If, When, and How to Perform Lane Change Maneuvers on Highways

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***Abstract*—**Advanced driver assistance systems or highly automated driving systems for lane change maneuvers are expected to enhance highway traffic safety, transport efficiency, and driver comfort. To extend the capability of current advanced driver assistance systems, and eventually progress to highly automated highway driving, the task of automatically determine if, when, and how to perform a lane change maneuver, is essential. This paper thereby presents a low-complexity lane change maneuver algorithm which determines whether a lane change maneuver is desirable, and if so, selects an appropriate inter-vehicle traffic gap and time instance to perform the maneuver, and calculates the corresponding longitudinal and lateral control trajectory. The ability of the proposed lane change maneuver algorithm to make appropriate maneuver decisions and generate smooth and safe lane change trajectories in various traffic situations is demonstrated by simulation and experimental results.

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I. Introduction

To increase traffic safety and driver comfort, the area of active safety has quickly evolved in the automotive industry during the last decades. Advanced Driver Assistance Systems (ADAS) such as Adaptive Cruise Control (ACC), Lane Keeping Aid (LKA), and Automatic Emergency Brake (AEB) have been shown to have a positive impact on traffic safety [1]. It is expected that further developed ADAS and eventually highly automated driving, will continue to increase traffic safety by reducing the impact of human errors [2]. Since the structured environment of highways renders a high level of vehicle autonomy realizable, current research on ADAS address the concept of assisting the driver in, or even autonomously perform, highway maneuvers e.g. lane change [3].

In order to further develop ADAS functionality and eventually progress to highly automated highway driving, this paper considers the problem of automatically determine if, when, and how to perform a lane change maneuver. In [4], this problem is modeled by a mixed logical dynamical system which is solved using a mixed-integer problem formulation. However, a drawback of the approach presented in [4] is that mixed-integer programming suffers from combinatorial complexity and as such it might not be suitable for real-time implementation in a standard vehicle platform. To overcome that limitation, this paper proposes a lane change maneuver algorithm which divides the considered problem into three steps

A) Decide whether a lane change maneuver is desirable.
B) Select the inter-vehicle traffic gap and time instance to perform the maneuver.
C) Plan the longitudinal and lateral control trajectory to execute the maneuver.

The decision regarding whether a lane change maneuver is desirable is achieved by means of an utility function which weights several decision-criteria against one another. The decision regarding which inter-vehicle traffic gap and time instance to perform the maneuver is achieved by approximating the intersection between the vehicle's reachable set and the safe lane change region of a certain inter-vehicle traffic gap [5]. The decision regarding the feasibility and execution of the maneuver is formulated as an optimal control trajectory planning problem in the Model Predictive Control (MPC) framework [6]. The proposed lane change maneuver algorithm has thereby the ability to make discrete decisions regarding which maneuver to perform by evaluating a number of decision-criteria, and generate smooth and safe trajectories to perform the selected maneuver with low computational resources. By decomposing the problem of determining if, when, and how to perform lane change

maneuvers on a highway into three steps, the proposed lane change maneuver algorithm ensures that although a lane change maneuver might be desirable it is not executed unless a safe collision-free trajectory exists. This is an essential quality of the algorithm due to the severity of possible consequences that may arise from inappropriate maneuver decisions. The proposed algorithm is thereby considered as a building block for ADAS regarding lane change maneuvers and eventually highly automated driving vehicles in a mixed highway traffic environment with both human drivers and automated vehicles with or without vehicle-to-vehicle and vehicle-to-infrastructure communication.

Methods for determining whether a lane change maneuver is desirable and selecting an inter-vehicle traffic gap and time instance to perform the maneuver, can roughly be divided into 1. rule-based approaches e.g. [7]–[8], 2. utility-based approaches e.g. [9] where the more advanced also accounts for uncertainties in e.g. sensor measurement and motion prediction of the surrounding vehicles e.g. [10]–[12], and 3. learning-based approaches e.g. [13]–[14]. The advantages of rule-based approaches are traceability and simple implementation for specific scenarios. However, for complex traffic situations a rule-based approach can require a substantial effort in order to be extended into more general scenarios. Approaches based on utility functions have the advantage of allowing evaluation of multiple decision-criteria by combined weighting and can thus more easily be extended to complex scenarios. However, a large amount of different weighting parameters can result in time-consuming parameter tuning and tractability difficulties. Learning-based approaches can be utilized either as a support to parameter tuning of utility-functions, or as a decision-making component on its own. However, learning-based approaches rely on data for off-line feature recognition and/or on-line training, and might be difficult to analyze and verify in order to guarantee the performance of the approach.

To allow for transparent decision-making and evaluation of multiple decision-criteria without time-consuming parameter tuning, this paper proposes an utility function that expresses the utility of each lane consistently in relation to time, which allows for an intuitive tuning process. The proposed utility function further allows for mandatory, discretionary, and anticipatory lane change decisions to be considered in one combined function. Furthermore, the decision regarding which inter-vehicle traffic gap and time instance to perform the maneuver is achieved by a separate selection function inspired by reachability analysis.

There are various approaches to trajectory planning for highly automated driving vehicles e.g. [15]–[19]. However, although these trajectory planning algorithms provide good results in a number of applications, they also come with various drawbacks where the main limitation involves the trade-off between required computational resources, solution optimality, and ability to generate smooth and safe trajectories. Furthermore, many of the commonly used trajectory planning methods lack formal stability analysis and verification methods and thereby rely heavily on extensive simulation and experimental testing.

Because of its ability to systematically handle system constraints, MPC is an attractive choice for lane change trajectory planning since due to the high velocity and intense traffic flow on highways, violating safety constraints can have severe consequences. However, since vehicle platforms have limited computational resources it is important to formulate the MPC trajectory planning problem as a low-complexity optimization problem. For that reason, in this paper the trajectory planning problem is formulated as loosely coupled longitudinal and lateral MPC problems in the form of low-complexity Quadratic Programs (QPs) which can be efficiently solved [20]. The general idea of the trajectory planning algorithm for lane change maneuvers was first introduced in [21]. This paper extends the results presented in [21] by integrating the trajectory planning algorithm with a method for selecting an appropriate inter-vehicle traffic gap and time instance to perform the lane change maneuver, as well as a decision-making framework for determining whether the maneuver is desirable. Furthermore, while [21] provides simulation result of the trajectory planning algorithm, this paper provides experimental results from lane change maneuvers performed at a test track using a Volvo V60.

The remainder of the paper is organized as follows: Section II describes the considered problem of determining if, when, and how to perform a lane change maneuver, while Section III explains the proposed problem solution. In Section IV simulation results regarding the proposed lane change maneuver algorithm are presented, and experimental results are given in Section V. Finally, conclusions are stated in Section VI.

II. Problem Description

In traffic situations where the ego vehicle, E, does not have right-of-way, it must be able to adapt its behavior to the surrounding traffic environment. For instance, as schematically represented in Fig. 1, for E to change lane to the left on a highway, it must position itself in a gap between vehicles traveling in the target lane, while maintaining a safe distance to the nearby vehicles in its current lane throughout the maneuver. Hence, for a lane change maneuver to be feasible it should be planned such that E

- avoids collision conflicts with all surrounding vehicles, S_i,
- respects traffic rules and regulations, and
- satisfies physical and design limitations.

For a lane change maneuver to be executed, in addition to the maneuver being feasible, it must also be desirable. A lane change maneuver is considered desirable if it is either

- discretionary i.e. a lane change maneuver initialized to improve the driving conditions of E e.g. in order to maintain its desired velocity, $v_{x_{\text{des}}}$, by passing a slow preceding vehicle,
- anticipatory i.e. a lane change maneuver initialized to improve the driving conditions of S_i e.g. in order to allow a fast trailing vehicle to pass,
- mandatory i.e. a lane change maneuver initialized by road conditions e.g. due to a lane drop.

The considered problem regarding if, when, and how to perform a lane change maneuver on a highway can thereby be formulated as follows: *given a highway traffic environment, determine whether it is desirable for E to perform a lane change maneuver, and if so, determine an appropriate inter-vehicle traffic gap and time instance to perform the maneuver, and calculate a feasible maneuver (if such exists) in terms of a longitudinal and a lateral trajectory, i.e. the control signals, which allow E to position itself in the selected gap at the desired time instance.*

III. Lane Change Maneuver Algorithm

As mentioned previously in Section I, the general idea of the lane change maneuver algorithm is to divide the considered problem into three steps for which further details are respectively provided in Sections A.-C. The proposed solution is formulated based on the following set of assumptions

*a*1 E is equipped with sensor systems which measure its position on the road as well as the respective relative positions and velocities of S_i within sensor range, i.e. all required sensor measurements are available.

*a*2 E is equipped with prediction systems which estimate the motion trajectories of S_i over a time horizon.

*a*3 E is equipped with low-level control systems capable of tracking the planned trajectories.

Examples of the assumed low-level control system and the necessary sensor technology are respectively given in [22] and [23]. Furthermore, any prediction model e.g. [24] can be used by the assumed prediction systems to estimate the motion trajectories of S_i over a time horizon. Uncertainties resulting from the sensor technology and/or motion prediction can be taken into account by e.g. increasing the safety distance which E must maintain to S_i over the prediction horizon in relation to the confidence level of the sensor and motion prediction systems. In addition, the re-planning nature of MPC allows changes in the perceived environment to be accounted for at each time instance.

A. Decide Whether A Lane Change Maneuver is Desirable

To determine whether it is desirable for E to change lane, the lane change maneuver algorithm must consider several different aspects of the maneuver. In accordance with many lane change models e.g. [25]–[27], the aspects to consider can roughly be expressed by the average velocity and time gap of S_i traveling in a certain lane $L_l, l \in \mathbb{L}$ where $\mathbb{L}$ denotes the set of lanes, in addition to the lane properties, and traffic rules. In order to develop an intuitive decision-making framework which considers the influence of the average velocity and time gap of S_i, as well as the lane properties when determining the desirability of a lane change maneuver, an utility function is suggested where the different aspects to consider are consistently expressed in relation to time. As such, the different aspects which should be considered when determining the desirability of a lane change maneuver, can be accounted for by the following factors

- U_{l_v}: average travel time in L_l,
- U_{l_g}: average time gap density in L_l,
- U_{l_d}: remaining travel time in L_l.

The utility of the average travel time in L_l, corresponds to the average longitudinal velocity of S_i in L_l, denoted by v_{l_μ}, over a prediction horizon, P, in relation to $v_{x_{\text{des}}}$. It is determined as

$$U_{l_v} = -\left| \frac{d_{\max}}{v_{x_{\text{des}}}} - \frac{d_{\max}}{\max(\gamma, v_{l_\mu})} \right|, \tag{1}$$

where $\gamma > 0$ is a parameter to avoid zero division and $d_{\max}$ is the maximum travel distance to consider determined as

$$d_{\max} = \beta v_{x_{\text{des}}}, \tag{2}$$

where $\beta > 0$ denotes a time horizon. From (1) it can be seen that U_{l_v} peaks when v_{l_μ} is equal to $v_{x_{\text{des}}}$ while it decays when v_{l_μ} is less or more than $v_{x_{\text{des}}}$. As such, (1) can be considered to account for both discretionary and anticipatory lane change decisions related to the average velocity of Si in L_l.

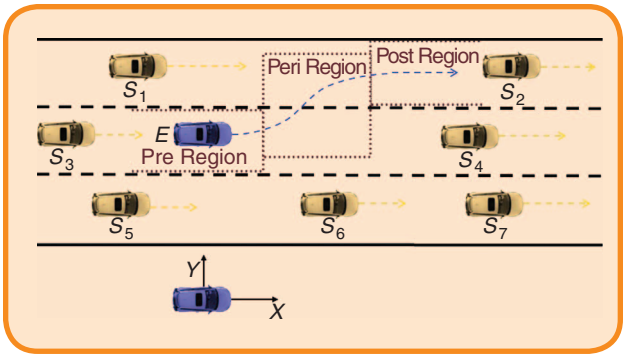

FIG 1 Vehicles traveling on a road with three lanes. The ego vehicle (E) is shown in blue and the surrounding vehicles ($S_1, S_2, S_3, S_4, S_5, S_6$, and S_7), are displayed in orange. The dashed arrows represent the predicted paths of $S_i, i = 1, \ldots, 7$, and the planned route of E. The space which E should traverse in order to perform a left lane change maneuver is schematically illustrated by the Pre, Peri, and Post regions.

Uncertainties resulting from the sensor technology can be taken into account by increasing the safety distance over the prediction horizon in relation to the confidence level of the sensor and motion prediction systems.

The utility of the average time gap density in L_l corresponds to the average traffic density in the lane. It can be determined as

$$U_{l_{tg}} = \min(\alpha \mathrm{tg}_{\mathrm{des}}, \mathrm{tg}_{l_\mu}), \tag{3}$$

where $\alpha > 1$ is a scaling parameter, $\mathrm{tg}_{\mathrm{des}}$ is the desired time gap of E, and tg_{l_μ} denotes the average time gap of S_i traveling in L_l over P. From (3) it can be seen that $U_{l_{tg}}$ increases with tg_{l_μ} until a larger time gap is not further beneficial as defined by $\alpha \mathrm{tg}_{\mathrm{des}}$. As such, (3) can be considered to account for both discretionary and anticipatory lane change decisions related to the average time gap of S_i in L_l in order to e.g. account for the possible risk of a lane change maneuver in dense traffic.

The remaining travel time in L_l corresponds to whether E will get to its destination by traveling in the lane. The utility of the remaining travel time in L_l can thus be determined as

$$U_{l_d} = \frac{\min(d_{\max}, d_{\mathrm{end}})}{v_{x_{\mathrm{des}}}}, \tag{4}$$

where d_{end} is the distance to L_l's end point e.g. a lane drop, the end of an entry ramp, or exit point. As such, (4) can be considered to account for mandatory lane change decisions related to the lane properties.

The utility of L_l can thereby be determined as

$$U_l = w_1 \frac{U_{l_v}}{N_{l_v}} + w_2 \frac{U_{l_{tg}}}{N_{l_{tg}}} + w_3 \frac{U_{l_d}}{N_{l_d}}, \tag{5}$$

where $w_j \geq 0$, $j = 1, 2, 3$ are optional weighting parameters, and N_{l_v}, $N_{l_{tg}}$, and N_{l_d} are normalizing factors defined as

$$N_{l_v} = \left| \frac{d_{\max}}{v_{x_{\mathrm{des}}}} - \frac{d_{\max}}{\gamma} \right|, \tag{6a}$$

$$N_{l_{tg}} = \alpha \mathrm{tg}_{\mathrm{des}}, \tag{6b}$$

$$N_{l_d} = \frac{d_{\max}}{v_{x_{\mathrm{des}}}}. \tag{6c}$$

Furthermore, in order to account for the traffic rule of right hand traffic to drive in the rightmost lane if possible, U_l is updated as

$$U_l = U_l - \zeta n, \tag{7}$$

where n denotes the number of lanes to the right of L_l, and $\zeta > 0$ is a scaling parameter. Similarly, left hand traffic can be taken into account by letting n denote the number of lanes to the left of L_l.

In terms of utility, a lane with high utility is considered as desirable and the desirability of a lane change maneuver into L_l is determined by comparing the expected utility of each lane. The decision whether to change lane or remain in the current lane can thus be accomplished by

$$L_{\mathrm{des}} = \underset{l \in \mathbb{L}}{\operatorname{argmax}} (U_l - (1 + \xi |l|)|U_0|), \tag{8}$$

where L_{des} denotes the desired lane, i.e. either a target lane or the current lane. The current lane is denoted by $l = 0$, while $l > 0$ denotes lanes to the left, and $l < 0$ denotes lanes to the right. From (8) it can be seen that for a lane change maneuver to be considered desirable, the expected utility of L_l must be higher than the expected utility of the current lane scaled by the threshold parameter ξ in order to account for the possible risk of a lane change maneuver as well as uncertainties in the sensor measurements and motion prediction systems i.e. Assumption $a1$ and $a2$, when determining v_{l_μ}, tg_{l_μ}, and d_{end}.

B. Select the Inter-Vehicle Traffic Gap and Initiation Time

If a lane change maneuver is deemed to be desirable, the lane change maneuver algorithm should determine an appropriate inter-vehicle traffic gap in the target lane, and at which time instance E should laterally move into the selected gap. As such, the algorithm must be able to crudely evaluate which inter-vehicle traffic gaps that are reachable at each time instance over the prediction horizon, and select an appropriate inter-vehicle traffic gap and time instance to perform the maneuver.

In order to simply estimate whether a certain inter-vehicle traffic gap is reachable, a "time-position"-area corresponding to an approximation of the intersection between the reachable set of E and the predicted safe lane change region of the inter-vehicle traffic gap i.e. the space that is not possessed by any S_i, can be created as

$$A_g = \sum_{k=0}^{K} \max(0, \min(x_{g_k}^{\max}, x_{E_k}^{\max}) - \max(x_{g_k}^{\min}, x_{E_k}^{\min})), \tag{9}$$

where k denotes the discrete time index, K is the discrete time version of P, and $x_E^{\max}$ and $x_E^{\min}$ respectively denotes the maximal and minimal position which E can reach at each time instance, i.e. its dynamical limitations. The maximum and minimum bounds on the safe lane change region of an inter-vehicle traffic gap are respectively denoted by $x_{g_k}^{\max}$ and $x_{g_k}^{\min}$ which can be determined as

$$x_{g_k}^{\max} = \min_{i \in \mathbb{F}_g} (x_{i_k} - m_{i_k}), \forall k = 0, \ldots, K, \tag{10a}$$

$$x_{g_k}^{\min} = \max_{i \in \mathbb{B}_g} (x_{i_k} + m_{i_k}), \forall k = 0, \ldots, K, \tag{10b}$$

where $\mathbb{F}_g$ and $\mathbb{B}_g$ respectively denotes the set of vehicles in front of or behind E in its current and target lane for the considered gap. The minimum safety margin, mi, which E should maintain to each Si is defined as

$$m_{i_k} = \begin{cases} \mathrm{tg}_F \min(v_{x_{\max}}, v_{x_{ik}}) + d_s, \\ \qquad \forall k = 0, \ldots, K, i \in \mathbb{F}_g, \\ \mathrm{tg}_B (v_{x_{ik}}) + d_s, \\ \qquad \forall k = 0, \ldots, K, i \in \mathbb{B}_g, \end{cases} \tag{11}$$

where tg_F and tg_B respectively denotes the minimum time gap to $S_i \in \mathbb{F}_g$ and $S_i \in \mathbb{B}_g$, $v_{x_{\max}}$ denotes E's maximal allowed velocity, and ds denotes a constant minimum safety distance which E should maintain to each S_i. In (10)-(11) it is assumed that the predicted longitudinal position, x_i,and velocity, v_{x_i}, of Si in the current and the target lane are given according to Assumption $a1$ and $a2$, for which uncertainty can be taken into account by for instance adjusting xi and v_{x_i} according to the confidence level of the assumed sensor and motion prediction systems. Furthermore, it is assumed that x_i denotes the position of the vehicle's rear for $S_i \in \mathbb{F}_g$ and the position of the vehicle's front for $S_i \in \mathbb{B}_g$.

Since A_g (9) is an approximation of the intersection between the reachable set of E and the safe lane change region of a certain inter-vehicle traffic gap, a large A_g indicates that there should exist a large set of trajectories which allow E to change lane in the inter-vehicle traffic gap, while a small A_g indicates that there should exist a small set of trajectories which allow E to change lane in the inter-vehicle traffic gap. Thereby, A_g can be utilized to crudely evaluate which inter-vehicle traffic gap that is most appropriate in terms of the expected number of trajectories which allow E to reach the gap, i.e. a large A_g is considered preferable since the chance of planning and performing a successful lane change maneuver is expected to increase with the size of A_g. Furthermore, for a lane change maneuver to be possible in a certain inter-vehicle traffic gap, A_g must fulfill the following

$$k_{A_g}^{\mathrm{end}} - k_{A_g}^{\mathrm{start}} \geq k_{\min}, \tag{12}$$

where $k_{A_g}^{\mathrm{end}}$ and $k_{A_g}^{\mathrm{start}}$ respectively denotes the discrete end and start time instances for the existence of A_g, and $k_{\min}$ is the discrete time version of the minimum time, $t_{\min}$, it takes for E to laterally move into the target lane. From the possible inter-vehicle traffic gaps which satisfies (12), the most appropriate gap is selected as the gap for which the corresponding A_g is the largest.

When a certain inter-vehicle traffic gap has been selected, the time instance to initialize the laterally movement into the gap, k^{Peri}, is determined as the time instance for which the magnitude of the required control signals i.e. acceleration/deceleration to reach the corresponding A_g at k^{Peri} are minimized while fulfilling

$$k_{A_g}^{\mathrm{start}} \leq k^{\mathrm{Peri}}, \tag{13a}$$

$$k^{\mathrm{Peri}} \leq K - k_{\min}. \tag{13b}$$

C. Plan the Longitudinal and Lateral Trajectory

If a lane change maneuver is deemed desirable, and an appropriate inter-vehicle traffic gap and time instance to perform the maneuver have been selected, the lane change maneuver algorithm must determine the longitudinal and lateral trajectory, i.e. the control signals, which allow E to position itself in the selected gap at the desired time instance. While further details regarding the trajectory planning for lane changes maneuvers are given in [21], the general idea of trajectory planning is captured by four main steps

1) *Determine the longitudinal safety corridor*
   The space which E should traverse when performing a lane change maneuver can be divided into three regions: Pre, Peri, and Post, as illustrated in Fig. 1. Hence, for a lane change trajectory to be feasible, E must be able to traverse the Pre, Peri, and Post regions while maintaining a safe distance to all relevant S_i in each region. This corresponds to upper and lower bounds on E's longitudinal position which define a longitudinal safety corridor which E must be positioned within in order to safely perform the lane change maneuver.
2) *Determine the longitudinal trajectory*
   When the longitudinal safety corridor has been determined, the longitudinal trajectory planning problem can be formulated and solved as a QP optimization problem. In the QP problem the motion of E is modeled by a simple double integrator so that the longitudinal dynamics of E can be linearly expressed [22]. Position constraints ensure that E remains within the longitudinal safety corridor while velocity bounds constrain the velocity of E to the allowed speed limits. Furthermore, constraints on acceleration and jerk allow for smooth and comfortable maneuvers, and ensure that the planned trajectory is within the capability of the assumed low-level control systems i.e. Assumption $a3$.
3) *Determine the lateral safety corridor*
   The longitudinal trajectory correlated to the road properties are used to determine the upper and lower bounds on E's lateral position when traversing the Pre, Peri, and Post regions, i.e. performing the lane change maneuver. These bounds corresponds to a lateral safety corridor which E must be positioned within when performing the lane change maneuver.

4) *Determine the lateral trajectory*
Respecting the position constraints given by the lateral safety corridor, the optimal lateral control signals are computed by QP optimization as in Step 2. Alternatively, in order to reduce the required computational time, the lateral control signals can be computed by a standard LQ-controller tracking a spline reference [28].

IV. Simulation Results

In this section, the lane change maneuver algorithm is evaluated in a simulated lane change traffic situation on a one-way, two-lane highway as illustrated in Fig. 2. In the considered lane change traffic situation, E initially drives at a velocity of 15 m/s in the right lane which merges into the left lane in 2000 m. The surrounding vehicles S_1, S_2, S_3, and S_4 drive in the adjacent left lane at an average velocity of $v_{1_\mu} = 20$ m/s, with a time gap of approximately $\mathrm{tg}_{1_\mu} = 2$ s, without performing any lane change maneuvers over the prediction horizon. Surrounding vehicles driving in the right lane are not considered in order to slightly simplify the traffic situation for ease of illustration. The assumptions regarding S_i are simple assumptions purely in order to illustrate the lane change maneuver algorithm. However, any predicted behavior, i.e. motion trajectory of S_i can be incorporated into the algorithm. Furthermore, in the considered traffic situation, $v_{x_{\mathrm{des}}} = 20$ m/s and $\mathrm{tg}_{\mathrm{des}} = 2$ s.

The aim of the lane change maneuver algorithm for the described traffic situation is to determine whether it is desirable for E to perform a lane change maneuver, and if so, determine an appropriate inter-vehicle traffic gap and time instance to perform the maneuver, and calculate a feasible trajectory in terms of the control signals which allow E to position itself in the selected gap at the desired time instance.

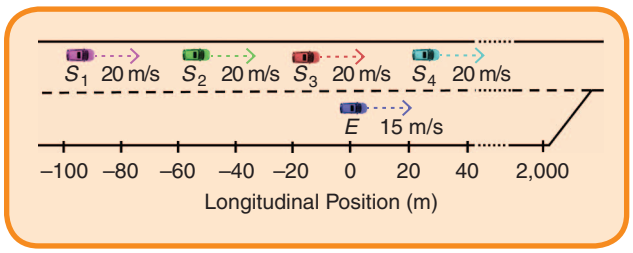

FIG 2 Vehicles traveling on a road with two lanes. The ego vehicle (E) is shown in blue and the surrounding vehicles (S_1, S_2, S_3, and S_4) are respectively displayed in magenta, green, red, and cyan.

Table 1. Design and weight parameters for the decision-making function and inter-vehicle traffic gap and initiation time selection.

$\alpha = 2$	$\beta = 300$ s	$\xi = 0.1$
$\gamma = 2$ m/s	$\zeta = 0.1$	
$w_1 = 5$ if $v_{l_\mu} \leq v_{x_{\mathrm{des}}}$ $w_1 = 12$ if $v_{l_\mu} > v_{x_{\mathrm{des}}}$	$w_2 = 0.5$	$w_3 = 1$
$\mathrm{tg}_F = 0.5$ s	$\mathrm{tg}_B = 0.5$ s	$d_s = 1$ m
$\mathrm{t}_{\mathrm{min}} = 3$ s	$P = 10$ s	

A. Lane Change Desirability Decision

In terms of decision-making regarding whether a lane change maneuver is desirable, the considered scenario illustrated in Fig. 2 entails the proposed decision-making function to determine whether E should move into the left lane due to a lane drop in the right lane. In the scenario, the average velocity and time gap of the vehicles in the left lane is $v_{1_\mu} = 20$ m/s and $\mathrm{tg}_{1_\mu} = 2$ s respectively. Furthermore, the left lane offers a longer remaining travel time duration since the right lane has a lane drop at $d_{\mathrm{end}} = 2000$ m. Hence, for the considered scenario with the design and weight parameters for the decision-making function as given in Table 1, the utility of E's current lane is $U_0 = 0.28$ while the utility of the left lane is $U_1 = 1.15$, thus rendering a left lane change maneuver to be deemed desirable since $U_1 > (1+\xi)U_0$.

In the considered scenario, it is assumed that $v_{1_\mu} = 20$ m/s and $\mathrm{tg}_{1_\mu} = 2$ s. However, noise and/or uncertainty in the sensor measurement and motion prediction systems i.e. Assumption $a1$ and $a2$, when determining v_{1_μ} and tg_{1_μ} could entail these values to not properly reflect the reality or alter at different time instances. Hence, to further illustrate and evaluate the capability of the proposed decision-making function in the presence of uncertainty, it is applied to a range of mean velocities $v_{1_\mu} = [10, 15, 20, 25, 30]$ m/s, and time gaps $\mathrm{tg}_{1_\mu} = [0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4]$ s, as shown in Table 2. Since a left lane change maneuver is deemed to be desirable in all scenarios for which $U_1 > (1+\xi)U_0$ i.e. $U_1 > 0.31$, it can be seen from the table that the decision whether a lane change maneuver is desirable is fairly robust in the presence of uncertainty.

From Table 2 it can further be seen that if the right lane would not have a lane drop at $d_{\mathrm{end}} = 2000$ m, the utility of the lane would be $U_0 = U_1 + \zeta = 0.94$ since $v_{0_\mu} = 15$ m/s, $\mathrm{tg}_{0_\mu} > 4$ s, and $n = 0$. Hence, in such a scenario a left lane change maneuver is deemed to be desirable for all scenarios for which $U_1 > (1+\xi)U_0$ i.e. $U_1 > 1.04$. Furthermore, Table 2 shows that the utility of a certain lane increases proportional to tg_{l_μ} and that the utility decreases when v_{l_μ} differs from $v_{x_{\mathrm{des}}}$. As a consequence of w_1 in Table 1, it can be seen that the utility decreases faster for velocities which are larger than $v_{x_{\mathrm{des}}}$ than for velocities which are smaller than $v_{x_{\mathrm{des}}}$.

B. Inter-Vehicle Traffic Gap and Initiation Time Selection

If a lane change maneuver is determined to be desirable, the lane change maneuver algorithm must select an appropriate inter-vehicle traffic gap and time instance to perform the maneuver. In the scenario depicted in Fig. 2, E

has the options of changing lane ahead of S_4, in the inter-vehicle traffic gaps between S_4 and S_3, S_3 and S_2, S_2 and S_1, or behind S_1. However, since the vehicles in E's target lane, i.e. the left lane, are driving at a velocity close to E's maximum allowed velocity $v_{x_{\max}} = 20$ m/s, E will not be able to accelerate and change lane ahead of S_4 and thus this is not an viable option for the maneuver.

In Fig. 3 the predicted longitudinal position trajectories of S_i, the dynamic limits on E's longitudinal position, and the corresponding approximation of the intersection between the reachable set of E and the predicted safe lane change region of a certain inter-vehicle traffic gap are shown for the gaps between S_4 and S_3, S_3 and S_2, and S_2 and S_1, utilizing the design parameters for the inter-vehicle traffic gap and initiation time selection as given in Table 1. In the two upper plots of Fig. 3 it can be seen that the inter-vehicle traffic gap between S_4 and S_3 as well as S_3 and S_2 are possible options for the lane change maneuver while the bottom plot of Fig. 3 shows that it is not possible for E to change lane in the gap between S_2 and S_1 since the approximation of the reachable set of E and the predicted safe lane change region of the inter-vehicle traffic gap do not intersect over the prediction horizon. Consequently, the option of changing lane behind S_1 is also not a possible option for planning the maneuver at the current time instance. However, E could reduce its velocity in order to reach the inter-vehicle traffic gap between S_2 and S_1 or behind S_1 at a later time instance, or wait for the gaps to approach. Both these options are viable and considered as backup options if the lane change maneuver algorithm fails to find a reachable inter-vehicle traffic gap at the current time instance. However, since the algorithm does find two possible inter-vehicle traffic gaps in the considered scenario, it selects the most appropriate inter-vehicle traffic gap that is currently available rather than approach another gap at a later time instance. As such, the algorithm can be considered as opportunistic rather than passive.

From Fig. 3 it can be concluded that although it is possible for E to change lane in the inter-vehicle traffic gap between S_4 and S_3, the inter-vehicle traffic gap between S_3 and S_2 is preferable. This is due to the fact that the gap between S_3 and S_2 allows for a larger intersection region of the reachable set of E and the predicted safe lane change region of the inter-vehicle traffic gap, which is preferable in order to allow for safe and smooth maneuvers. Furthermore, when considering noise and/or uncertainty in the sensor measurement and motion prediction systems i.e. Assumption $a1$ and $a2$, when determining the predicted longitudinal position trajectories of S_i and corresponding safety margins, as mentioned in Section B, the approximation of the intersection between the reachable set of E and the predicted safe lane change region of a certain inter-vehicle traffic gap is altered as shown in Fig. 4. In the figure it can be seen that in comparison with Fig. 3 where S_i are assumed to drive at 20 m/s, the approximation of the intersection between the reachable set of E and the predicted safe lane change region of a certain inter-vehicle traffic gap becomes smaller when preceding vehicles are

Table 2. The utility of the left lane in Fig. 2 when the decision-making function is applied to a range of mean velocities $v_{1_\mu} = [10, 15, 20, 25, 30]$ m/s, and time gaps $tg_{1_\mu} = [0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4]$ s, assuming $v_{x_{des}} = 20$ m/s, and $tg_{des} = 2$ s.

tg_{1_μ} \ v_{1_μ}	10	15	20	25	30
0.5	–0.70	0.41	0.97	0.16	–0.37
1	–0.64	0.47	1.03	0.23	–0.31
1.5	–0.58	0.53	1.09	0.29	–0.25
2	–0.52	0.59	1.15	0.35	–0.18
2.5	–0.45	0.66	1.21	0.41	–0.12
3	–0.39	0.72	1.28	0.48	–0.06
3.5	–0.33	0.78	1.34	0.54	0.01
4	–0.27	0.84	1.40	0.60	0.07

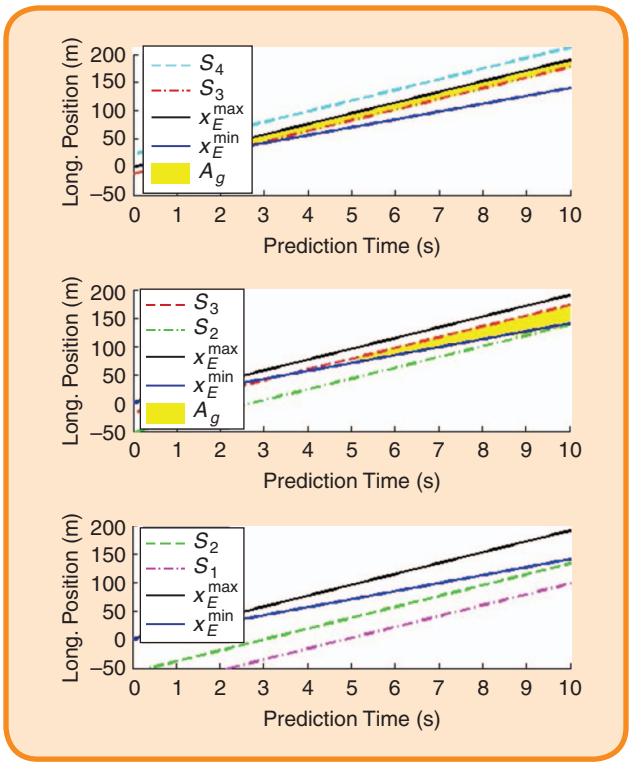

FIG 3 The predicted longitudinal position trajectories of the surrounding vehicles (S_4, S_3, S_2, and S_1), the dynamic limitations on the ego vehicle's (E's) longitudinal position, and the corresponding approximation of the intersection between the reachable set of E and the predicted safe lane change region of a certain inter-vehicle traffic gap are from top to bottom shown for the gaps between S_4 and S_3, S_3 and S_2, and S_2 and S_1.

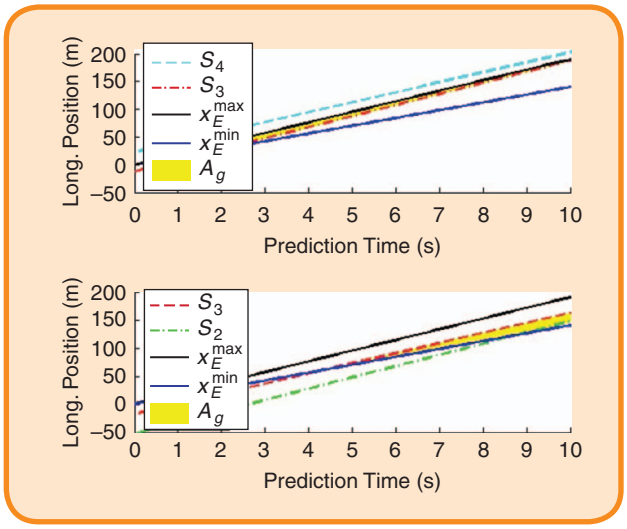

FIG 4 The predicted longitudinal position trajectories of the surrounding vehicles (S_4, S_3, S_2, and S_1) when considering noise and/or uncertainty in the sensor measurement and motion prediction systems, the dynamic limitations on the ego vehicle's (E's) longitudinal position, and the corresponding approximation of the intersection between the reachable set of E and the predicted safe lane change region of a certain inter-vehicle traffic gap are from top to bottom shown for the gaps between S_4 and S_3, and S_3 and S_2.

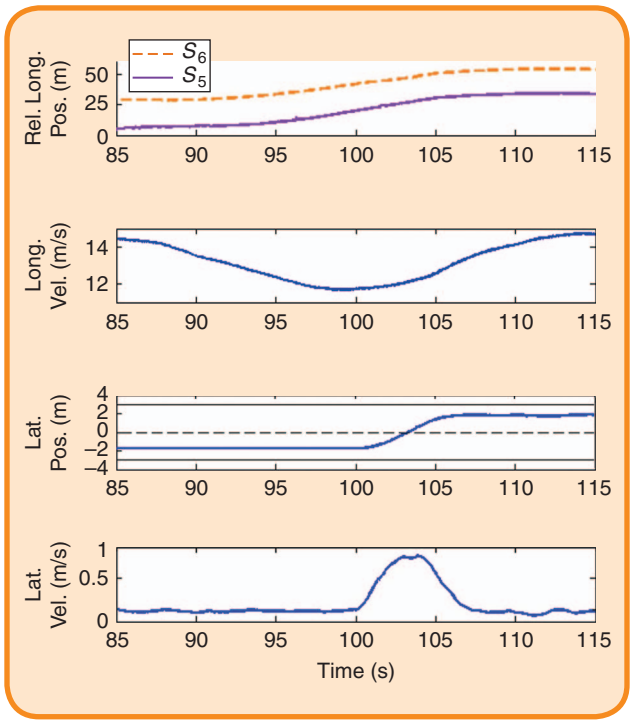

FIG 5 The ego vehicle's (E's) lane change maneuver. From top to bottom the plots respectively illustrates the longitudinal position trajectory of the surrounding vehicles (S_6 and S_5) relative to E, E's longitudinal velocity trajectory, E's lateral position trajectory, and E's lateral velocity trajectory towards the road.

assumed to drive at 19 m/s and trailing vehicles are assumed to drive at 21 m/s to account for uncertainties in relation to the confidence level of the sensor measurement and motion prediction systems. Hence, Fig. 4 further enforces the decision that the inter-vehicle traffic gap between S_3 and S_2 is preferable to the inter-vehicle traffic gap between S_4 and S_3.

When the inter-vehicle traffic gap and time instance to perform the lane change maneuver have been determined, the lane change maneuver algorithm must calculate the required control signals, i.e. longitudinal and lateral acceleration/deceleration, which allow E to position itself in the selected gap at the desired time instance. Simulation results of the lane change trajectory planning for various lane change traffic situations are provided in [21].

V. Experimental Results

To further study the ability of the lane change maneuver algorithm, an experimental lane change traffic situation is considered, in which E initially drives in the right lane with a preceding vehicle S_6 driving in the same lane and a surrounding vehicle S_5 driving in the adjacent left lane. In the scenario, the initial velocity of all vehicles is approximately 14 m/s and $v_{x_{\text{des}}} = 20$ m/s. As in the simulated traffic situation, S_6 and S_5 do not perform any lane change maneuvers and drive at approximately constant velocity throughout the scenario. In the scenario it is assumed that E is required to do a mandatory lane change into the left lane, and thereby the decision-making is not part of the vehicle system implementation i.e. the lane change request is set manually in the system.

Upon a lane change request, the lane change maneuver algorithm determines an appropriate inter-vehicle traffic gap and time instance to perform the maneuver and plans the corresponding lane change trajectory. In the vehicle implementation the longitudinal trajectory planning problem with a prediction horizon of 10 s is implemented as a C-coded s-Function using CVXGEN [20] running at 4 Hz, while the lateral planning problem is performed by a standard LQ-controller tracking a spline reference. When not performing a lane change maneuver E is longitudinally controlled by an ACC system and laterally controlled by a LKA system.

The lane change tests have been performed at the test track Hällered on an oval four lane road. The vehicle platform is a Volvo V60 model year 2013 equipped with a forward looking camera system, forward looking long range radar, and one medium range radar with a wide field of view in each corner of the vehicle rendering the vehicle a forward, rearward, and sideward view of approximately 200 m, 70 m, and 40 m respectively.

In Figs. 5–6 the results from two automated lane change maneuvers are shown. From top to bottom the plots in the figures respectively illustrates the longitudinal position trajectory of S_6 and S_5 relative to E, E's longitudinal velocity trajectory, E's lateral position trajectory, and E's lateral velocity trajectory towards the road. From Fig. 5 it can

be seen that since S_5 is initially positioned slightly ahead of E, E reduces its velocity in order to fall back in relation to S_5 to safely and comfortably change lane. From Fig. 6 it can be seen that since S_5 is initially positioned behind E, E can accelerate and perform the lane change maneuver ahead of S_5. In the figure it can also be seen that when E changes lane at time instance 412, sensor noise causes the sensor system to perceive a ghost vehicle of S_6 positioned in the left lane. Since E adapts its behavior to all perceived surrounding vehicles, it follows the ghost vehicle at a safe distance and does not accelerate until the ghost vehicle is no longer perceived at time instance 416.

The lane change trajectories in Figs. 5–6 show that throughout the maneuver E maintains a safe distance to both S_6 and S_5. Hence the considered traffic situation illustrates the ability of the lane change maneuver algorithm to plan appropriate maneuvers which require E to decelerate or accelerate into the inter-vehicle traffic gap and perform a smooth lane change maneuvers from its current lane center into the center of the adjacent left lane.

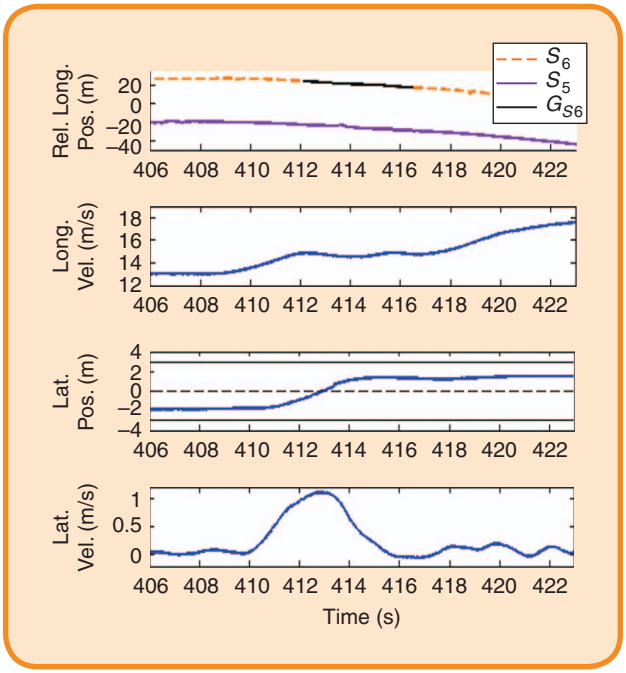

FIG 6 The ego vehicle's (E's) lane change maneuver. From top to bottom the plots respectively illustrates the longitudinal position trajectory of the surrounding vehicles (S_6 and S_5) relative to E, E's longitudinal velocity trajectory, E's lateral position trajectory, and E's lateral velocity trajectory towards the road.

VI. Conclusions

This paper considers the problem of automatically determine if, when, and how to perform a lane change maneuver and presents a lane change maneuver algorithm which consists of three parts

A) An utility function for decision-making regarding whether a lane change maneuver is desirable.
B) A selection function inspired by reachability analysis for determining an appropriate inter-vehicle traffic gap and time instance to perform the maneuver.
C) A low-complexity model predictive control trajectory planning optimization.

By decomposing the problem of determining if, when, and how to perform a lane change maneuver into three parts, the proposed approach provides an intuitive, transparent, and low-complexity lane change maneuver algorithm which ensures that although a lane change maneuver might be desirable it is not executed unless a safe collision-free trajectory exists. This is an essential quality of the algorithm due to the severity of possible consequences which may arise from inappropriate lane change maneuvers.

Simulation and experimental results show the ability of the proposed lane change maneuver algorithm to generate smooth and safe trajectories which are appropriate in various traffic situations. These results motivate future work in incorporating a dynamic prediction model of the traffic environment which includes prediction uncertainty and sensor noise, in order to test the proposed algorithm in real-world traffic situations. Furthermore, the issue of determining when and how to generate backup trajectories to abort a lane change maneuver in case it becomes unfeasible is an important topic which should be investigated in order to develop a functional safety concept to ensure the overall safety of the intelligent vehicle system in terms of e.g. the safe management of likely operator errors, hardware failures, and changes in the surrounding traffic environment.

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