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RESEARCH ARTICLE

The Driver Experience Under Extreme Lane Change Conditions

Joop Pauwelussen

The objective of this paper is to examine the driver's mental workload experience during extreme nonlinear high slip driving conditions, i.e. with the tyres being close to saturation. This is done for the ISO Double Lane Change manoeuvre, based on extensive test data from two professional test drivers, for different speeds, and with varying tyres. Optimal double lane change closed loop performance is defined and determined and compared to the actual test performance, showing and explaining differences in this performance. A path-tracking driver model has been applied to examine the driver model parameters steering gain and preview time. It is shown that these parameters, which can easily be derived from the closed loop vehicle handling data, vary with mental workload as experienced by these test drivers. This correlation has been demonstrated in previous research for normal driving conditions, where workload, in this paper determined through RSME (Rating Scale Mental Effort) scores, is affected by traffic conditions, where fatigue, experience and learning effects play a significant role. Hence, this paper shows that this, i.e. using the driver model as a virtual sensor to estimate mental workload, can be extended to high slip conditions.

Driver model parameters vary in time, and are not independent. Different combinations of preview time and steering gain lead to the same closed loop performance. We have extended the application of the driver model, the relationship between the driver model parameters and closed loop stability to high slip conditions, before we applied it to severe, i.e. high slip lane change performance.

Keywords: driver behaviour; lane change; path tracking; closed loop; preview time

Introduction

Moving a vehicle is largely controlled by a driver. The roadmap towards ultimately safe driving by taking the driver completely out of the loop, as described by the hierarchy of autonomous driving as derived by SAE-International (Society of Automobile Engineers, 2016) still needs a considerable time to be fulfilled. And even when the ambitious goal of zero accidents is reached, a driver will expect a vehicle to feel comfortable with smooth and acceptable handling properties. In the intermediate SAE levels 2–4 (partial, conditional and high automation, respectively), there is a need to understand whether the driver is able to deal appropriately with the situation at hand. And there is no "one solution fits all". Drivers vary significantly regarding driving skills, their ability to vary between supervisory (awareness) and primary handling mode, and their acceptance of advanced support systems (ADAS). This is related to age and driving experience, as well as to the mental or fatigue situation at the specific moment. In addition, avoiding an accident doesn't start when the risk is already high (the reaction phase), but should be anticipated in advance of the critical moment (the regulation phase).

HAN University of Applied Sciences, NL
joop.pauwelussen@han.nl

As discussed by Joop Pauwelussen (2015), a driver acts at different task levels with the guidance and stabilization levels being the most relevant ones, which are related to the driver's rule-based and skill-based behaviour, respectively. For both levels, the driver is responding to information from the environment (road, other road users) and the vehicle. This response may be at conscious or at unconscious level, depending on the driver and the driver's experience with similar traffic conditions. Dick de Waard (1996) distinguished two areas for the driver referred to as state related effort and task related effort. The area of task related effort corresponds to the transition from normal routine traffic behaviour to more demanding traffic behaviour, where mental workload will increase and, as a consequence, driving performance is expected to reduce.

An approach to understand the driver state during this transition phase is by matching the driver performance with a driver model and to adjust the model parameters for best closed loop performance, with these parameters typically being a delay or lead time, a gain, a preview time and alike. It is then of interest to see whether these model parameters vary during this transition phase. Saskia Monsma (2015) has carried out studies on driver performance and perception to understand the impact of different tyre characteristics, and methodologies how to judge that. Her research has been based on experiments ranging up to extreme lane change performance by professional test drivers as well as by non-professional but still skilled drivers. She used different versions of the closed loop path tracking model (a driver model is tracking a path, some distance ahead of the vehicle), being a special case of the McRuer crossover model, and being discussed in various textbooks, such as by Massato Abe (2009), Giancarlo Genta and Lorenzo Morello (2009) and Richard Jagacinski and John Flach (2009). Saskia Monsma used fixed parameters along the manoeuvre. Joop Pauwelussen showed for a simple version of the path tracking model that parameters change during the manoeuvre, and this variation in parameter value may be well interpreted in terms of driver mental workload perception and driving experience (Pauwelussen 2012; Pauwelussen and Patil 2014). In addition, different driver model parameters may lead to a similar closed-loop performance. For example, consider a driver following a certain path applying therefore a steering angle depending on path and speed. Increasing the preview time means in general that the observed path deviation ahead of the vehicle increases. Therefore the steering gain has to be reduced to end up with the correct steering angle and the same closed-loop performance. For fixed lag time, and in case of steady state vehicle performance, preview time and steering gain appear to follow a hyperbolic relationship (Pauwelussen 2012).

In case of linear vehicle behaviour, this relationship is independent of the curve radius. As a consequence, if a vehicle is not in the situation of extreme steady state conditions (high slip), this relationship between preview time (with which the driver model is observing path deviations ahead of the vehicle) and steering gain (the ratio between the steering action and the observed path deviation) still holds, and is therefore applicable for much more different handling conditons than only steady state. In addition, it was observed that this relationship is almost invariant with respect to speed. This is a great advantage in judging driver performance under practical conditions, when vehicle speed will definitely not be constant. Other studies treat handling performance of experienced vs. inexperienced drivers on a public road (Pauwelussen and Patil 2014) showing an effect of experience on average preview time including learning effects for inexperienced drivers, and the assessment of handling performanc of elderly drivers with respect to (1) differences between the drivers, (2) change during route due to fatigue and (3) relationship with mental workload (Lupker and Van Baardwijk 2015).

Most of these studies assume driving conditions, not being very critical, in the sense that tyre behaviour is still far from slip saturation. In the research by Saskia Monsma however, this assumption does not hold. It therefore makes sense to investigate to what extent the approach in driver state assessment as introduced by Joop Pauwelussen could be used likewise under high slip conditions. This may allow a better understanding of the relationship between the extreme driving behaviour and driver's judgement of vehicle performance based on the ISO Double Lane Change (DLC) test (ISO 2002), and therefore a better interpretation of these driver's judgements. A first approach is to determine the optimal (i.e. lowest lateral acceleration) lane change behaviour depending on the specific tyre characteristics, and to compare this with the test results. One remarkable result is that this comparison may show considerable differences in performance between optimal behaviour and test results, with higher lateral acceleration than necessary, to be explained by the actual path and yaw history of the tests. A second approach is to apply the path tracking model with varying parameters to these extreme slip conditions and to interpret the resulting model parameters (by matching the model with the test) in terms of driver's handing performance and assessment. A path-tracking model is basically a feed-back model with the driver correcting the steering based on expected path deviation. Of course, we use the driver model primarily as an assessment tool (a 'virtual sensor' for mental workload). But since experienced test drivers tend to behave more feed-forward during a DLC, one may expect the derived model parameters to be different from the situation of non-extreme closed loop conditions. In all our analyses, we will make use of the test results as obtained in the research by Monsma (2015) restricting to the professional test drivers, and the first day of testing. More tests were performed and some comments on them with respect to the validation of our findings will be included.

The paper is organized as follows. In the next chapter, we will review the path tracking model under linear, almost steady state conditions, as treated by Pauwelussen (2012) and Pauwelussen & Patil (2014), and with emphasis on the interpretation with respect to mental workload. In chapter 3, we will derive optimal lane change behaviour in dependence of the vehicle model parameters (with emphasis on the different axle characteristics) and discuss the available test results against this optimal behaviour. In chapter 4, we will extend the path tracking model to handing situations where nonlinear axle characteristics cannot be neglected, and the steady state behaviour is definitely lost. The application to the DLC, the derivation of driver model parameters (assumed to be non-constant during the DLC) and the interpretation are treated in chapter 5. The average preview time data will be compared with Rating Scale Mental Effort scores, taken from Monsma (2015). Finally, concluding remarks and discussions are included in chapter 6.

A path tracking driver model for normal, smooth, driving conditions

A path tracking model as treated in this paper assumes that a vehicle aims to follow a certain path, with the driver observing the path deviation over a preview distance L_p from the vehicle CoG (Centre of Gravity). The path deviation D_p is transferred to a steering action with a steering gain K_p, and a lag time τ. This lag is assumed to cover both the actual (neuromuscular) lag and the driver reaction time. Lead effects are neglected. See **Figure 1** for a schematic layout within a global reference frame (X, Y). The path deviation (distance between points T and A) consists of two parts, the initial vehicle deviation y(t) and a second part due to the difference in yaw angle between vehicle

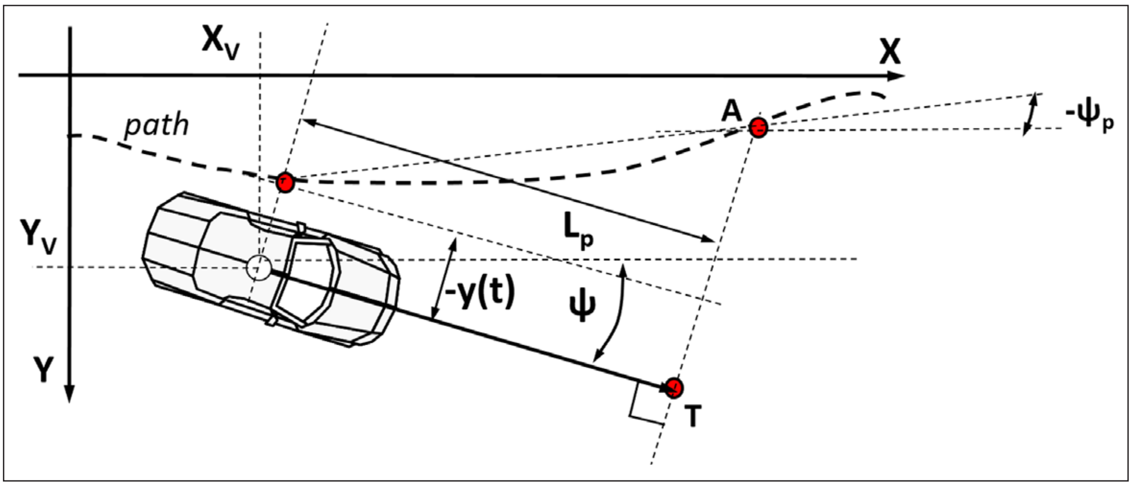

Figure 1: A simple path tracking model.

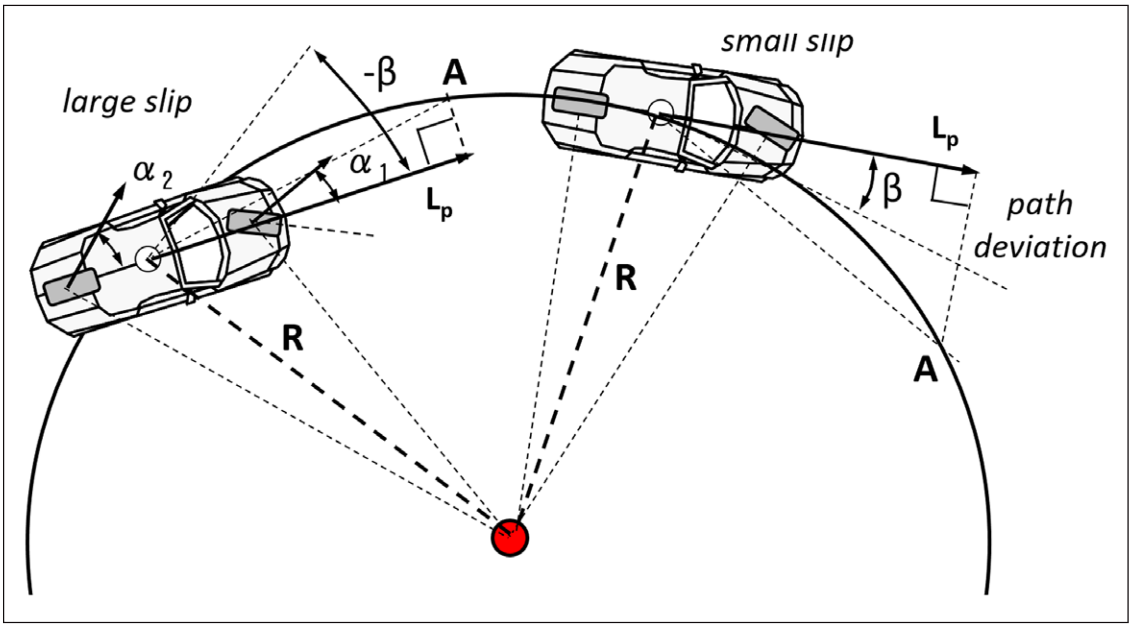

Figure 2: Steady state path tracking under different slip conditions.

(ψ) and path (ψ_p). In most cases, the initial deviation of the vehicle y(t) is much smaller than the deviation due to yaw behaviour, and we will neglect the first one. In the time domain, the front axle steering angle δ(t) satisfies the following differential equation:

$$\tau.\dot{\delta}(t)+\delta(t)=K_p.D_p(t;L_p)=K_p.L_p.(\psi_p(t;L_p)-\psi(t)) \qquad (1)$$

This is the most simple version of this model. Extensions of this model exist, such as including more preview lengths (e.g. Salvucci & Gray (2004)), or including also the deviation in yaw orientation. Taking y(t) = 0 means that the vehicle is following the path exactly. This has the advantage that the path is known when we use this model to identify the parameters L_p and K_p, from the time history of the vehicle states. In general, the contribution of y(t) in D_p is small compared to the contribution from $\psi_p - \psi$, as shown by Pauwelussen & Patil (2014), especially if the preview length is not too small.

Under steady state conditions, following a circular path with radius R, equation (1) reduces to:

$$\delta(t)=K_p.L_p.(\psi_p(t;L_p)-\psi(t)) \qquad (2)$$

We have indicated this situation in **Figure 2** for two cases, for small slip (close to kinematic conditions, vehicle at the right) and in case of large slip. The angle size has been exaggerated for reasons of clarity. One observes the effect of slip on the position of the vehicle with respect to the circular path. Small slip (close to kinematic conditions) means that the front of the vehicle points outward w.r.t. to the path. Increased slip angles at both axles make the vehicle front point inward (with negative body slip angle β, with consequences for the path deviation). The ratio L_p/R is assumed to be small. Note that L_p is usually in the order up to 25 meter.

It has been shown (Pauwelussen 2012; Pauwelussen 2015; Pauwelussen & Patil 2014) that parameters K_p and

L_p satisfy a hyperbolic relationship, given by the following expression

$$K_p = \frac{A_2}{L_p.(A_1 + \frac{1}{2}L_p)} \tag{3}$$

with

$$A_1 = b - \frac{a.m}{L.C_{\alpha 2}}.V^2 \;;\; A_2 = L + \eta.\frac{V^2}{g} \tag{4}$$

with vehicle parameters a and b (longitudinal distance between CoG and front and rear axle, respectively), mass m, wheelbase L, acceleration of gravity g, understeer coefficient η, rear axle cornering stiffness $C_{\alpha 2}$, and vehicle speed V. Data for vehicle parameters as used in model analysis are given in annex A1. Observe that this relationship does not include the curve radius, as indicated earlier. As a consequence of relationship (3), a higher preview length leads to a smaller steering gain. This can also be explained from **Figure 2**. A fixed circular path determines a fixed steering angle. A larger preview length means in general a larger previewed path deviation for which a higher gain is needed to end up at the same steering angle. We have summarized the driver model in relationship with vehicle and path observation in **Figure 3**.

In case of nonlinear axle characteristics, we use the Magic Formula (MF) model, also known as the Pacejka model (Pauwelussen 2015; Pacejka 2006):

$$F_{yi}(\alpha_i) = D_i.\sin(C.\arctan(B_i.\alpha_i - E_i.(B_i.\alpha_i - \arctan(B_i.\alpha_i)))) \tag{5}$$

for lateral axle force F_{yi} in terms of slip angle α_i where i = 1, 2 for front and rear axle respectively, and for axle Magic Formula parameters C, B_i, D_i and E_i. Our interest is in the impact of the change from linear axle (with cornering stiffnesses $C_{\alpha i} = B_i.C.D_i$) to nonlinear axle characteristics. Tests were carried out for three different tyres, one (1) being a winter tyre and two (2, 3) being summer tyres. The MF-axle data were determined by matching test results with model results, see also annex A1.

It can be shown that, in the case of nonlinear axle characteristics (e.g. for high slip), the parameters K_p and L_p are also related according to (3) but with A_1 and A_2 depending on the steady state lateral acceleration a_y (= V^2/R):

$$A_1(a_y) = b - R.\alpha_2 \;;\; A_2(a_y) = L + R.(\alpha_1 - \alpha_2) \tag{6}$$

and where the slip angles are derived from:

$$F_{y1}(\alpha_1) = \frac{b}{L}.a_y \;;\; F_{y2} = \frac{a}{L}.a_y \tag{7}$$

We have determined the relationship between preview time T_p (= L_p/V) and steering gain K_p for vehicle speed V = 95 km/h for linear and nonlinear axle characteristics. Results are shown in **Figure 4**. The steady state vehicle states are shown in **Figure 5**, with vehicle states and steering angle as defined earlier, all in SI units. All $T_p - K_p$ curves for linear axles are the same and shown with one curve. **Figure 4** shows that relationship (3) for nonlinear axles is not significantly changing with respect to speed and curve radius for various lateral accelerations. The steering gain is reduced for increasing lateral acceleration. This depends on the axle characteristics and the resulting nonlinear steady state handling performance. As we observed earlier, increasing the slip means that the vehicle will point more into the circular curve and the path deviation at the preview length distance ahead of the vehicle will increase. More steering is needed to compensate for the slip which means that more gain is needed for the same path deviation, or a similar gain is needed for increased path deviation. The change of vehicle states with increasing lateral acceleration is shown in **Figure 5**. Consequently, the effect of nonlinear slip on the $T_p - K_p$ relationship is depending on the nonlinear body-slip gain β/δ. If that is high, the steering gain is expected to reduce for increasing ay, as indicated in **Figure 4**. If it is low, the steering gain will increase. Nevertheless, the quantitative effect is limited.

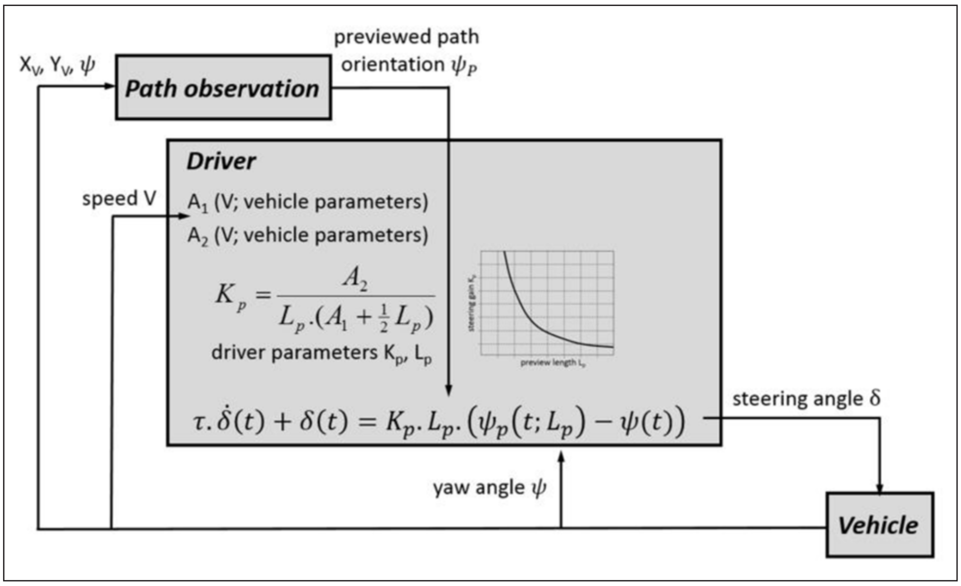

Figure 3: Functional relationship driver model with vehicle and path observation.

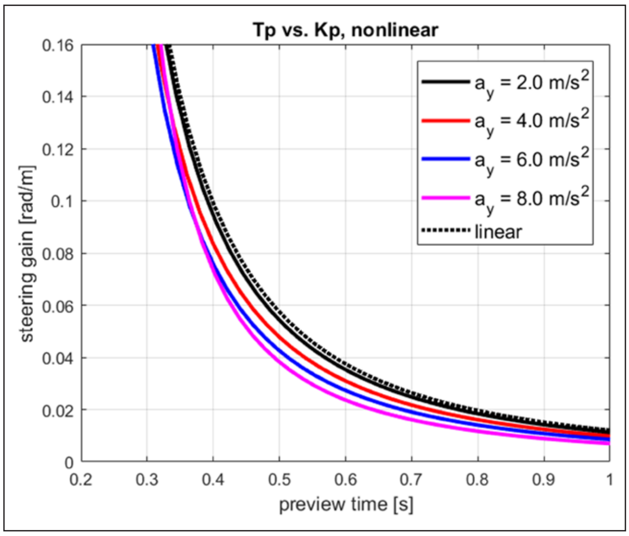

Figure 4: Preview time versus steering gain for linear and nonlinear axle characteristics and for different lateral accelerations.

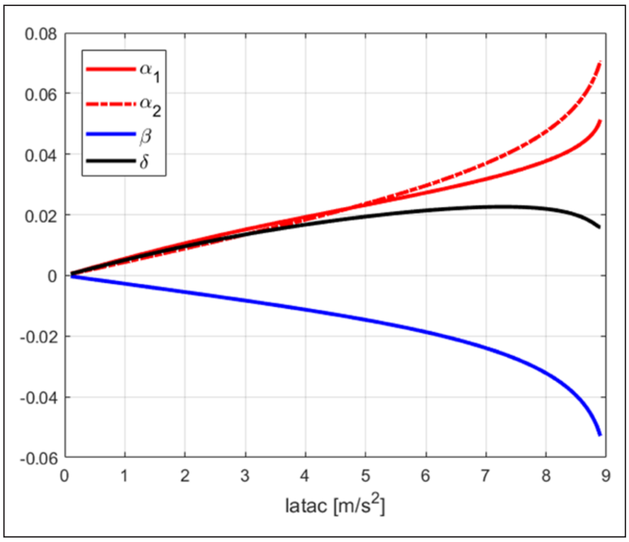

Figure 5: Steady state vehicle performance up to large slip.

Varying the driver parameters along the track

An important question is how the model parameters can be used for driver state estimation. Large steering gain could be interpreted as a situation of higher workload, or likewise, small preview time. One might assume constant values for gain and preview time throughout a manoeuvre, which is often done. The closed loop simulation is able to follow experimental results more accurately when steering gain and preview time are allowed to change during a manoeuvre, where the combination of steering gain and preview time is expected to follow the hyperbolic relationship cf. (3), or at least be close to it. It was suggested by Pauwelussen (2015) to use the **average T_p** as a metric for driver handling assessment. This concept has been applied by Pauwelussen and Patil (2014), and in the Smart Mobility project (Lupker & van Baardwijk 2015). Pauwelussen and Patil carried out tests on a public road, with four different drivers, two being experienced and two being inexperienced. Part of the route was situated at an office park, with a length of about 3 km, being driven clockwise and anti-clockwise. Vehicle speed varied up to 18 m/s, and maximum lateral acceleration was around 5 m/s². As discussed earlier, we applied equation (1), i.e. we neglected y(t) and took the vehicle path as the path to be tracked. To be more specific and to justify replacing the intended path by the *actual driven* path, we observed in the previous research (Pauwelussen & Patil 2014) a filtering effect on the preview length (and therefore also on the steering gain), but the final difference in the average T_p was found to be small. For shorter preview lengths, the error increases (because the relative contribution of the vehicle path deviation y(t) becomes larger), but the ranking for different driver behaviour in terms of this metric appeared to be maintained.

Matching a linear vehicle model to the test results and taking account of (1), we were able to identify the driver parameters with results as shown in **Figures 6** and **7** (taken from Pauwelussen (2015)). Please note that the relationship between preview time and steering gain depends strongly on the tyre characteristics (according to

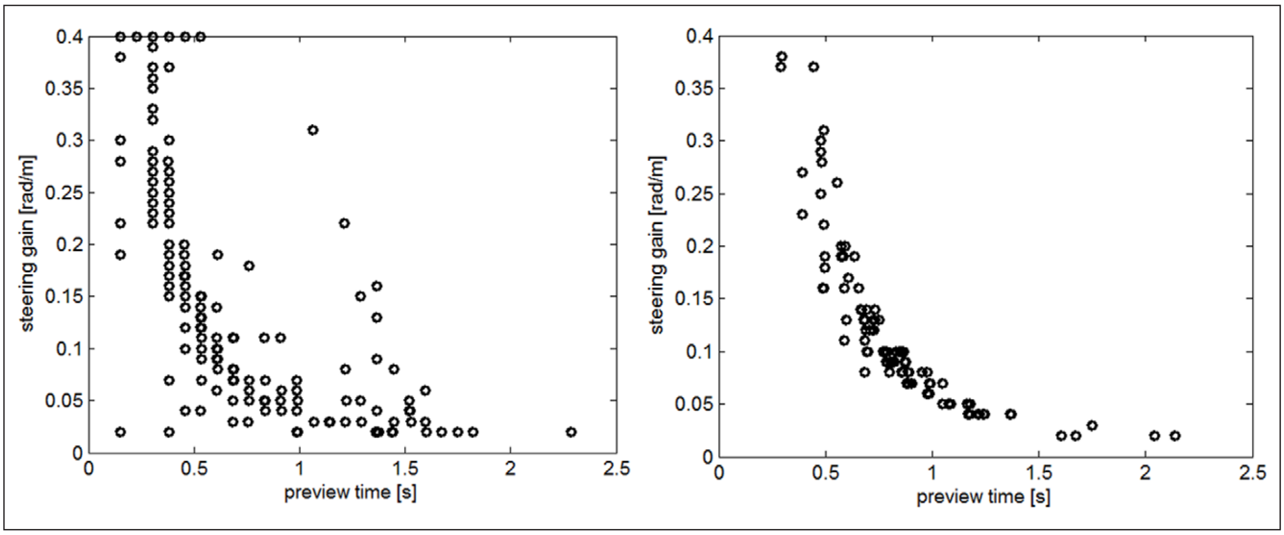

Figure 6: Preview time vs. steering gain; inexperienced driver (left), experienced driver (right).

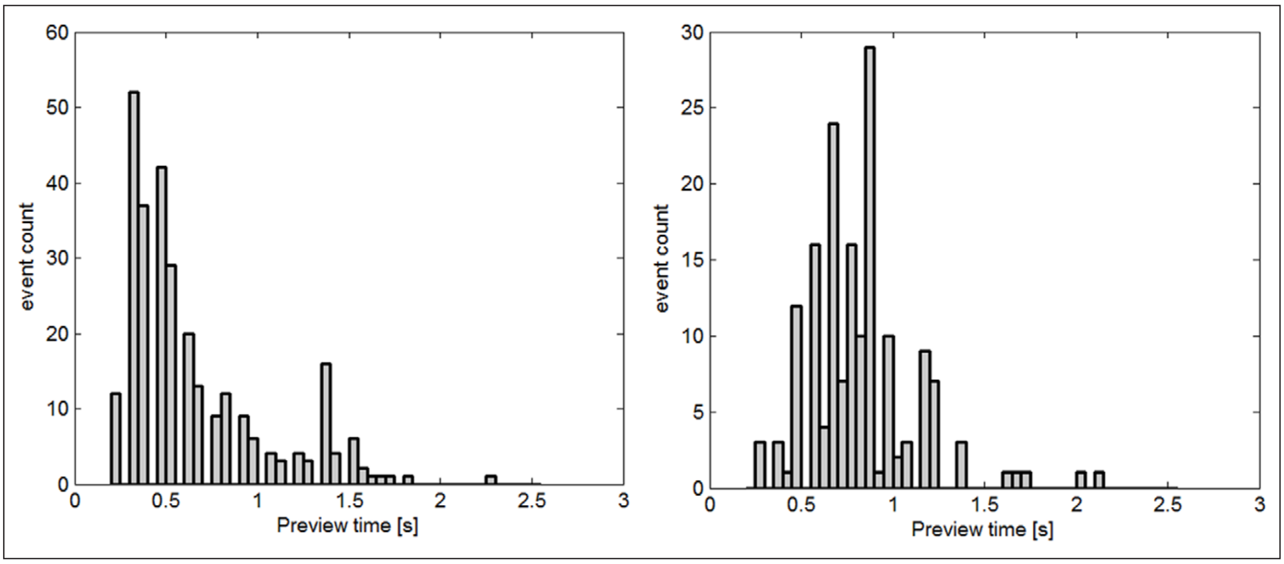

Figure 7: Preview time frequency distributions; inexperienced driver (left), experienced driver (right).

(3) and (4)), which were quite different in (Pauwelussen & Patil 2014) compared to the data in this paper. In addition, the range in preview time was different because of the lower speed used in the earlier research.

A number of observations was made from the previous results:

1. The results for the experienced driver confirms the hyperbolic relationship defined by (3), whereas the inexperienced driver shows more deviations from that curve. This may indicate that the latter driver needs more time to build up an effective steering response, also yielding larger path deviations.
2. The average steering gain for the inexperienced driver exceeds that of the experienced driver, and likewise the preview time will be less, also demonstrated in **Figure 6** with the dominant part in the T_p – frequency distribution moved more to lower T_p-values.
3. Repeating the same path several times resulted for the inexperienced driver to move, in his behaviour, to the experienced driver, i.e. to higher average T_p, which could be interpreted as a learning effect.

An application, behaviour of elderly drivers

The second application deals with driving simulator tests where elderly drivers had to follow a route of about 8 km, repeatedly, up to a total driving time between 1 and 1.5 hours. Within this route, the driver had to pass six cornering situations with curve radii of approximately 250 m. The route was equipped with various traffic lights, with (randomly) one of these lights turning red, once per complete round where the driver had to stop. Lateral accelerations were always below 5 m/s^2.

In addition to the elderly drivers (age over 70 years), also young drivers (age 20–24 years) and drivers with intermediate age (50–70 years) were participating. For most of the tests, the average preview time tended to increase slightly during the first round, and reduce again at the end of the test (after 1 hour of driving). This might be interpreted as getting familiar with the test at the beginning, and getting

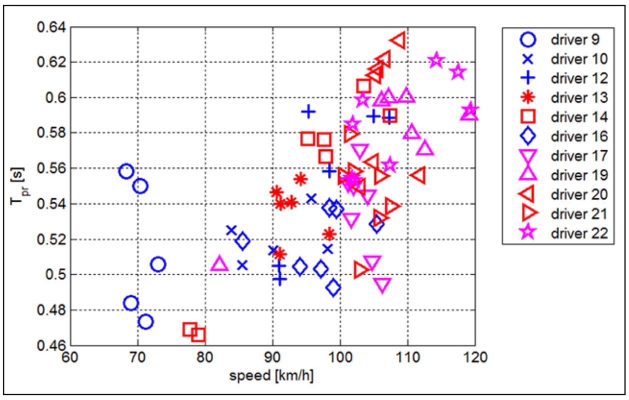

Figure 8: Preview time versus average cornering speed, for different drivers (young drivers in red, elderly > 70 in blue, and intermediate between 50 and 70 years in magenta), from Pauwelussen (2015).

tired at the end. On the other hand, there may be an effect of giving information to the driver that the end of the test is near. Test results were not discriminative enough to draw clear conclusions on this. In **Figure 8**, we have plotted the average preview time against the average cornering speed. These results show that there exists a large variation in behaviour for the different drivers. There is a tendency that young drivers drive faster, show a larger preview time and therefore a lower steering gain. This may be an indication of lower workload, but please note that the reference level for workload assessment is very driver specific. On the other hand, some elderly drivers (e.g. driver 12) drive fast, and some young drivers (e.g. driver 14) keep their speed limited. The speed dependency may be due to the closed loop stability under steady state cornering (cornering during the simulator tests was almost steady state), being reduced with higher speed, pushing the driver to higher preview time, see also Pauwelussen (2015) and Abe (2009). We shall come back to closed loop stability in chapter 4. Another observation (Lupker & van Baardwijk 2015) was that some drivers show a significant deviation from the hyperbolic steady state relationship (3) whereas other drivers don't, especially when the difference between straight driving speed and cornering driving speed is larger (and therefore the match between the cornering results and steady state conditions is less).

Please note that the two examples treated in this chapter 2 are not comparable in the sense that we distinguished between experienced and inexperienced vs. young and elderly. The first example describes driving on a public road, whereas the second example is based on very specific driving simulator tests. Learning effects may be at hand, being not accounted for in the second example.

Optimal double lane change performance

In this chapter, closed loop performance for the ISO double lane change (DLC, see ISO (2002)) will be considered, with emphasis on the driver model parameters. We will discuss the optimal way to carry out a DLC. Test drivers aim in general to carry out a DLC with maximum speed, with the ultimate limit corresponding to hitting a cone, with the driver having insufficient control to avoid it. Consequently, the optimal DLC performance corresponds with a driver-vehicle performance for which the lateral acceleration is as low as possible. The DLC is shown in **Figure 9** with the cones indicated by yellow dots, and data given in annex A1. Note that the lateral distance between the cones (denoted as h_i, I = 1, 2, 3) is different for the three different DLC-parts, ranging from 2.5 m at the start up to 3.12 m at the end. The possible path for the vehicle's CoG (Centre of Gravity) is indicated by a red line.

The driver should prevent to hit any cone. This means that the vehicle's CoG should remain at the right side of points A_1 and A_4 and to the left of points A_2 and A_3 where these points are at least half of the vehicle-width away from the cones. With a vehicle width of 1.81 m (BMW 320i Touring), the first part is quite narrow whereas the final part offers more manoeuvring space, which can be exploited to keep the lateral acceleration low. With additional vehicle drifting, more space is needed to prevent hitting cones. We have chosen a vehicle half-width of w_1 = 1 m for the first DLC part, and $w_2 = w_3$ = 1.1 m for part 2 and 3, respectively. Consequently, the lateral position of the vehicle's CoG path has to remain:

$$\begin{aligned}
&\text{Part 1: } -h_1 + w_1 < CoG_y < h_1 - w_1 \\
&\text{Part 2: } H - h_2 + w_2 < CoG_y < H + h_2 - \\
&\text{Part 3: } -h_3 + w_3 < CoG_y < h_3 - w_3
\end{aligned} \tag{8}$$

The DLC includes two lane-transitions, transition 1 (from first lane to second lane) and transition 2 (back to the first lane). With different geometrical parameters for the three DLC parts, the optimal vehicle behaviour will show a different lateral acceleration history at the two transitions. During each of the transitions, the lateral acceleration a_y shows two peaks, with opposite sign. A fair guess is that these peak-values are more or less equal in absolute value for each transition. Starting from that situation, suppose we could reduce one of these absolute values, then one would expect the other peak-value to increase, reducing the maximum allowable vehicle velocity to pass the DLC due to increased tyre slip. In addition, one would like to have the maximum lateral acceleration values to spread out along a larger part of the transition. A more local extreme a_y means a higher $|a_y|$ – value, which we try to avoid. This brings us to the suggestion of a piecewise constant lateral acceleration history for each transition, which is expected to be close to a real optimal a_y – performance. For the path between DLC part 1 and part 2, this means that it consists of two circular arcs with the same radius, assuming a constant vehicle speed. We call this the theoretical path. Hence, we define as the **theoretical path** for the first transition:

> The path connecting part 1 and part 2 of the DLC, just hitting points A_1 and A_2, satisfying the conditions under (8), consisting of two circular arcs with radius R_1, with the value of R_1 as large as possible.

In the same way, one can define the theoretical path for the second transition with circular arc radius R2, where both parts of the total theoretical parts must match smoothly (position and orientation). It is assumed that the vehicle starts at lateral position y = 0 while entering the lane change. At the end of the lane change, ending at position $y = -h_3 + w_3$ will result in the lowest R_2 – value. We have determined the theoretical path based on these circular arcs and their radii, as shown in **Figure 10**. The curve radii for the DLC with parameters as given in annex A1 were found to be equal to 133.1 m and 155.4 m. Supposing a vehicle speed of 95 km/h = 26.39 m/s, one would expect the lateral accelerations at first and second transition not to be far from V^2/R = 5.23 and = 4.48 m/s^2. Observe in **Figure 10** that the theoretical path corresponds to a vehicle just not hitting the cones while leaving part 1 and part 2, and while entering part 2 and part 3 of the DLC.

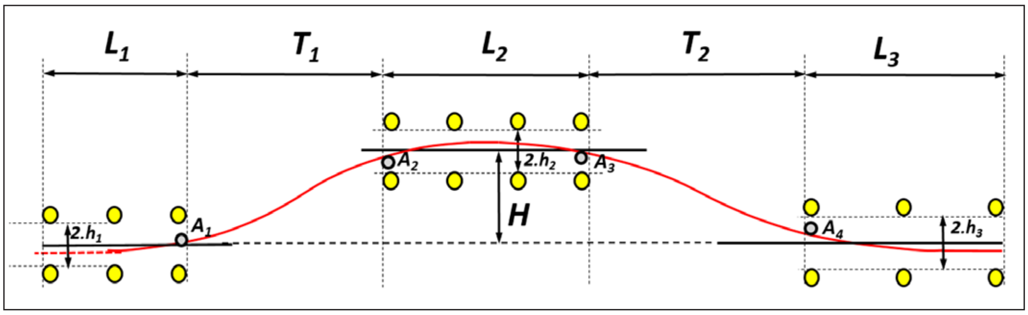

Figure 9: The Double Lane Change.

Clearly, no driver can steer a vehicle through a DLC with piecewise constant a_y. What we have done next is follow this theoretical (target) path with the vehicle with non-linear axle characteristics (cf. annex A1) and driver model cf. (1), with $\tau = 0.05$ s, and with model parameters K_p and L_p chosen such that the final vehicle path is just (not) hitting the points $A_1 - A_4$ from **Figure 9**. Furthermore, conditions (8) must be satisfied and the vehicle finally reaches a lateral position at the end of the lane change as far to the right as possible. That means that the theoretical path will change. We denote the final vehicle path as the **optimal path**. This analysis has been carried out separately for the three different axle characteristics and for a speed of 95 km/h.

The total test period lasted several days where both experienced test drivers and nonprofessional (but highly skilled) drivers would carry out the DLC-test for different tyres. In order to make the manoeuvre more challenging at not too high speed, most tests were carried out where the offset between the lanes was set at 5.5 m instead of 3.5 m. During the first day, however, when professional test drivers would carry out this task, the track humidity was judged to be too high for this increased offset and the offset remained 3.5 m. With the intention to restrict ourselves for this paper to professional drivers, we have decided to focus only on the 3.5 m tests, and such that the axle characteristics cf. annex A1 could be used in comparison with the test results. The speed during these tests did not exceed or was close to 95 km/h.

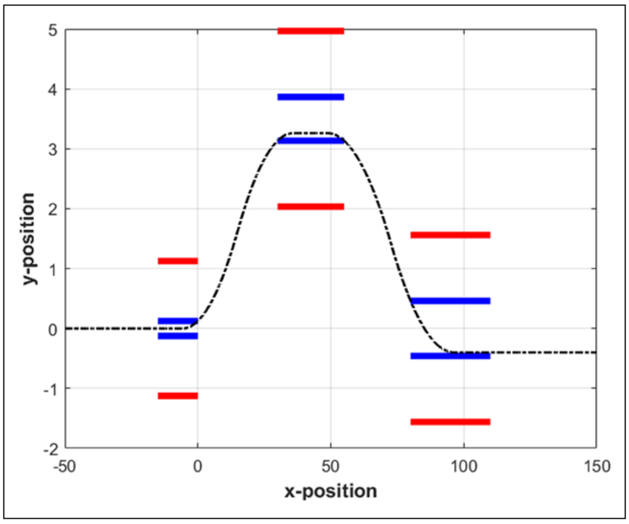

Figure 10: The theoretical path, based on circular arcs. Red lines indicate the positions of the cones. Blue lines are the boundaries for the vehicle CoG as defined in (8).

The optimal path is shown in **Figure 11** for tyre 2, as well as the resulting lateral acceleration (not exceeding 5.5 m/s^2), and the axle steering angle in degrees. Observe the optimal path just 'touching' the blue boundaries at the points $A_1 - A_4$, remaining nicely between these boundaries during the DLC, and showing overshoot at the final part of the lane change before arriving at a straight line condition.

The lateral acceleration shows peaks slightly above 5 m/s^2 during the first transition, and slightly lower values (larger circular arc radius of the theoretical path) during the second transition. This analysis has been repeated for tyres 1 and 3, with results for the three tyres given in **Table 1**.

For tyre 1 (winter tyre, used under non-winter conditions), one observes that both curve radii (i.e. for the transition from lane 1 to lane 2, and back again) for the target (theoretical) path have reduced, with likewise a higher lateral acceleration value than expected from these curve radii. With 95 km/h, a curve radius of 133.1 m (corresponding to the curve in **Figure 10**) would correspond with $a_y = 5.32$ m/s^2. With R = 117.0 m during the first transition, that would change to 5.95 m/s^2 being close to the value for the optimal path. For tyres 2 and 3, this situation

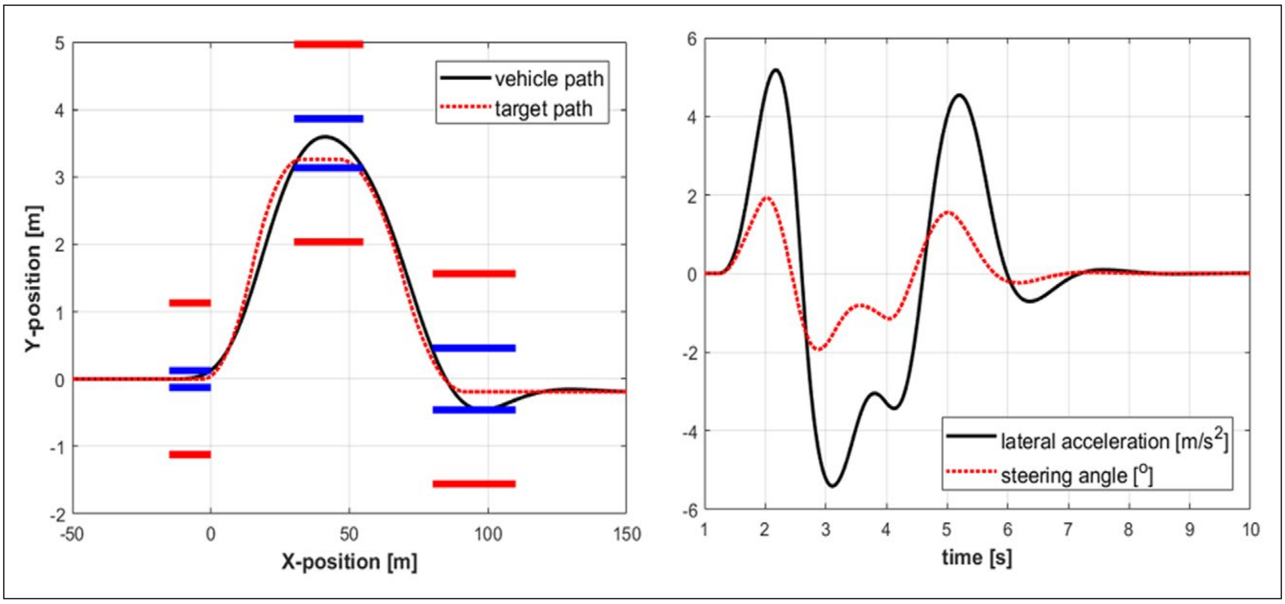

Figure 11: Optimal and theoretical (target) path for tyre 2 during the DLC for 95 km/h (left) and the resulting steering angle and lateral acceleration (right).

Table 1: Optimal path data for the three different tyres.

	Description	Tyre 1	Tyre 2	Tyre 3
Max $\|a_y\|$ [m/s²]	Maximum lateral acceleration	5.88	5.41	5.43
R_1 [m]	Radius circular parts target path, first transition	117.0	96.8	105.6
R_2 [m]	Radius circular parts target path, second transition	131.3	151.7	153.7
L_p [m]	Preview length for minimum a_y – peak value	13.6	15.0	13.6
K_p [rad/m]	Steering gain for minimum a_y – peak value	0.054	0.033	0.044

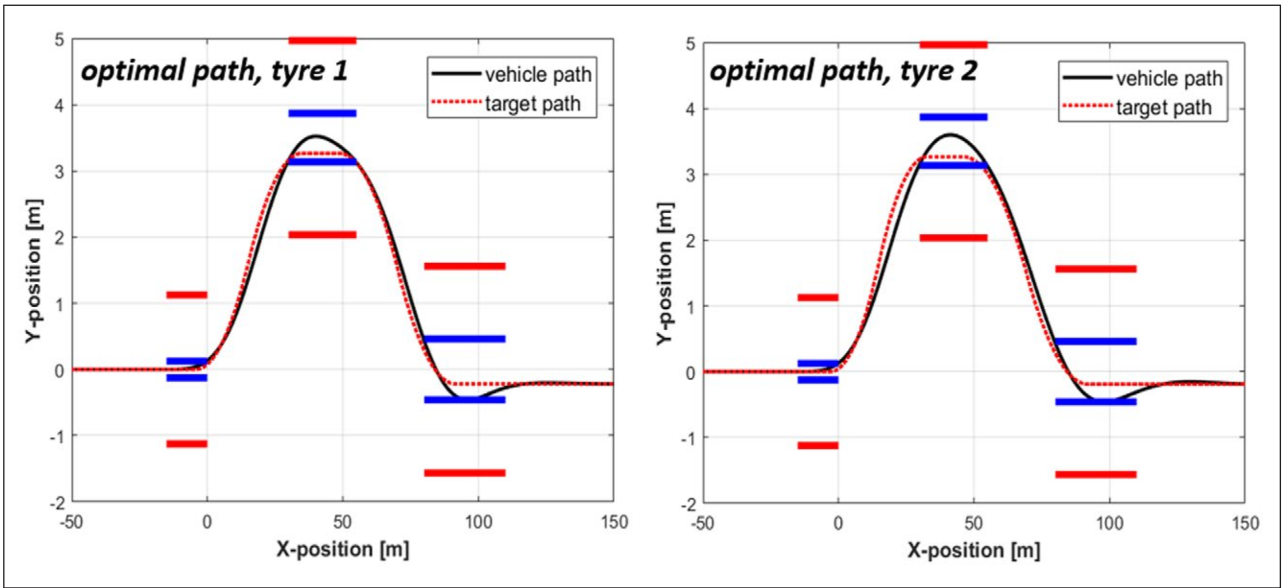

Figure 12: Optimal paths for tyres 1 and 2.

is different. The 'calculated' value V^2/R is now in the order of 6.6 – 7.2 m/s² whereas the maximum a_y - value for the optimal path is much lower. We have plotted the optimal paths for tyres 1 and 2 in **Figure 12**. Both paths try to follow a circle with small radius at the first transition and a large circle at second transition. The second transition has more room for lower acceleration, and may compensate for the acceleration in the first transition. This is more visible for tyre 2 where the vehicle approaches the left cones more in lane 2 before returning to the first lane.

After the tests, Rating Scale Mental Effort (RSME) scores were determined by the driver. This is a rating scale with 150 mm line marked with several anchor points with a descriptive label such as 26: a little effort, 72: considerable effort. It was stated by Monsma (2015) that this scale proved to give good results in many studies on driver's mental workload. See also Zijlstra and Doorn (1985). For the tests being considered, the RSME scores are listed in **Table 2**, with distinction between the two test drivers and low and high speed. Low speed means here between 85 and 90 km/h whereas high speed is at most 95 km/h due to the humid road conditions, as explained earlier. Especially for the high velocity tests, **Table 2** shows the highest RSME scores for tyre 1 and the lowest for tyre 3, which corresponds with the observed larger a_y – value for the optimal DLC path. In other words, tyres 2 and 3 allow you to pass the DLC with a lower a_y (i.e. with a higher speed), which is likely to contribute to a lower driver assessment for tyre 1.

Table 2: RSME scores per tyre, test driver and test-speed.

Tyre	Driver	Velocity	RSME
1	1	Low	72
		High	82
	2	Low	36
		High	45
2	1	Low	34
		High	68
	2	Low	30
		High	41
3	1	Low	39
		High	34
	2	Low	14
		High	25

According to Monsma (2015), the high speed value for the different tests was chosen such that the drivers were just able to drive the DLC without hitting cones for the less handling tyre 1. The low speed value was chosen such that the DLC was less but still demanding.

Now that we have determined the optimal manoeuvres for the three tyres, let us see how that compares to the actual driving performance from the tests. Remember that the optimal path corresponds to 95 km/h whereas the actual speed will be different and, in most cases, lower. For all test-histories, we have varied the initial lateral position and yaw angles such that the path remains between the blue boundaries as indicated in previous figures and described in (8), with a minimum error with (i.e. as close as possible to) the optimal path for that tyre.

We have selected four representative tests as shown in **Table 3**, with the test numbers as used by Monsma (2015). That means that we show results for tyre 3 for different drivers. We have carried out comparisons for all tests during the first morning of testing and carried out by the drivers 1 and 2, and the results as shown in **Figures 13–16** are similar to the results for other tests for the specific tyre and driver.

Table 3: Selected tests for comparison with optimal path.

Test nr.	Average speed [km/hr]	Driver	Tyre
21	93.72	1	1
34	91.36	2	2
71	95.95	1	3
61	91.72	2	3

We show the actual vehicle path compared to the optimal path, and the lateral acceleration compared to the lateral acceleration for the optimal path. Tests and optimal path were set to start at time = zero at a distance 50 m before the end of the first part of the DLC (x = –50). We start with the first two tests, see **Figures 13** and **14**. For both drivers, the path in the second lane is rather straight, meaning that the steering during both transitions much have been more sharp compared to the optimal performance. Consequently, the acceleration extreme values are considerably higher. Driver 1 seems to follow the optimal path well, moving from lane 1 to lane 2, but then shows similar extreme values in ay as driver 2. There is still space between the path and the boundaries cf. (8). Driver 1 tries to take benefit of the larger gap

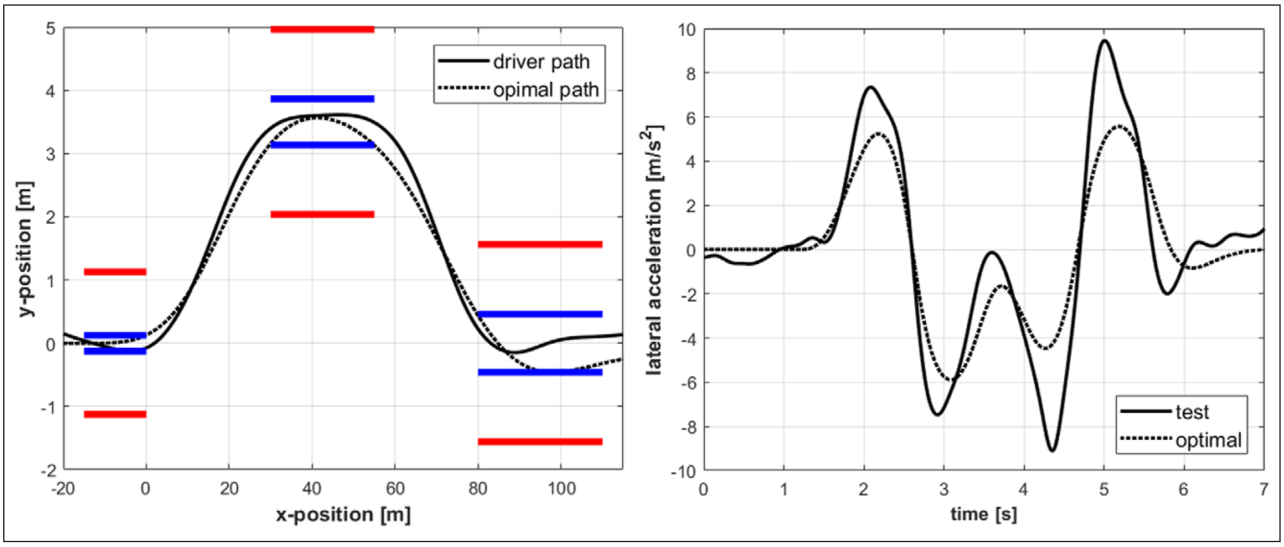

Figure 13: Test results compared to optimal performance for test 21 (tyre 1, driver 1).

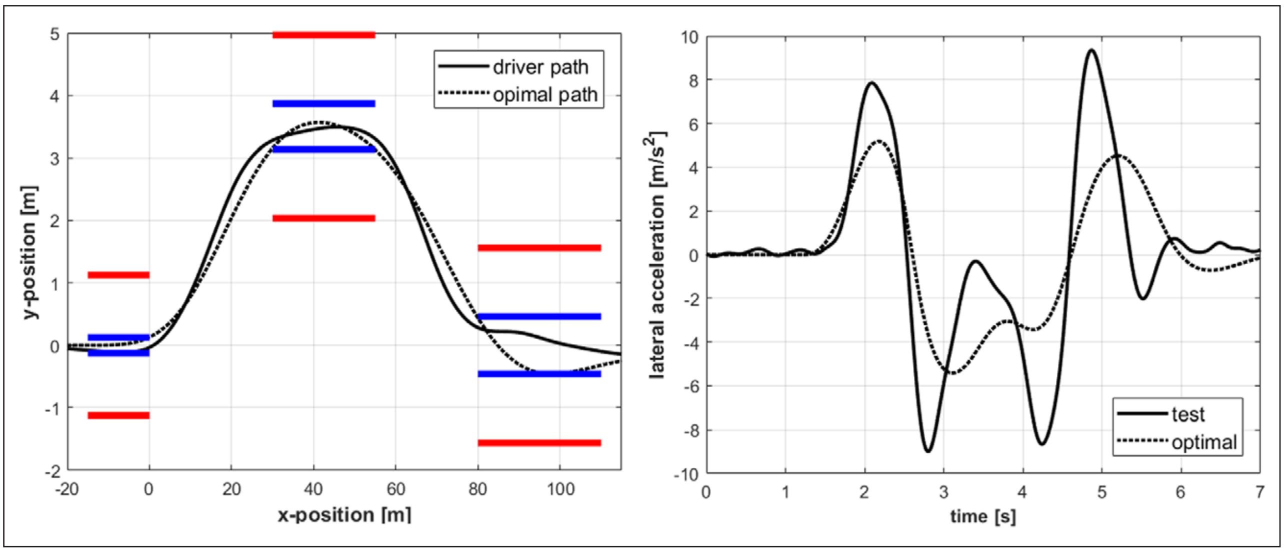

Figure 14: Test results compared to optimal performance for test 34 (tyre 2, driver 2).

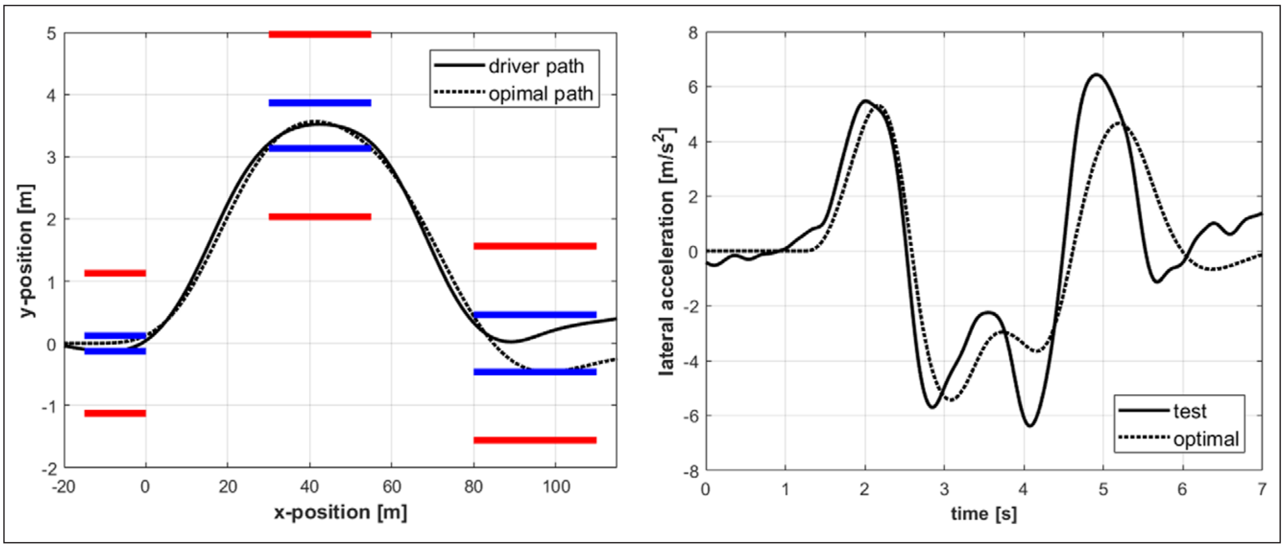

Figure 15: Test results compared to optimal performance for test 71 (tyre 3, driver 1).

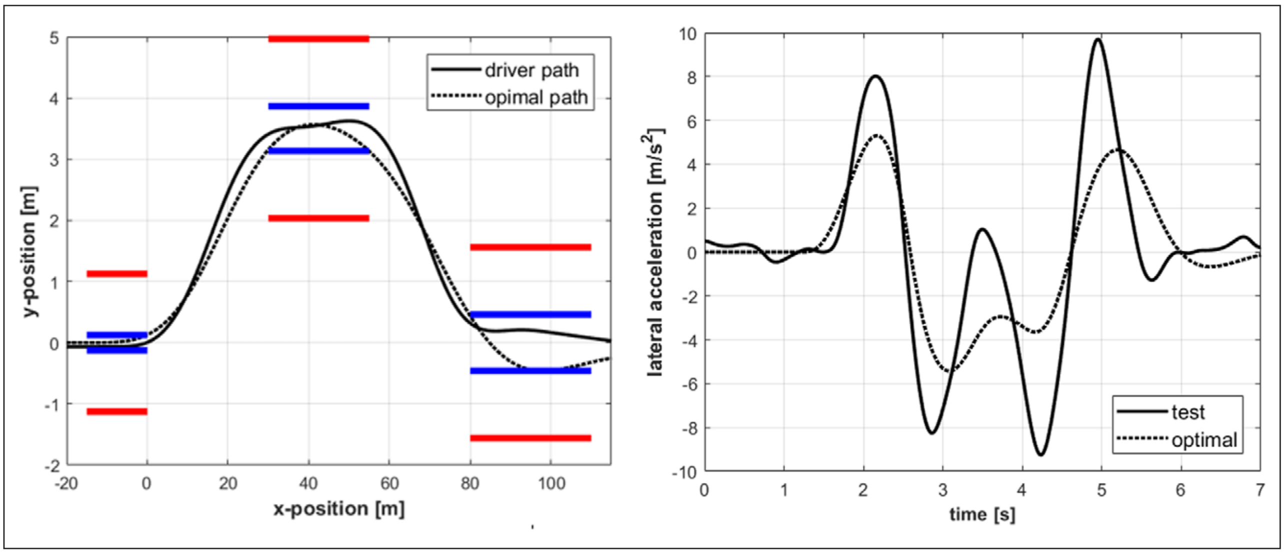

Figure 16: Test results compared to optimal performance for test 61 (tyre 3, driver 2).

between the cones in the third part of the DLC by steering relatively late towards the longitudinal x-direction. One may argue that we have set the (blue) boundaries too sharp. However, if one considers **Figure 15** (driver 1, tyre 3), one observes driver 1 to be able to get close to the cones, resulting in much smaller a_y values. Compared to tyre 1 and 2, tyre 3 was rated for a lower workload as indicated in **Table 2** (high speed). Driver 2 appeared to be less discriminating between the tyres in RSME-score.

We conclude that a significant difference is observed between optimal performance and the test-results for the different tyres and drivers. The humid conditions may have played a role, but the resulting axle characteristics have been determined by matching with the vehicle test results under the same conditions. For driver 1, the variation in RSME scores and in test performance seem to be consistent where, for the best rated tyre, the test performance was close to optimal performance.

Extending the closed loop driver model to extreme handling conditions

In chapter 2, we described the impact of high slip on the steady state relationship between closed loop driver model parameters K_p (steering gain), L_p (preview length) and T_p (preview time). The examples showed applications, where the combinations of steering gain and preview time were discussed, with possible attribution to closed loop stability. It was shown by Pauwelussen (2015) that closed loop stability is lost for small preview length (or small preview time) or large gain, with the closed loop stability boundary depending on vehicle parameters, vehicle speed and lag time τ. With slip increasing, the open loop stability is lost and one might expect the closed loop stability to be reduced as well. We have determined the closed loop stability boundaries for different values of a_y for fixed vehicle speed of 95 km/h, and for the non-linear vehicle parameters from annex A1 for tyre 2, see **Figure 17**. The dotted line is for the case of linear axles.

One observes a strong contribution from the increased slip, as expected.

Let us next apply the driver model (1) to the double lane change manoeuvre where we allow the preview time and steering gain to vary along the lane change, to be determined by comparing the real steering angle with the steering angle following from (1). In more detail, we have determined the preview time and steering gain parameters for each following 0.1 second during the double lane change, for all tests, where we have determined T_p and K_p from time periods of 0.25 second (Pauwelussen & Patil 2014).

Typical output is shown in **Figures 18** and **19** for a test under humid road conditions for a professional driver. The maximum preview length is set at 25 m. Driving along a straight line is assumed to correspond to large preview length and therefore also to high preview time. This explains the initial part of **Figure 18**, and the final part beyond 6 seconds. One observes the preview time to drop at the start of the lane change, to increase again up to about 0.8 s, reducing again to low values, followed again by a raise up to 0.9 s, reduction and finally settling at high value when leaving the lane change. The periods of low T_p correspond to the situation where the driver is approaching the end of the first part of the lane change before moving to the second lane, and the second part of the lane change at the second lane, just before moving back to the first lane. In **Figure 19**, we have also depicted the hyperbolic curve describing T_p vs. K_p assuming linear axle characteristics. One observes that the (T_p – K_p) values during the lane change closely follow this hyperbolic relationship closely, according to our findings in chapter 2, with some outliers. Please note that the values for T_p and K_p correspond to different lateral accelerations and therefore different closed loop stability boundaries during a DLC manoeuvre.

The driver model response can be illustrated by plotting the preview position together with the vehicle path and the lane change path. The lane change path is taken as the mid-points between the cones, with a smooth (sinusoidal) transition between the lanes. The preview position corresponds to point A in **Figure 1**, i.e. on the path. For clarity, we have projected this point on the lane change path. The result is shown in **Figure 20**. One observers

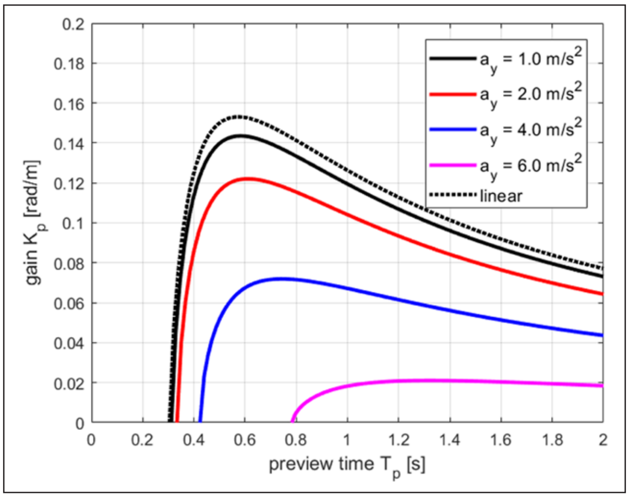

Figure 17: Closed loop stability boundaries for different ay-values and fixed curve radius.

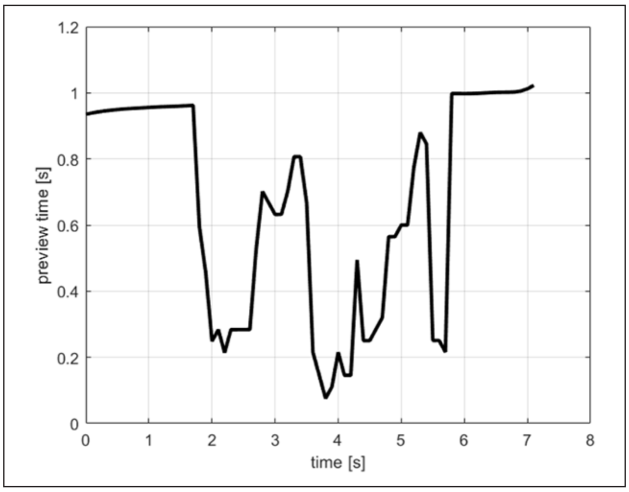

Figure 18: Variation of preview time during the double lane change.

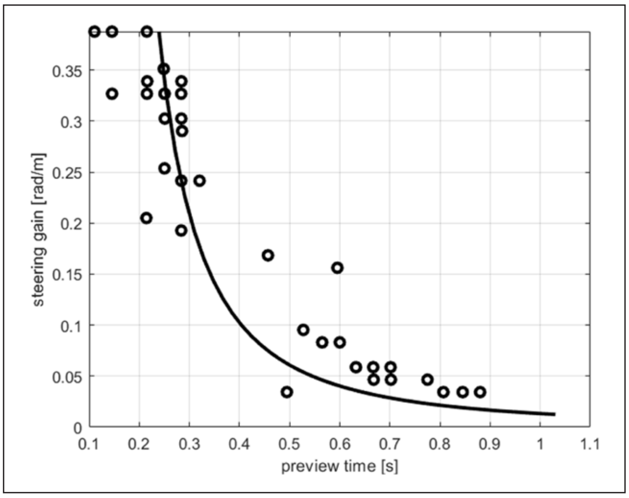

Figure 19: Preview time T_p vs. steering K_p.

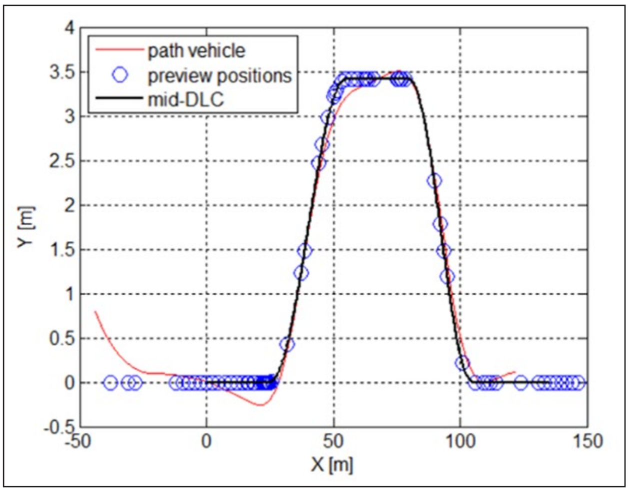

Figure 20: Preview positions for the ISO double lane change for a professional driver.

the virtual driver to approach the first point of transition, while focussing on the end of that part of the first lane (15 m after the beginning of the DLC). Points of the path between both lanes are hardly considered. The virtual driver cf. model (1) moves the attention (i.e. preview point A on the path) to the second lane, shown by the high concentration of preview positions in the plot. Again, before moving back to the first lane, the driver is hardly considering the transition path. This correspond to the area of high T_p in **Figure 18**. He moves his attention to the first lane. As soon as he reaches this lane the preview time is increasing, shown by 'empty' area between 110 and 150 m. The interpretation for the real driver is that the steering is changed on a feed forward basis, with the driver not considering points in both transition phases.

Workload assessment under extreme lane change conditions

Each combination of driver, tyre and speed was applied at least six times, and we have determined the mean of the average T_p value for these six tests, denoted as T_p-average. Please note that the T_p score is not a judgement by the driver but a result of the manoeuvring during the lane change. One could say that this is a kind of 'footprint' of the driver, whereas the RSME scores is based on subjective judgement. That means that we are comparing the driving performance (the 'footprint') of the driver with his own judgement.

Lower preview time leads to higher steering gain. If, under extreme lane change conditions, a higher steering gain can still be interpreted as higher workload, one would expect a negative correlation between average preview time and the RSME scores. Both T_p-average and RSME are shown in **Figure 21** for the first morning of testing. One observes indeed a correlation between T_p average and RSME. We have also considered the results for the afternoon, when the road had become less humid, resulting in a less challenging testing task for these professional test drivers. RSME scores varied between 10 and 82 in the morning with a score of 80 corresponding to considerable to great effort, see also **Table 2**. In the afternoon, scores were found between 20 (a little effort) up to 40 (some effort) with one outlier at about 60, where the axle characteristics were adjusted for the new (dry) road conditions. Likewise, the range in T_p was found to be reduced (from [0.45–0.62] to [0.41–0.53]).

The correlation between RSME and T_p was found to be significant in the morning. Values were found of –0.81 for driver 1 and –0.66 for driver 2, determined from tests with low and high speed. In the afternoon, the correlation for driver 2 has totally disappeared. But also the variation in RSME values has become very low (less than half of the variation in the morning), confirming the fact that weather conditions were too good to be discriminative for the three different tyres.

If one considers T_p-average and RSME scores for the different tyres and the speed conditions, as shown in **Figures 22** and **23**, respectively, one observes that RSME distinguishes between different speeds and different tyres, except for a relatively low RSME assessment by driver 1

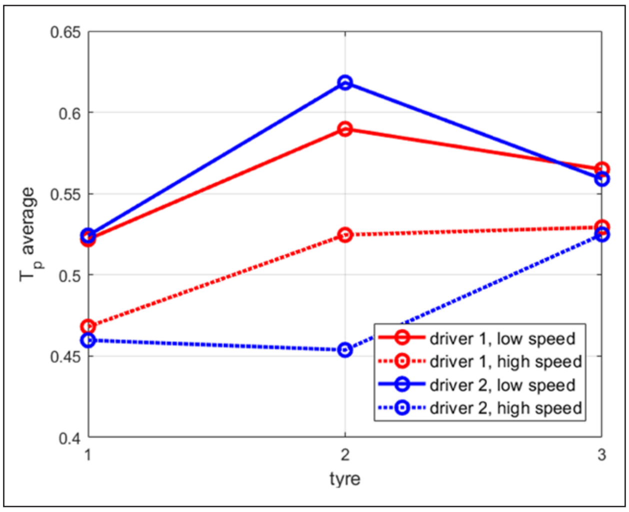

Figure 22: T_p (average) scores for different tyres, and speeds (professional drivers).

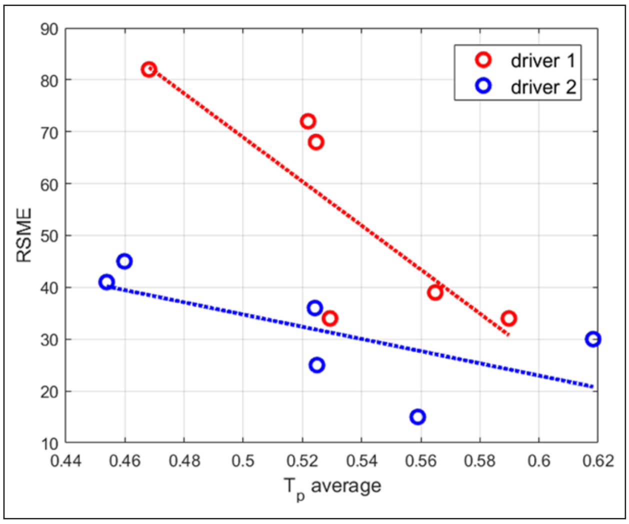

Figure 21: RSME versus T_p (average), professional test drivers, day 1, morning.

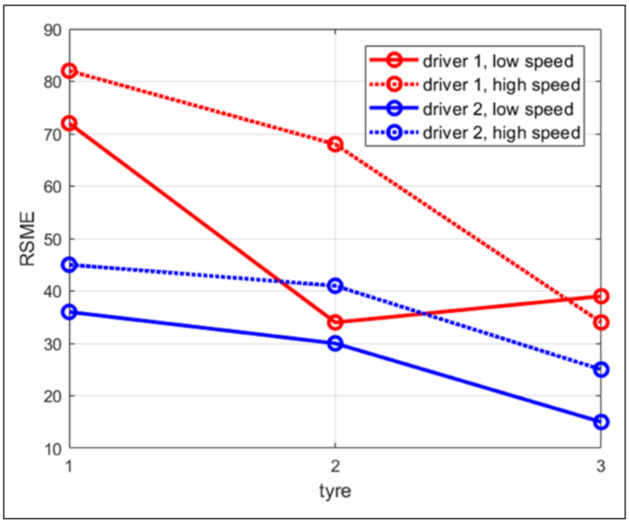

Figure 23: RSME scores for different tyres and speed (professional drivers).

under low speed conditions for tyre 2. As expected, summer tyres (2 and 3) are judged better than the winter tyre (with tests being carried out during non-winter conditions). The T_p scores show in general an increasing score and a good distinction between low and high speed. Tyres 2 and 3 resulted in higher average preview time, compared to tyre 1. For tyre 3, the T_p scores were lower than those for tyre 2. Tests for tyre 3 were carried out when the road was getting more dry. As a result, the workload was rated as low, shown by the RSME scores being less than 40. These low RSME scores were not only due to the possibly better performance by tyre 3, but also by the improved test conditions. The T_p values appear all to be quite similar, near 0.55 s. The standard deviation for the T_p score varied for most of the tests between 0.01 and 0.03 s. Consequently, some overlap between low and high speed scores, especially for driver 1 could be expected.

The RSME scores for the professional drivers tend to overlap as well, as also reported by Monsma (2015). In general, one may conclude that average preview time indicates changes in workload, if a significant variation in workload is apparent. According to **Figure 21**, driver 1 shows more variation in driving performance (larger range in preview time) compared to driver 2, for the same variation in RSME-workload assessment. This suggests that a driver reference need to be taken into account. Furthermore our results confirm that tests have to be designed in a way that challenging circumstances are part of it, described by Dick de Waard (1996) as the area of task related effort, corresponding to the transition from normal routine driving behaviour to more demanding driving conditions, and where mental workload variations up to maximum level are to be expected.

We give some results for the nonprofessional drivers, having carried out the DLC with a larger offset, and for better road conditions. The values for T_p-average were determined by a single set of average tyre characteristics for the different tyres. Nonprofessional drivers were divided in different groups, with drivers no. 5 and

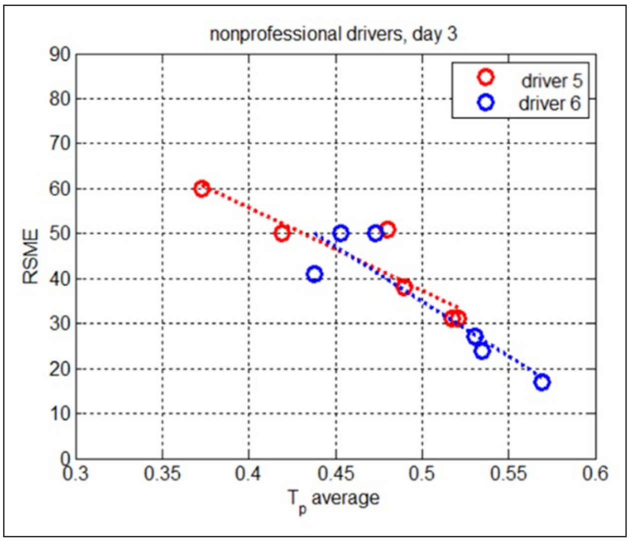

Figure 24: RSME vs. T_p (average), nonprofessional test drivers, day 3.

6 testing at day 3, drivers 7 and 8 testing at day 4, and drivers 9 and 10 carrying out the severe DLC at day 5 (notation cf. Monsma (2015)). The comparison of RSME and T_p for day 3 is shown in **Figure 24**, with high T_p corresponding to low speed. Especially for driver 6, the correlation is very good. Observe that driver 5 tends to score at higher level than driver 6. Unfortunately, the results of drivers 9 and 10 showed less correlation, especially driver 10. This may be driver specific, since they are less experienced. For these drivers, further analysis revealed that the T_p-value gives a good distinction between low and high speed, and between tyre 1 and both tyres 2 and 3, but not between the two summer tyres 2 and 3. The RSME scores appeared not to show such clear distinction, especially for high speed (with RSME scores almost all close to 70). In terms of the research by De Waard, one could say that, for high speed, these drivers are in the overload region with maximum workload, i.e. no variation to lower workload values.

Conclusions and discussion

We have examined double lane change behaviour for professional drivers, with the objectives to understand optimal lane change performance and the difference between this optimal performance and the driver test results. In addition, we have examined driver model parameters as a possible indication of driver mental workload by comparing them with the so-called RSME ratings. The experimental part of these investigations is based on tests, carried out within the scope of the PhD research by Saskia Monsma (2015), where we have restricted ourselves to tests by professional test drivers. From our analysis, the following conclusions can be drawn:

- It is possible to determine optimal lane change performance, i.e. the performance for minimum lateral acceleration.
- Test drivers do not always follow the optimal path. Sometimes they do and sometimes they don't, in the latter case with larger lateral acceleration than necessary. Tests were carried out under humid road conditions (being accounted for in the axle characteristics). Results suggest the match with the optimal path to be improved for a drier road.
- Under non-extreme conditions, path tracking driver model handling parameters such as steering gain and preview time are related to one another. They follow a hyperbolic relationship where different combinations yield the same closed loop handling behaviour. For extreme conditions with high slip, a similar hyperbolic relationship is found (confirmed by the test results), being close to the relationship for low slip. Preview time is observed to vary during the lane change, which can be interpreted as the driver model to switch attention to the next lane, at both transitions of the lane change.
- Closed loop stability drops quite dramatically with increasing slip.
- It appears that mental workload has an effect on the driver model parameters preview time and steering

gain, even under extreme handling conditions. This has been observed earlier under normal driving conditions where experienced and non-experienced drivers were compared. It has also been observed during simulator experiments where the driving skills of elderly drivers were examined. Hence, the path tracking driver model can be used as a virtual sensor to estimate mental workload, which has now been extended to high slip conditions.
- We have introduced a predictive parameter T_p-average. This is the mean of the average preview time values for repeated Double Lane Change tests for a specific combination of test driver, selected tyres and speed. Increased workload (characterized by RSME-scores) appeared to correspond to reduced T_p-average. This was true for tests discriminating between low and high workload conditions (i.e. with sufficient range in the RSME scores). Some situations occurred where the test conditions were not challenging enough. Also in case of overload for the driver (i.e. high workload for all tests, as occurred for a set of tests with non-professional drivers), no clear relationship between RSME and T_p-average was found. In both cases, the range of RSME was small. This confirms the findings of De Waard (1996) that tests on driver response need to include a state of task related effort, corresponding to the transition from low to high workload.

Professional test drivers are experienced in judging tyres in a reproducible way. We noticed that most batches of tests for a specific tyre showed a high level of reproducibility but some did not. It is therefore recommended to collect and analyse more similar data under DLC conditions, including the available non-professional DLC data.

We close this paper with the statement that the presented approach (i.e. using the driver model as virtual sensor, in the sense that driver model parameters are determined by matching a closed loop driver-vehicle model with the actual vehicle performance, and applying them as a measure for mental workload) has a significant value for driver state assessment under every day practical traffic conditions. Interpreting high steering gain as increased workload indicating a potentially risky situation, one might be able to support the driver effectively to relax such situations. Think of special target groups such as elderly drivers. The paper shows that even for an extreme double lane change manoeuvre, this approach gives meaningful results.

Additional Files

The additional file for this article can be found as follows:

- **Annex A1.** Vehicle parameters and double lane change data. DOI: https://doi.org/10.5334/ijds.7.s1

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Competing Interests

The author has no competing interests to declare.

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