Analysis of a trial-by-trial adaptive lane change assistance system on a motion-based simulator

Nico James van Leeuwen[1], Barys Shyrokau[1], Christiaan Koppel[2] and David Abbink[1]

(1) Delft University of Technology, Mekelweg 2, 2628 CD Delft, The Netherlands, e-mail: N.J.vanLeeuwen@student.tudelft.nl; B.Shyrokau@tudelft.nl; D.A.Abbink@tudelft.nl
(2) Cruden B.V., Pedro de Medinalaan 25, 1086 XP Amsterdam, The Netherlands, e-mail: C.Koppel@cruden.com

Abstract - *This study proposes a Lane Change Assistance (LCA) system that provides haptic guidance during lane changes. This system is fully integrated with Lane Keeping Assistance (LKA) functionality to provide continuous lateral support during highway driving. Two different system configurations of this LCA are investigated. One is a generalized LCA and the other is an adaptive LCA that provides personalized lane change reference trajectories through trial-by-trial adaptation to lane change duration of previous lane changes. The effects of these systems with respect to mental workload, lateral control performance and user acceptance are investigated. This is done during an experiment with three different driving sessions, consisting of a manual session and two sessions in which either the generalized or adaptive LCA is active. The experiments are conducted on a 6 DoF motion-based simulator with 34 participants, driving in a simulated three-lane highway environment with a scripted traffic scenario. To measure mental workload, an auditory cognitive secondary N-back task is introduced. The results show that the introduction of a generalized or adaptive LCA does not significantly influence the measured mental workload. When the adaptive LCA is introduced, lateral control performance and subjective usefulness is enhanced compared to the generalized LCA and manual driving.*

Keywords: *lane change assistance, trial-by-trial adaptation, haptic shared control, mental workload, simulator*

Introduction

To enable a transition from automation level 2 to 3, as defined by the Society of Automotive Engineers (SAE), it is important to consider integration of ADAS. Level 2 is defined as partial automation, in which the driver is supported by several automated functions. Level 3 is defined as conditional automation, in which the full driving task is automated under certain conditions (SAE, 2021). Most currently available vehicles are partially automated and have Lane Keeping Assistance (LKA) systems installed that do not provide support during lane changes. Instead, lane keeping functionality is switched off when the indicator is engaged.

Furthermore, mental workload is found to increase significantly during a Lane Change (LC) maneuver (Kim, et al., 2013). Therefore, the goal of this research is to design a system that can mitigate this increase of mental workload, thus enhancing safety and comfort during lane changes. To achieve this goal, this study proposes a Lane Change Assistance (LCA) system that provides haptic support during lane changes. This LCA system is completely integrated with an LKA system to enable continuous lateral support during highway driving.

The increasing amount of installed ADAS in modern vehicles require an effective collaboration between these systems and the driver. Haptic Shared Control (HSC) is a commonly encountered solution to balance the control authority between ADAS and drivers (Lazcano, et al., 2021). To enhance smooth collaboration (van Dintel, et al., 2020) and increase user acceptance (Chen and Wang, 2018) of such an HSC system, adaptation to a driver's personal preferences is desirable. Furthermore, adaptation to individual driving style can enhance usability and comfort, hence preventing disuse of the system (Hasenjager and Wersing, 2018). This can be done by implicit or explicit personalization, adapting either to observed user data or explicitly stated preference settings, respectively.

Implicit personalization is expected to be more effective, since up to 67% of drivers have been shown to incorrectly identify their own driving style when explicitly stating their preferred driving style (Basu, et al., 2017). Driving behaviour varies widely between drivers, known as inter-driver variability, but also within a driver, known as intra-driver variability (Koppel, et al., 2019). Since it is shown that there is a significant intra-driver modeling uncertainty when observing driving behaviour during two hours of lane keeping (Chen and Ulsoy, 2001), continuous adaptation is expected to be more effective than implicit or explicit personalization

In this study, an LCA system is designed that adapts its reference trajectory to the moving average of previous lane change durations. This is implemented by means of trial-by-trial adaptation, which has successfully personalized trajectories for haptic assistance during a non-driving task (De Jonge, et al., 2016). The effect of this adaptive LCA system is investigated by comparing it to manual driving and driving with a generalized LCA, which is based on a fixed value for

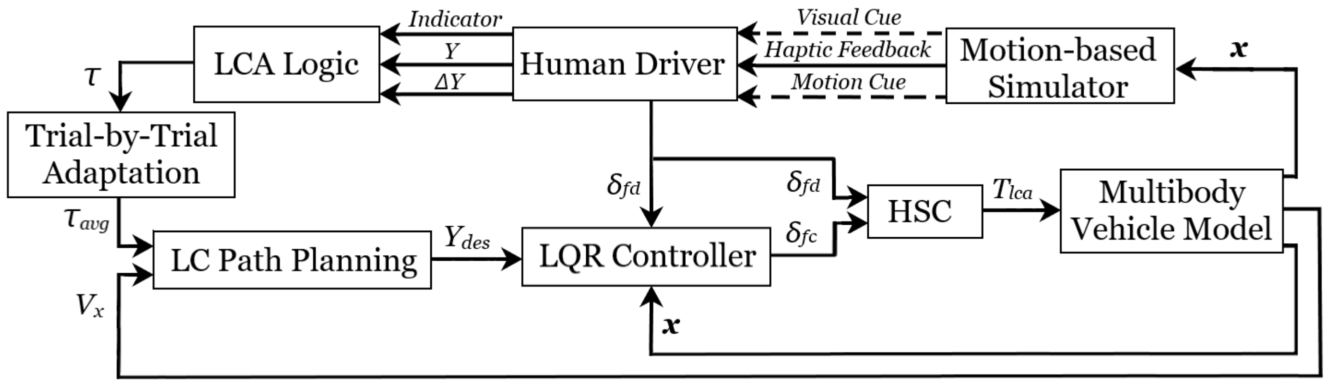

Figure 1: Schematic of the Lane Change Assistance system

average lane change duration. The research question is formulated as follows:

Does trial-by-trial adaptation to lane change duration of a haptic lane change assistance system reduce mental workload and increase lateral control performance during highway driving?

This leads to the following hypotheses:

1. A trial-by-trial adaptive lane change assistance system reduces mental workload of drivers during highway driving.
2. A trial-by-trial adaptive lane change assistance system increases lateral control performance during highway driving.

LCA system design

The novel adaptive LCA system is designed by integrating the concept of trial-by-trial adaptation in an LCA system. The planned reference path is adapted to the duration of previous LC maneuvers. The reference path is generated by a double fifth order polynomial path planning algorithm and subsequently fed to a path-following Linear Quadratic Regulator (LQR) controller. The state-space equations of the lateral controller are formulated using a bicycle model and driver model, the resulting gains are scheduled with longitudinal velocity. All subsystems are schematically shown in Fig. 1.

Trial-by-Trial Adaptation

Intra-driver variability has been shown to be greater than inter-driver variability during long driving sessions (Chen and Ulsoy, 2001). Therefore, a learning-based adaptive system using current driving information is preferred rather than a personalized system that statically characterizes ones driving style based on historical data. It is shown that trial-by-trial adaptation reduces control effort and torque conflict without degrading the performance in a non-driving task (De Jonge, et al., 2016). Therefore, this method is chosen for implementation in the proposed LCA to reduce mental workload during an LC maneuver, increase user acceptance and enhance lateral control performance. The trial-by-trial adaption is based on the duration of previous LC maneuvers and is applied to the planned reference path of the LCA system. The LC maneuver duration resulting from the collaborative steering behaviour on the HSC interface is registered by the LCA logic, stored and used to compute a moving average over 10 trials. This computed value is subsequently used to determine the desired duration for the reference path planning of the next LC maneuver. The registration of an LC maneuver in the LCA logic is initiated by the trigger of the indicator and is considered completed when the absolute value of both the lateral error $\Delta Y = Y - Y_{des}$ and lateral preview error ΔY_p, shown in Eq. 9, are within the lateral margin of 1 meter from the target lane center. The lane change is aborted when the indicator is switched off before crossing the lane boundary, after which the lane keeping functionality is continued in the original lane.

Haptic Shared Control

The HSC algorithm is designed according to the virtual spring model (Ghasemi, Jayakumar, and Gillespie, 2019), which is expressed in Equation 2. The HSC stiffness k_{hsc} is tuned for lateral control performance and user acceptance to a value of $k_{hsc} = 0.25$. The HSC interface of the steering wheel is used to combine the inputs of the driver and the LCA system as follows. First, the front wheel steering angle δ_{fc} resulting from the LQR controller is multiplied by the steering ratio i_{st} to obtain the steering wheel angle desired by the controller θ_c, shown in Eq. 1. Subsequently, the measured steering input of the driver θ_d is subtracted to determine the steering wheel angle error θ_{er}. This angle is multiplied by the HSC stiffness to obtain the assistance torque T_{lca}. This assistance torque is added to the torque from the multibody vehicle model T_{mod} to obtain the total torque T_{tot}, shown in Eq. 3. The total torque is sent to the servomotor that provides torque to the simulator's steering column.

$$\theta_c = \delta_{fc} \cdot i_{st} \tag{1}$$

$$T_{lca} = k_{hsc} \cdot \theta_{er} = k_{hsc}(\theta_c - \theta_d) \tag{2}$$

$$T_{tot} = T_{mod} + T_{lca} \tag{3}$$

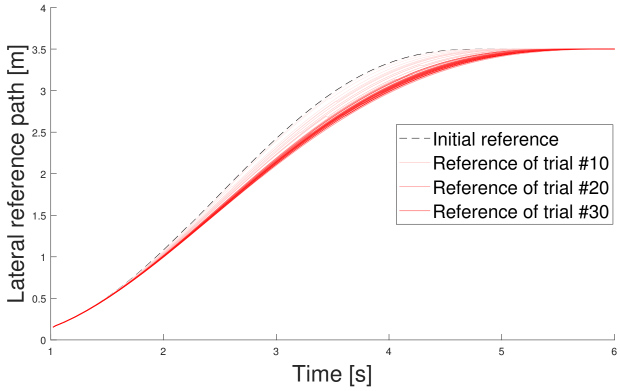

Figure 2: Reference path planning of the trial-by-trial adaptive LCA for the 37 trials of participant 25

Path Planning

The most commonly used method to plan the path of an LC maneuver is a fifth order polynomial. However, with a conventional fifth order polynomial replanning of the path is not possible. This could potentially lead to unsafe situations, therefore an adjustment is needed to enable the possibility to abort an LC maneuver after initiation (Zheng, et al., 2019). Furthermore, a human driver uses a higher lateral acceleration for steering out of the initial lane than for steering back into the target lane (Sporrer, et al., 1998). This asymmetric human steering behavior cannot be replicated by using a single quintic polynomial. By combining two different quintic polynomials, the asymmetric path can be generated to represent human LC maneuvers more accurately. Therefore, a double quintic polynomial (Heil, Lange, and Cramer, 2016) is implemented to determine the reference path for the path following controller.

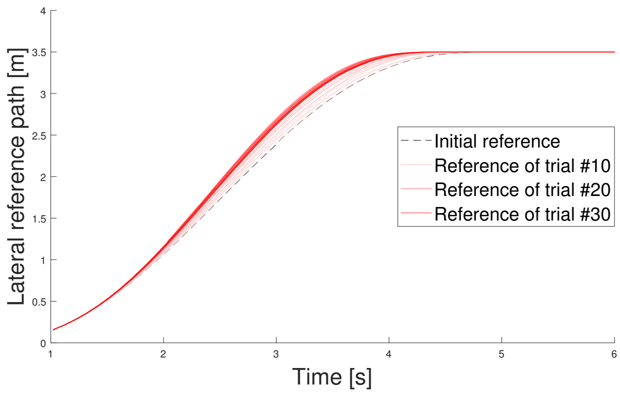

Figure 3: Reference path planning of the trial-by-trial adaptive LCA for the 34 trials of participant 34

$$\begin{aligned} s_1(t) &= c_0 + c_1\, t + c_2\, t^2 + c_3\, t^3 + c_4\, t^4 + c_5\, t^5 \\ s_2(t) &= c_6 + c_7\, t + c_8\, t^2 + c_9\, t^3 + c_{10}\, t^4 + c_{11}\, t^5 \end{aligned} \tag{4}$$

By defining the maximum desired lateral acceleration as $a_{max} = 1\ m/s^2$, the maximum desired lateral jerk as $j_{max} = 1.5\ m/s^3$ and the lane width of $w = 3.5\ m$, the two polynomials are solved with the symbolic toolbox of Matlab.

$$\begin{aligned} t_{a_{max}}(s_1) &= -\frac{2 \cdot c_4 \pm \sqrt{4 \cdot c_4^2 - 10 \cdot c_3 \cdot c_5}}{10 \cdot c_5} \\ t_{j_{max}}(s_1) &= -\frac{c_4}{5 \cdot c_5} \end{aligned} \tag{5}$$

The coefficients can be solved using Equation 5 for s_1 and s_2, under assumption that the maneuver is initiated without lateral acceleration, velocity or deviation from the lane center. Continuity is guaranteed by enforcing that the initial values of the second polynomial s_2 are equal to the final values of the first polynomial s_1. Since the LCA is integrated with an LKA, lane position metrics such as Time to Lane Crossing (TLC) are expected to cause conflict between the functionalities of these systems. Furthermore, most lane change intent prediction algorithms require eye-tracking or head movement tracking to accurately predict lane changes in real-time (Xing, et al., 2019), which were not available for this study. Therefore, the manual trigger of the indicator is used to switch from lane keeping to lane changing functionality.

To ensure smooth transition between the two polynomials, especially in the case of replanning, a hyperbolic tangent blending function with a one-sided blending time $t_b = 0.5$ seconds is used, as expressed in Eq. 6. LC maneuver paths are computed for lane change duration values between $\tau = 1$ and $\tau = 10$ seconds and stored in a lookup table. This lookup table enables interpolation for the exact value for τ_{avg} whilst minimizing computational power during simulation. The fixed value $\tau_{avg} = 4$ that is used as lane change duration for the generalized LCA is based on the distribution of average lane change duration found in literature (Toledo and Zohar, 2007).

$$\begin{aligned} s(t) =& \frac{1 - tanh(\frac{(t-\tau_{s_1})}{t_b})}{2} \cdot s_1(t) + \\ & \frac{1 + tanh(\frac{(t-\tau_{s_1})}{t_b})}{2} \cdot s_2(t) \end{aligned} \tag{6}$$

Controller Design

A state feedback controller was selected as path-following controller, since it shows similar performance to state-of-the-art path-following algorithms in highway driving conditions (Lu, et al., 2018). The selected state feedback controller is a gain-scheduling LQR controller (Wang, et al., 2017). State vector $\boldsymbol{x}$ containing 7 states is used to determine the additional steering angle δ_{fc} that the controller should provide to the front wheels of the vehicle, which is shown in Eq. 7 to 9.

$$\delta_{fc} = \boldsymbol{k}(V_x) \cdot \boldsymbol{x} \tag{7}$$

$$\boldsymbol{x} = [V_y \quad \dot{\psi} \quad \psi \quad Y \quad \delta_{fd} \quad \dot{\delta}_{fd} \quad \Delta Y_p] \tag{8}$$

$$\Delta Y_p = Y_p - Y - t_p \cdot V_x \cdot \psi \tag{9}$$

By considering multiple objectives including path-tracking error, driver's physical and mental workloads and control effort in the LQR controller, the cost function described in Eq. 10 is minimized. J_1 represents the cost for lateral preview error, J_2 and J_3 represent the driver's mental and physical workload, respectively, and J_4 represents the control effort of the LCA system. To minimize computational power during simulation, the closed-loop control gains are calculated offline for a range of longitudinal velocities and integrated in the model by means of a lookup table. The control equations are formulated to schedule the gain based on longitudinal velocity. The preview time is determined to be 2 seconds based on the relation to longitudinal velocity (Schnelle, et al., 2017) and road curvature (Yang, et al., 2020).

$$J = \int_0^\infty (J_1 + J_2 + J_3 + J_4)\, dt \tag{10}$$

Experiment Design

Figure 4: A lane change maneuver during the experiment in the highway scenario on the 6 DoF motion-based simulator

To determine the effect of the adaptive and generalized LCA on mental workload, lateral control performance and user acceptance, experiments with human participants in the loop are executed on a motion-based driving simulator. This 6 DoF driving simulator utilizes a projected view of 210 degrees horizontally and 50 degrees vertically, two exterior rear-view mirrors, one interior rear-view mirror and a dashboard depicting all relevant dials.

The vehicle model used for the simulation in the experiment is a 13 DoF dSpace multibody ASM with the parametrization of a generic sedan. The selected signals of the vehicle model are recorded at a frequency of 100 Hz. The vehicle is equipped with Cruise Control (CC), which is set at 100 km/h and can be adjusted by the driver when necessary. A traffic scenario with 30 recurring entities is scripted such that the vehicles in the right lane drive at 90 km/h, 95 km/h in the center lane and 105 km/h in the left lane. The participants are instructed to adjust the longitudinal velocity as infrequently as possible and return to the right lane after overtaking, such that a high amount of LC maneuvers is encouraged.

The experiments were executed with 34 participants in total, of which five measurements contained corrupted signals. To ensure equal distribution over the three groups described in Tab. 1, two participants were eliminated randomly to obtain 9 participants per group, thus 27 in total. The demographics parameters of the 27 participants that are used for the analysis of the results are shown in Tab. 2. The measurements were rearranged such that the results can be presented per system configuration.

Table 1: Participant groups and corresponding sequence of system configuration in the different driving sessions

Group	Session 1	Session 2	Session 3
A	Manual	Generalized	Adaptive
B	Generalized	Adaptive	Manual
C	Adaptive	Manual	Generalized

Table 2: Demographic parameters and corresponding distribution of the 27 participants included in the results

Parameter	Mean	σ	Unit
Participant age	36.8	15.6	years
Driver's license	17.8	16.2	years
Average driving	4.52	3.90	hours/week
CC driving	2.18	3.22	hours/week
LKA driving	0.50	1.95	hours/week
Simulator driving	0.29	0.57	hours/week

Metrics

Mental workload is measured during the complete duration of the experiment by means of an auditory N-back task (Layden, 2018), which is introduced as a cognitive secondary task.

In this task participants are asked to respond by tapping a touchscreen when the audio fragment of a recorded letter is identical to the letter played N trials before. N is chosen to be one, considering the substantial workload required for the driving task. Furthermore, it is shown that the 1-back auditory task results in lower variability of lateral position compared to the 0-back, 2-back and baseline measurement (Jaeggi, et al., 2010). The resulting score is expressed as Discrimination Index (DI), which is calculated by using the hit rate H and false-positive rate F, as shown in Eq. 11.

$$DI = \frac{1}{2} + sign(H-F) \cdot \frac{(H-F)^2 + abs(H-F)}{4 \cdot max(H,F) - 4HF}$$
$$H = \frac{\#hits}{\#signal\ trials} \qquad F = \frac{\#false\ positives}{\#noise\ trials} \tag{11}$$

Steering Reversal Rate (SRR) can be used as complement or alternative to lane position metrics to quantify lateral control performance (Markkula and Engström, 2006). It is easier to measure in real-world scenarios compared to lane position metrics, therefore SRR is often used as driving performance metric in field studies (Carsten, et al., 2005). Furthermore, the introduction of an auditory secondary task does not influence steering wheel angle variability, although it might influence mental workload (Hurwitz and Wheatley, 2002). Since a cognitive secondary task is introduced in this study, the corresponding parameters are used to obtain the highest sensitivity for this scenario.

The steering wheel angle signal θ is filtered with a second order Butterworth filter with a 3dB cut-off frequency of 0.6 Hz to obtain θ_{filt}. If the difference in θ_{filt} of the current and previous time step is larger than the gap value $\theta_{gap} = 0.1\ deg$, it is registered as a reversal. These are expressed in SRR as reversals per minute. The SRR metric is also computed for the LC maneuvers only, by extracting the lane change sections of the steering wheel angle signal.

To express user acceptance of the participants, a subjective van der Laan (Van Der Laan, Heino, and De Waard, 1997) questionnaire is used, in which the generalized and adaptive LCA system configurations are rated with respect to the manual driving session. The participants are requested to score the system configurations on 9 different aspects of the system, leading to a Usefulness score (USE) and a Satisfaction score (SAT). It is stated that Cronbach's coefficient of reliability α should be higher than 0.65 for the results to be valid. No prior knowledge about the LCA systems is provided to the participants to ensure unbiased results.

For all presented mean results, a linear mixed-effect model regression analysis is applied to obtain the statistical significance of the metrics. In this way, the individual participants were regarded as a random effect with no a-priori expectations. Since the data is obtained with repeated measurements of one individual participant and different system configurations, repeated-measures ANOVA is more suitable than a one-way or two-way ANOVA. However, mixed-effect modeling is more robust against systematic inter-driver variability than repeated-measures ANOVA (Van Dongen, et al., 2004). Since inter-driver variability is expected to be an important influence, linear mixed-effect model regression analysis is used to determine the statistical significance of results.

For all presented variance results, Levene's test of homoscedacity is applied to investigate the homogeneity of variances across system configurations. It is chosen over the two-sample F-test of equality of variance due to its robustness against non-normality in the data and the possibility to compare the variance of three system configurations. For both the linear-mixed regression analysis and Levene's test of homoscedacity a 95% confidence interval is applied, resulting in a significance level of 0.05.

Results

The means and statistical significance of the objective metrics for each system configuration are presented in Tab. 3. The variances of the objective metrics and corresponding statistical significance are presented in Tab. 4. The means, statistical significance and Cronbach's coefficient of reliability α for the subjective metrics are shown in Tab. 5. The results are displayed graphically in Fig. 5 to Fig. 8 by means of boxplots. These show the median of participants in red, the Interquartile range (IQR) in blue and the whiskers in black, of which the maximum length is defined as 1.5 times the IQR. Furthermore, the mean results of individual participants are shown in different colours, connected by dotted lines between the different system configurations.

Table 3: Resulting means of objective metrics and statistical significance obtained by mixed-effect linear regression

Metric	Man	Gen	Ada	F	p
DI	0.808	0.810	0.810	0.216	0.806
SRR	34.67	33.22	32.34	9.390	$<$0.001
LC-SRR	56.48	54.03	53.55	2.961	0.058

Table 4: Resulting variances of objective metrics and statistical significance obtained by Levene's test of homoscedacity

Metric	MAN	GEN	ADA	F	p
DI	$4{\cdot}10^{-4}$	$2{\cdot}10^{-4}$	$1{\cdot}10^{-4}$	3.57	0.033
SRR	28.93	29.37	28.28	0.021	0.980
LC-SRR	48.70	91.57	31.22	3.59	0.032

Mental Workload

In Tab. 3 it is shown that the small change of mean DI after introducing an LCA system compared to the manual driving session is regarded insignificant by the mixed-effect linear regression analysis. The variance of mean DI decreases across the three system configurations, as can be seen in Fig. 5. This is regarded as a significant change in variance according to Levene's test with an associated p-value of 0.032, as shown in Tab. 4.

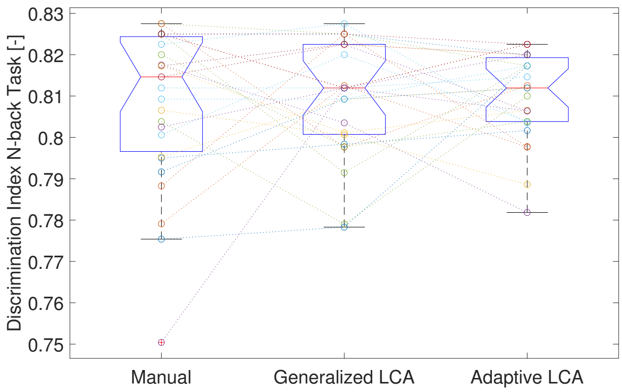

Figure 5: Mental workload measured by the cognitive N-back task per system configuration for 27 participants

Lateral Control Performance

As can be seen in Fig. 6 and in Tab. 3, the mean value of SRR decreases when the adaptive LCA is introduced compared to the generalized LCA and manual driving. In Tab. 4 it can be seen that the variance of SRR remains unchanged across the system configurations with a p-value of 0.98. Therefore, it passes Levene's test for equality of variances.

It can be seen in Fig. 7 that the variance of SRR during LC maneuvers increases from manual to generalized LCA. The variance of SRR during LC maneuvers of the adaptive LCA decreases compared to both the generalized LCA and the manual driving session. In Tab. 4 it is shown that this reduction of variance is significant according to Levene's test, with a p-value of 0.032.

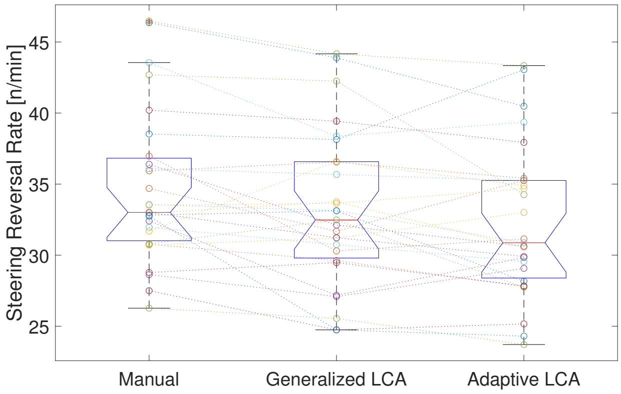

Figure 6: Steering reversal rate during complete driving sessions per system configuration for 27 participants

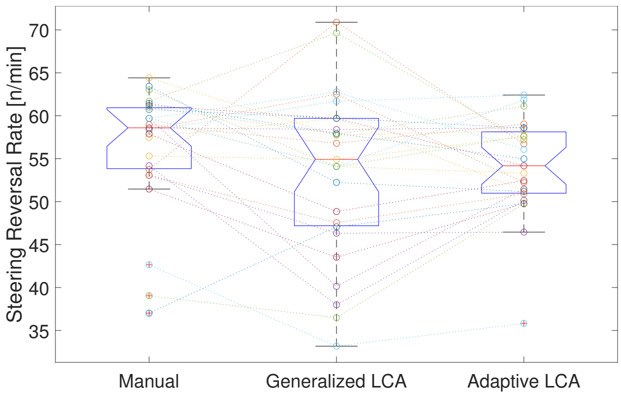

Figure 7: Steering reversal rate during lane change maneuvers per system configuration for 27 participants

User Acceptance

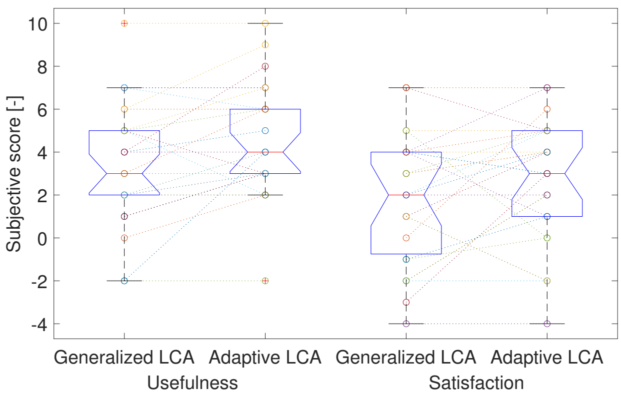

Figure 8: Subjective usefulness score and satisfaction score per system configuration for 27 participants

Table 5: Resulting means of subjective metrics and statistical significance obtained by mixed-effect linear regression

Metric	GEN	ADA	α	F	p
USE	3.444	4.407	0.901	7.773	0.007
SAT	1.889	2.667	0.765	2.338	0.132

In Fig. 8 it is shown that both the subjective usefulness score and the subjective satisfaction score increase with the introduction of the adaptive LCA system compared to the generalized LCA system. However, in Tab. 5 it is shown that this increase is only significant for the subjective usefulness score USE with a p-value of 0.007. Furthermore, it can be seen in Fig. 8 that the usefulness score for both the generalized and the adaptive LCA are higher than the respective satisfaction score values. The subjective results are regarded as valid since Cronbach's coefficient of reliability α is higher than 0.65 for both system configurations, as is shown in Tab. 5.

Discussion

The unchanged mental workload measured by DI after introduction of the trial-by-trial adaptive LCA system does not agree with the expectations expressed in hypothesis I, thus the hypothesis is rejected. The negligible change in mean DI might be explained by the fact that the N-back task was executed continuously with random hits to prevent an expectation pattern. Therefore workload was measured during both lane keeping and lane changing, possibly reducing visibility of the effect during LC maneuvers. Additionally, it could be explained by the low error rate measured for the auditory 1-back task (Mehler, et al., 2009) in a lane keeping task. Alternatively, the small change in measured mental workload across system configurations could be explained by the large dependence on traffic environment complexity (Patten, et al., 2006). This is in agreement with observations made during the experiment, in which it seemed that secondary task performance degraded in situations with high traffic complexity.

Lateral control performance and SRR are inversely related, since the performance is considered to be reduced when many steering corrections have to be made. Therefore, the lateral control performance is increased by introducing the adaptive LCA system compared to manual driving and the generalized LCA system. This in agreement with hypothesis II, which is therefore accepted. The validity of SRR as metric representing absolute steering performance can be questioned, since it is affected by the steering task difficulty. However, it is found that the metric is a valid representation of driving performance and can therefore be used to compare different drivers or conditions (McLean and Hoffmann, 1975).

The increased steering wheel activity may be associated with both increased cognitive load and reduced lateral control performance (Markkula and Engström, 2006). However, literature shows that SRR is not significantly affected by a cognitive secondary task (Knappe, et al., 2007), indicating that the change in SRR is more probable to be an effect of the different system configurations or traffic complexity rather than the introduced secondary task.

The reduction in variance of SRR during lane changes indicates that the inter-driver variability of performance is reduced by introducing the trial-by-trial adaptation. This could result from the fact that the adaptive LCA accommodates to the personal preferences of different drivers, thus increasing the lateral control performance resulting from the HSC interface of the steering wheel. This is in agreement with previous studies that applied a personalized driver model to both an LKA and an Adaptive Cruise Control (ACC) system (Lefevre, et al., 2015) and a personalized LCA system based on identification of cautious, normal and aggressive driving style (Zhu, et al., 2018). These studies also show that the differences in driving behaviour were accommodated and thus inter-driver variability could be reduced.

The significantly increased usefulness score of the adaptive LCA compared to the generalized LCA system is in agreement with results from a previous study that applied continuous adaptation to personal preference of the longitudinal assistance system ACC to Time to Collision (TTC). This study also showed a higher user acceptance compared to a standard ACC (Wang, et al., 2013). The unchanged user acceptance expressed as satisfaction score is not in agreement with the expectations, this might be explained by conflicts of lane change intention caused by the limitations of the LCA logic.

Limitations

For the purpose of this study, longitudinal control is supported by means of a CC instead of an ACC system. This was done to stimulate lane changing rather than car-following behaviour. However, it was observed during the experiments that the longitudinal control task required a lot of additional mental workload capacity in situations with high traffic density. Therefore it is expected that this has distorted the measurements of multiple metrics, which could have been mitigated by integration of the LCA system with an ACC system.

In this study it was chosen to embed a safety feature in the LCA logic, by aborting a lane change if the indicator is switched off before crossing the lane boundary. However, aborted LC maneuvers were almost never encountered during the experiments, whereas many people switched off the indicator before crossing the lane boundary during an intentional LC maneuver. This led to a relatively large number of conflicts between the LCA logic and the participants. These conflicts could have been mitigated by enlarging the time duration in which the lane boundary has to be crossed.

Furthermore, two subsequent left or right LC maneuvers could not be identified as such if the indicator was not switched off between the maneuvers. The conflicts resulting from this could have been prevented by executing the simulation on a two-lane highway. More preferably, the LCA logic should be able to detect the intention of two subsequent lane changes.

Conclusion

The hypotheses of this study were stated as follows:

1. A trial-by-trial adaptive lane change assistance system reduces mental workload of drivers during highway driving.
2. A trial-by-trial adaptive lane change assistance system increases lateral control performance during highway driving.

The first hypothesis is rejected, since there is no significant change in mental workload, measured by the mean discrimination index of the cognitive secondary N-back task, when the generalized or adaptive LCA system is introduced.

The second hypothesis is accepted, since the lateral control performance, measured by the mean steering reversal rate, is increased significantly when introducing trial-by-trial adaptation to lane change duration in the adaptive LCA when compared to the generalized LCA and manual system configuration.

Furthermore, inter-driver variability of lateral control performance during lane changes is reduced significantly by introducing trial-by-trial adaptation to lane change duration in the adaptive LCA compared to the generalized LCA and manual driving. In addition to this, user acceptance expressed as subjective usefulness is increased significantly by introducing the adaptive LCA system.

Future Work

During this study, several observations are made of aspects that could be improved upon and topics to be researched in future studies. First of all, to achieve fully integrated longitudinal and lateral functionality of lane change assistance, implementation of HSC on a longitudinal control interface such as the acceleration or brake pedal would be preferable. By doing this, excessive braking or acceleration to complete a safe lane change could be made redundant. By integrating longitudinal control as proposed in (Dang, et al., 2015), the functionalities of these systems could be optimized to complement one another and thus lead to more consistent results with reduced effect of traffic complexity.

Furthermore it is recommended to adjust the LCA logic to enable a more universal detection of lane change intention. It is expected that this will further enhance user acceptance and driving performance, whilst ensuring safe driving behaviour. For example, the lateral margins defining the end of an LC maneuver could be reduced to a smaller value to capture more of both the intra-driver and inter-driver variability. Alternatively, different metrics could be chosen to define the start and end of an LC maneuver.

To improve upon the learning speed of the adaptive LCA system, naturalistic driving data of participants could be used to obtain initial values for the adaptive LCA, opposed to the generalized value for lane change duration of 4 seconds. Additionally, the effect of different values for the moving average window length could be investigated. Alternatively, other learning algorithms could be applied to obtain the desired value of lane change duration. Also, further research could be done to investigate the effect of adaptation to driver parameters other than lane change duration, such as preferred lateral acceleration (Fleming, et al., 2019).

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