3)}$$

The running mean is defined as

$$\tilde{y}_{\mathrm{mean}}(t) = \frac{1}{t_{\mathrm{mean}}} \sum_{i=t-t_{\mathrm{mean}}}^{t} \tilde{y}_0(i) \qquad \text{(C.4)}$$

Using the definition $\tilde{y}_0 = (y_0 + y_{\mathrm{const}})$ and comparing with equation (C.2) results in

$$\tilde{y}_{\text{mean}}(t) = \frac{1}{t_{\text{mean}}} \sum_{i=t-t_{\text{mean}}}^{t} y_0(i) + \frac{1}{t_{\text{mean}}} \sum_{i=t-t_{\text{mean}}}^{t} y_{\text{const}} = y_{\text{mean}} + y_{\text{const}} \quad \text{(C.5)}$$

The results of equation (C.5) and the definition $\tilde{y}_0 = (y_0 + y_{\text{const}})$ inserted in equation C.3 yields

$$\tilde{A}_{\text{ora}}(t) = \frac{1}{T} \sum_{i=t-t_{\text{ora}}}^{t} |y_0(i) + y_{\text{const}} - y_{\text{mean}}(t) - y_{\text{const}}| \, \Delta t = A_{\text{ora}} \quad \text{(C.6)}$$

Thus the LAA system using ORA as criterion is offset neutral.

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