A Unified Approach to Threat Assessment and Control for Automotive Active Safety

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Abstract—This paper presents the design of a novel active safety system preventing unintended roadway departures. The proposed framework unifies threat assessment, stability, and control of passenger vehicles into a single combined optimization problem. A nonlinear model predictive control (MPC) problem is formulated, where nonlinear vehicle dynamics, in closed-loop with a driver model, is used to optimize the steering and braking actions needed to keep the driver safe. A model of the driver’s nominal behavior is estimated based on his observed behavior. The driver commands the vehicle, whereas the safety system corrects the driver’s steering and braking actions in case there is a risk that the vehicle will unintentionally depart from the road. The resulting predictive controller is always active, and mode switching is not necessary. We show simulation results detailing the behavior of the proposed controller and experimental results obtained by implementing the proposed framework on embedded hardware in a passenger vehicle. The results demonstrate the capability of the proposed controller to detect and avoid roadway departures while avoiding unnecessary interventions.

Index Terms—Active safety, collision avoidance, predictive control, threat assessment.

NOMENCLATURE

\[\alpha\] Tire slip angle [rad].
\[\beta_r\] Braking ratio [\text{\text{-}}].
\[\delta_c\] Corrective steering angle [rad].
\[\psi\] Turning rate [rad/s].
\[\dot{x}\] Longitudinal velocity [m/s].
\[\dot{y}\] Lateral velocity [m/s].
\[\delta_d\] Estimated driver steering angle [rad].
\[\psi/l\] Angle of the tangent to the road centerline [rad].
\[\epsilon_y\] Lateral position in lane [m].
\[\epsilon/\psi\] Orientation in lane [rad].
\[F_x\] Longitudinal tire force in vehicle frame [N].
\[f_x\] Longitudinal tire force in tire frame [N].
\[F_y\] Lateral tire force in vehicle frame [N].
\[f_y\] Lateral tire force in tire frame [N].
\[H_c\] Control horizon [\text{\text{-}}].
\[H_i\] Input blocking factor [\text{\text{-}}].
\[H_p\] Prediction horizon [\text{\text{-}}].
\[J_2\] Vehicle yaw inertia [kg \cdot m^2].
\[l_f\] Distance from vehicle center of gravity (CoG) to front axle [m].
\[l_r\] Distance from vehicle CoG to rear axle [m].
\[m\] Vehicle mass [kg].
\[w_t\] Vehicle track width [m].

I. INTRODUCTION

ADVANCES in sensing technologies have enabled the introduction and commercialization of several automated driving features over the last two decades. Examples of such applications are threat assessment warning strategies [1], adaptive cruise control [2], rear-end collision avoidance systems [3], and lane keeping systems [4]. In safety applications, autonomous interventions are automatically activated. Overactivation of automated safety interventions might be felt as intrusive by the driver, whereas on the other hand, a missed or delayed intervention might lead to a collision.

A typical active safety system architecture is modular [5], with separate threat assessment, decision-making, and intervention modules. In particular, the threat assessment module deals with the task of determining whether interventions are necessary and plays an important role in the interaction with the driver. The threat assessment module repeatedly evaluates the driver’s ability in maintaining safety in each situation, and this information is used by the decision-making module to decide whether and how to assist the driver. It is a challenge for an active safety system to properly assess when to intervene. In the literature, a large variety of threat assessment and decision-making approaches can be found [3], [6]–[8]. In the simplest approaches, used in production vehicles, automated steering or braking interventions are issued when simple measures such as the time-to-collision [3] or time-to-line crossing [6] pass certain thresholds.

More sophisticated approaches, on the other hand, include the computation of Bayesian collision probabilities [7] or sets of safe states from which the vehicle can safely evolve [8]. In advanced safety systems such as roadway departure prevention, the intervention module has the goal of both determining a safe trajectory and coordinating vehicle actuators. The literature on vehicle path planning and control is rich (see, e.g., [9]–[12]).

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Because of its capability to systematically handle system nonlinearities and constraints, work in a wide operating region and close to the set of admissible states and inputs, model predictive control (MPC) has been shown to be an attractive method for solving the path planning and control problem [9], [13]. Previous approaches to lane departure prevention using predictive control, as in [14], make the assumption that the vehicle is traveling at a constant velocity (and can therefore not consider braking) and does not use any information about the human driver.

In this paper, we design a novel active safety system for prevention of unintended roadway departures with a human-in-the-loop. Rather than separately solving the threat assessment, decision-making, and intervention problems, we reformulate them as a single combined optimization problem. In particular, a predictive optimal control problem is formulated, which simultaneously uses predicted driver behavior and determines the least intrusive intervention that keeps the vehicle in a region of the state space where the driver is deemed safe. The proposed controller is always active, which avoids the design of switching logic or the tuning of a sliding scale. In addition, since the proposed controller is designed to only apply the correcting control action that is necessary to avoid a constraint violation, the intrusiveness of the safety application is minimal. Furthermore, nonlinear vehicle dynamics are considered in the optimization problem, and the corrective action can augment the driver’s steering and braking. Preliminary findings were reported by Gray et al. in [15] and [16] with simulation results. In this paper, we detail the proposed framework and successfully show its effectiveness through experimental results implemented on a passenger vehicle.

This paper is organized as follows. In Section II, we introduce the vehicle dynamics and driver models. In Section III, we introduce the safety constraints. In Section IV, the proposed predictive controller is presented. In Section V, we present validation results of the proposed method with real-time simulations, and in Section VI, we present results from experimental tests implemented on a passenger vehicle. Section VII provides concluding remarks and outlines future work.

II. MODELING

Here, we present the mathematical models used for the combined threat assessment and control design. Section II-A introduces the vehicle dynamics and Section II-B introduces the model used to predict driver behavior.

<Fig. 1. Modeling notation depicting the forces in the vehicle body fixed frame, the forces in the tire fixed frame, and the rotational and translational velocities.>

A. Vehicle Model

Consider the vehicle sketch in Fig. 1. We use the following set of differential equations to describe vehicle motion within the lane:

\[
\begin{align}
\dot{x} &= f_x = f_{xi} + \sum_{i=1}^{4} F_{xi} \\
\dot{y} &= f_y = f_{yi} + \sum_{i=1}^{4} F_{yi} \\
J_z \dot{\psi} &= J_{z \psi} = l_f (F_{y1} + F_{y2}) - l_r (F_{y3} + F_{y4}) \\
&\quad + \frac{d}{r_i} (F_{x1} + F_{x2} - F_{x3} - F_{x4}) \\
\dot{\psi} &= \dot{\psi}_d - \psi \\
\dot{\theta} &= \dot{\theta}_y = \frac{\dot{y}}{r} \cos(e_{\psi}) + \frac{\dot{x}}{r} \sin(e_{\psi})
\end{align}
\]

where \(e_{\psi}\) and \(e_y\) (see Fig. 1) denote the vehicle orientation and the lateral position in a road-aligned coordinate frame, respectively, and \(\psi_d\) is the angle of the tangent to the road centerline in the fixed coordinate frame.

The longitudinal and lateral tire force components in the vehicle body frame are modeled as

\[
\begin{align}
F_{xi} &= f_{xi} \cos(\delta_i) - f_{yi} \sin(\delta_i) \\
F_{yi} &= f_{xi} \sin(\delta_i) + f_{yi} \cos(\delta_i), \quad i \in \{1, 2, 3, 4\}
\end{align}
\]

where \(\delta_i\) is the steering angle at wheel \(i\). We introduce the following assumption on the steering angles.

Assumption 1: Only the steering angles at the front wheels can be controlled, and the steering angles at the right and left wheels of each axle are assumed to be the same, i.e., \(\delta_1 = \delta_2 = \delta\) and \(\delta_3 = \delta_4 = 0\). In addition, an actuator that corrects the driver-commanded steering angle, such that \(\delta = \delta_d + \delta_c\), is available, where \(\delta_d\) is the driver-commanded steering angle, and \(\delta_c\) is the correcting steering angle component.

The longitudinal force in the tire frame, i.e., \(f_{xi}\), is calculated as

\[f_{xi} = \beta_r \mu_s F_{zi}\]

where \(\beta_r \in [-1, 1]\) is referred to as the braking ratio. \(\beta_r = -1\) corresponds to full braking, and \(\beta_r = 1\) corresponds to full braking.
throttle. \( f_{yi} \) is computed using a modified nonlinear Fiala tire model [17], i.e.,

\[
f_{yi} = \begin{cases} 
-C_{\alpha_i} \tan(\alpha_i) + \frac{C_{\alpha_i}^2}{\eta \mu F_z} |\tan(\alpha_i)| \tan(\alpha_i) \\
-\frac{C_{\alpha_i}^2}{\eta \mu F_z} \tan^3(\alpha_i), & \text{if } |\alpha_i| < \alpha_{sl} \\
-\eta \mu \frac{F_z}{z_i} \tan(\alpha_i), & \text{if } |\alpha_i| \geq \alpha_{sl}
\end{cases}
\]

(4)

Fig. 2. Lateral tire force characteristics compared with the tire slip angle for different levels of braking.

\( \forall i \), where \( \alpha \) denotes the tire slip angle, \( \mu \) denotes the friction coefficient, and \( F_z \) denotes the vertical load at each wheel. \( C_{\alpha_i} \) is the tire cornering stiffness, and \( \eta = \sqrt{\mu^2 F_z^2 - f_i^2} / (\mu F_z) \), which can be written as \( \eta = \sqrt{1 - \beta_i^2} \). The lateral tire force characteristics are shown in Fig. 2, where the region in dashed lines corresponds to \( |\alpha| \leq \alpha_{sl} \), where \( \alpha_{sl} = \tan^{-1}(3\eta \mu F_z / C_{\alpha_i}) \).

Tire slip angles \( \alpha_i \) in (4) are approximated as

\[
\begin{align*}
\alpha_1 &= \frac{\dot{y} + l_f \dot{\psi}}{x} - \delta, \\
\alpha_2 &= \frac{\dot{y} + l_f \dot{\psi}}{x}, \\
\alpha_3 &= \frac{\dot{y} - l_r \dot{\psi}}{x}, \\
\alpha_4 &= \frac{\dot{y} - l_r \dot{\psi}}{x}.
\end{align*}
\]

(5)

We make use of the following assumptions.

**Assumption 2:** In (4), vertical forces \( F_z \) are assumed constant and determined by the vehicle’s steady-state weight distribution when no lateral or longitudinal accelerations act at the vehicle CoG.

**Assumption 3:** The friction coefficient is assumed to be known and the same at all wheels, i.e., \( \mu_i = \mu, \forall i \), and constant over a finite time horizon. At each time instant, an estimate of \( \mu \) is assumed available.

**Assumption 4:** Signal \( \dot{\psi}_d \) is assumed to be known, and at each time instant, an estimate of \( \dot{\psi}_d \) is available over a finite time horizon. (See [18] for an overview of sensing technologies that can be used to obtain this signal.)

**B. Driver Model**

The proposed control design uses a model of the driver’s steering behavior. In general, an accurate description of the driver’s behavior requires complex models accounting for a large amount of exogenous signals [19], [20]. We are interested in very simple model structures, enabling the design of a low-complexity model-based threat assessment and control design algorithm. In this paper, the driver’s steering behavior is described by a model, where the vehicle state and the road geometry information are exogenous signals, the steering angle is the model output, and the steering model parameters are estimated based on the observed behavior of the driver. The modeling and estimation of the driver behavior considered in this paper was presented in [8] and is described here for the sake of completeness. Define orientation error \( e_{\psi} \), w.r.t. a look-ahead point as in Fig. 1, i.e.,

\[
e_{\psi} = \psi - \psi_d = e_{\psi} + \Delta \psi_d
\]

(6)

where \( \psi_d \) is the desired orientation at time \( t + t_{lp} \), with \( t \) as the current time, \( \Delta \psi_d = \psi_d - \psi_d^{lp} \), and \( t_{lp} \) as the preview time that can be mapped into preview distance \( d_{lp} \) under the assumption of constant speed \( \dot{x} \).

We compute an estimate of driver-commanded steering angle \( \delta_d \) as

\[
\delta_d = K_y e_y + K_{\psi} e_{\psi} = K_y e_y + K_{\psi} e_{\psi} + K_{\psi} \Delta \psi_d
\]

(7)

with \( K_y \) and \( K_{\psi} \) as gains that are, in general, time varying and are updated online. Clearly, \( \Delta \psi_d \) in (6) depends on preview time \( t_{lp} \) that, in our modeling framework, is considered as a parameter of the driver model. We also remark that steering model (7) is velocity dependent since \( \Delta \psi_d \) also depends on vehicle speed \( \dot{x} \).

Estimation results of the driver model parameters in (6) and (7), which are obtained using a nonlinear recursive least squares algorithm, are presented in [8] for both normal and aggressive driving styles.

We write models (1)–(7) in the following compact form:

\[
\dot{x}(t) = f(x(t), u(t), w(t))
\]

(8)

where \( x = [\dot{x}, \dot{y}, \dot{\psi}, e_{\psi}, e_y]^T \), \( u = [\delta_c, \beta_c]^T \), and \( w = [\mu, \psi_d, \Delta \psi_d]^T \) are the state vector, the input vector, and an exogenous signal of known parameters, respectively.

**III. SAFETY CONSTRAINTS**

We recall that the aim of the safety system proposed in this paper is to keep the vehicle in the lane while maintaining stable vehicle motion. Here, we express the requirements that the vehicle stays in the lane while operating in a stable operating region as constraints on the vehicle state and input variables.

Let \( e_{yi} \), \( i \in \{1, 2, 3, 4\} \), be the distances of the four vehicle corners from the lane centerline. The requirement that the vehicle stays in the lane is then expressed as

\[
e_{y_{min}} \leq e_{yi} \leq e_{y_{max}} \quad \forall i.
\]

(9)
In addition to staying in the lane, we require that the vehicle operates in a region of the state space where the vehicle is easily maneuverable by a normally skilled driver. Consider the nonlinearity in the lateral tire force characteristics shown in Fig. 2. In the shaded region, the nonlinearity in the lateral tire force characteristics is milder.

In this region, vehicle behavior is predictable by most drivers, and electronic stability control systems are inactive [21], [22]. The requirement that the vehicle operates in stable operating conditions is thus ensured by limiting tire slip angles \( \alpha_i \), i.e.,

\[
\alpha_{i_{\text{min}}} \leq \alpha_i \leq \alpha_{i_{\text{max}}}, \quad \forall i. \tag{10}
\]

Constraints (9) are compactly written as

\[
h(x, u, w) \leq 0 \tag{11}
\]

where 0 is the zero vector of appropriate dimension.

IV. PREDICTIVE CONTROL PROBLEM

Here, we formulate the threat assessment and control problems as an MPC problem. At each sampling time instant, an optimal input sequence is calculated by solving a constrained finite-time optimal control problem. The computed optimal control input sequence is only applied to the plant during the following sampling interval. At the next time step, the optimal control problem is solved again, using new measurements.

We discretize system (8) with fixed sampling time \( T_s \) to obtain

\[
x_{k+1} = f^d(x_k, u_k, w_k) \tag{12}
\]

and formulate the optimization problem to be solved at each time instant as

\[
\min_{\Delta u} \sum_{k=0}^{H_c-1} \left[ \|u_{t+k,t}\|_Q^2 + \|\Delta u_{t+k,t}\|_R^2 + \rho \epsilon \right] \tag{13a}
\]

s.t. \[
x_{t+k+1,t} = f^d(x_{t+k,t}, u_{t+k,t}, w_{t+k,t}), \quad k = 0, \ldots, H_p - 1 \tag{13b}
\]
\[
h_k(x_{t+k,t}, u_{t+k,t}, w_{t+k,t}) \leq 1 \epsilon, \quad k = 0, \ldots, H_p \tag{13c}
\]
\[
\epsilon \geq 0 \tag{13d}
\]
\[
u_{t+k,t} = \Delta u_{t+k,t} + u_{t+k-1,t} \tag{13e}
\]
\[
u_{\text{min}} \leq u_{t+k,t} \leq u_{\text{max}}, \quad k = 0, \ldots, H_c - 1 \tag{13f}
\]
\[
\Delta u_{\text{min}} \leq \Delta u_{t+k,t} \leq \Delta u_{\text{max}}, \quad k = 0, \ldots, H_c - 1 \tag{13g}
\]
\[
\Delta u_{t+k,t} = 0, \quad k = H_c, \ldots, H_p \tag{13h}
\]
\[
u_{t-1,t} = u(t - 1) \tag{13i}
\]
\[
x_{t,t} = x(t) \tag{13j}
\]

where \( t \) denotes the current time instant, and \( x_{t+k,t} \) denotes the predicted state at time \( t + k \) obtained by applying control sequence \( U_t = [u_{t,t}, \ldots, u_{t+k,t}] \) to system (12) with \( x_{t,t} = x(t) \). We denote by \( H_t \) the input blocking factor. The optimization variables are kept constant over a horizon of \( H_t \). The total number of optimization variables is then \( H_c / H_t \cdot m_x + 1 \), where \( m_x \) is the number of inputs. Safety constraints (11) have been imposed as soft constraints, by introducing slack variable \( \epsilon \) in (13a) and (13d). \( Q, R, \) and \( \rho \) are weights of appropriate dimension penalizing control action, change rate of control, and violation of the soft constraints, respectively. In this optimization problem, the control inputs are \( u = [\delta_c, \beta_c] \).

Remark 1: We note that no penalty on deviation from a tracking reference is imposed in cost function (13a). The objective here is to ensure that safety constraints (11) are not violated, while utilizing minimal control action. If driver steering model (7) is, by itself, capable of steering the vehicle without violating safety constraints (11), no control action will be applied, and the optimal cost will thus be zero. This motivates the choice of the cost function in (13a) to minimize the corrective action to the driver’s steering and braking only.

Remark 2: By modeling the nominal steering behavior, we postpone intervention until the driver deviates from his or her nominal steering behavior. We point out that interventions could potentially be even further delayed if a reliable model of the driver’s braking behavior is also included. Such modeling is currently the topic of ongoing research activities.

Remark 3: The problem formulation in (13) is a nonlinear and nonconvex receding horizon optimization problem, and in general, such problems can be associated with local optima. We find in practice that the solver converges to a solution in the given sampling time to the required accuracy.

In addition to the soft constraints, we have imposed hard constraints (13e)–(13g), which reflect limitations set by the actuators. Constraint (13h) enables \( H_{p} \) to be chosen larger than \( H_{c} \) and the control kept constant during the prediction time beyond \( H_{c} \). This constraint is useful for real-time execution when computational resources are limited.

V. SIMULATION RESULTS

Here, we present computer simulations showing the behavior of the proposed framework. The following section will present experimental results of the proposed controller implemented on a passenger vehicle. In Section V-A, we present results from simulations using MATLAB and TOMLAB/NPSOL to solve the optimization problem. In Section V-B, we implement the controller on a dSPACE embedded control unit and run simulations using real drivers interacting with CarSim vehicle simulation software.

Remark 4: Parameters \( Q, R, H_{p}, H_{c}, \) and \( H_{i} \) are regarded as tuning parameters and are appropriately chosen. The values used are reported in Tables II and III for simulation and experimental implementations, respectively.

A. Simulation Results With Offline Human Driver Data

Here, we validate the behavior of the proposed active safety system by analyzing the results from MATLAB simulations. We consider scenarios where the driver

1) safely negotiates a curve;
2) approaches a right curve while distracted;
3) unintentionally veers into oncoming traffic.
Human drivers interacting with a driving simulator were used to collect the data for the results presented. The estimation algorithm in [8] is implemented to estimate parameters of driver model (7). The vehicle and design parameters in Tables I and II were used to implement predictive controller (13).

The driver estimation algorithm adapts and updates the parameters of the driver model as new data become available. Since the estimation is conducted in nominal driving conditions, the resulting driver model is expected to be representative of the nominal behavior of the driver. The implications of this are discussed in the following section, as the behavior of the suggested predictive controller is analyzed for the three considered scenarios.

1) Nominal Behavior: Consider Fig. 3(a), which shows a driving situation where the driver is attentive and is safely steering the vehicle down the center of the lane, within the road boundaries. The circled vehicle indicates the current vehicle position, which is marked $t_{curr}$, and the others illustrate future vehicle positions, predicted by the predictive controller. We refer to this trajectory as Trajectory 1. In this situation, the estimated driver model is capable of keeping the vehicle in the lane, which indicates that the nominal behavior of the driver is safe. The action that minimizes cost function (13a) is thus zero corrective steering and braking; hence, the driver remains in control of the vehicle.

Fig. 3(b) shows a comparison of the predicted steering trajectory, i.e., Trajectory 1, and the actual steering trajectory of the driver, who was allowed to remain in full control of the vehicle. We note that corrective steering action $\delta_c$ is zero in Trajectory 1; hence, the closed-loop trajectory is predicted by the driver model only, i.e., $\delta = \delta_d$. We also note that steering angle $\delta_d$ in Trajectory 1 corresponds well with the driver’s actual steering angle $\delta_d$. In this situation, the adopted predictive controller could correctly predict the nominal behavior of the driver and thus avoided intervention.

2) Distracted Driver Approaching a Curve: Next, we consider a scenario where the driver is approaching a curve while distracted. An intervention from the active safety system is required to keep the driver safely within the constraints of the lane.

In Fig. 4(a), two trajectories are shown. The circled vehicle shows the vehicle’s current position. The vehicles shown in boxed outline illustrate the future trajectory of the vehicle controlled by the driver model only (Trajectory 2). Trajectory 2 indicates that the driver’s nominal behavior leads to a violation of position constraints (9). Consequently, the predictive controller corrects the driver’s control action to avoid the constraint violation. The vehicles in Fig. 4(a) show the trajectory predicted by the predictive controller (Trajectory 3). Compared with Trajectory 2, vehicle motion has been slightly corrected such that the vehicle remains in the lane.

Fig. 4(b) shows steering angles $\delta$, $\delta_d$, and $\delta_c$ in Trajectories 2 and 3, and Fig. 4(b) shows braking signal $\beta_r$ in Trajectory 3. Fig. 4(b) shows that, as indicated by $\delta_d$ in Trajectory 2, the driver is expected to steer and attempt to follow the path prescribed by the road. However, we note that the magnitude of $\delta_d$ in Trajectory 2 is too small; hence, to maintain the vehicle within the road boundaries, the driver would have to deviate from the nominal behavior described by the estimated driver model. Fig. 4(b) and (c) shows how the predictive controller simultaneously corrects the driver’s steering and brakes the vehicle. In particular, we note that steering magnitude $|\delta|$ in Trajectory 3 is initially significantly higher than $|\delta_d|$ in Trajectory 2. We also note that control signals $\delta_c$ and $\beta_r$ smoothly vanish as the vehicle path has been recovered and the driver model is again capable of keeping the vehicle in the lane. During this intervention, the safety system implemented
braking to reduce the vehicle’s speed. This action was needed to ensure that there was no violation of tire slip angle constraints and, thus, maintain stable operating conditions. The front and rear tire slip angles and the enforced constraints are shown in Fig. 5.

3) Unintentional Drifting: Consider Fig. 6 where the driver is distracted and is veering off the shoulder of the lane. In Trajectory 4, the vehicle is controlled by the driver model and is illustrated with the vehicles in outline. In Trajectory 5, the vehicle is instead controlled by the predictive controller. At the points of the drawn vehicles in Fig. 6, the nominal driver behavior is no longer sufficient to keep the vehicle in the lane, as indicated by Trajectory 4.

Since the lane departure in this situation is related to distraction rather than excessive speed, the predictive controller does not brake. Instead, we note that the predictive controller corrects the driver’s steering to steer the vehicle back in the lane. We also note that in Trajectory 5, signal $\delta_c$ smoothly vanishes to zero as the vehicle’s path is recovered and the driver model is again capable of keeping the vehicle in the lane. We remark that the adopted driver model does not capture the driver’s distraction. Consequently, the predictive controller does not explicitly account for this. In the considered scenarios, the predictive controller simply identified that although it is still possible to keep the vehicle in the lane, the driver would have to deviate from the nominal behavior described by the driver model. Although the performance of the considered approach could potentially be enhanced by incorporating a driver monitoring system, we observed that in these two scenarios, the proposed approach is beneficial without depending on such a system.

B. Real-Time Simulation Results With Human Driver

Here, the proposed framework is tested through real-time simulation using human drivers. The controller is run on a dSPACE MicroAutobox. A high-fidelity vehicle model is simulated using the state-of-the-art vehicle simulation software CarSim. The controller considers the four-wheel model presented in Section II where the vehicle parameters from CarSim are used and are reported in Table I. The scenario is tested live with a real driver interacting with the system by manipulating steering, braking, and throttle inputs.
Remark 2: Each control input, i.e., $\delta_c$ and $\beta_r$ (the solution from the optimization problem), is held constant for three sampling times, i.e., $H_i = 3$. This reduces complexity, and the number of optimization variables becomes $H_c/H_i \cdot m_r + 1 = 9$, where $m_r$ is the number of inputs, and the addition of 1 comes from slack variable $\epsilon$.

Three scenarios are detailed, i.e., two scenarios are shown in Fig. 7 insets A and B, and the third scenario is shown in Fig. 9.

1) Distracted Driver Approaching a Curve: In Fig. 7 inset A, the driver approaches a curve and simulates distraction by removing his hands from the steering wheel. The vehicle enters the curve at 90 km/h. The controller correctly predicts that the vehicle will exit the lane and adds corrective steering to safely negotiate the curve. After exiting the curve, the driver resumes control.

In Fig. 7 inset B, the driver again simulates distraction while driving on a straight section of the road to let the car stray off the road. The controller predicts roadway departure and adds corrective steering to keep the vehicle within the lane. In both situations, i.e., A and B, braking was not needed to keep the driver and the vehicle safe.

Fig. 8 plots the corrective steering action needed for the two interventions detailed in Fig. 7 insets A and B. Note that during the simulation depicted in inset A, the driver did not manipulate the steering wheel to demonstrate the behavior of the controller during this scenario. Therefore, three steering corrections were needed to steer the vehicle back within the lane as the vehicle navigated the turn. To apply only the needed corrections, the interventions are as fast and as minimal as possible. In scenario B, only a brief intervention was needed to correct the vehicle from straying out of the lane.

2) Distracted Driver Drifting Out of the Lane: A scenario is shown in Fig. 9 where the driver unintentionally drifts over to the left side of the road. In this scenario, the driver is distracted and is heading for a collision by roadway departure. The active safety system adds corrective steering to keep the vehicle on the road. As shown in Fig. 11, only corrective steering and a minimal amount of braking were needed. The controller briefly augments the steering angle to straighten the vehicle trajectory, and the safety constraints are not violated. A plot of four vehicle states of interest, i.e., $[e_y, e_\psi, \dot{x}, \dot{\psi}]$, are shown in Fig. 10. The lateral error offset, i.e., $e_y$, clearly indicates that the vehicle is corrected to stay within the upper road bound of 5 m (see Fig. 11).

VI. EXPERIMENTAL RESULTS

Here, we present the results from real-world tests performed on an experimental test bed, which is a prototype Volvo S60 passenger vehicle. The experiments were performed at Volvo’s headquarters in Gothenburg, Sweden. The controller was written in C-coded S-functions and compiled to a dSPACE embedded control platform using MATLAB’s Realtime Workshop. The ECU is equipped with a 1-GHz DS1005 PPC board. All road information, such as lane boundaries, curvature, road angles, and the vehicle state within the lane, is calculated using vision processing from an optical camera and communicated through the system using a controller area network interface. The S60 accepts acceleration commands to the engine and utilizes brake boosters for deceleration. The steering commands are input as angle requests where a low-level controller inputs the required torque to the electric-power-assisted steering
Fig. 10. Plot of four vehicle states, i.e., \([e_y, e_\psi, \dot{x}, \dot{\psi}]\), during the intervention shown in Fig. 9. The controller intervenes just before the vehicle reaches 800 m in the \(X\)-direction. The lateral offset, i.e., \(e_y\), is constrained by the upper limit of the roadway, which is 5 m.

Fig. 11. Plot of the inputs added by the controller during the intervention shown in Fig. 9. The controller briefly adds corrective steering to keep the vehicle on the road. In this scenario, very little braking action was required.

**TABLE III**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Units</th>
<th>Parameter</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>(u_{\text{max}})</td>
<td>([0.2, 0.5])</td>
<td>rad, [−]</td>
<td>(H_p)</td>
<td>12</td>
<td>-</td>
</tr>
<tr>
<td>(u_{\text{min}})</td>
<td>([-0.2, 0.5])</td>
<td>rad, [−]</td>
<td>(H_c)</td>
<td>12</td>
<td>-</td>
</tr>
<tr>
<td>(\Delta u_{\text{max}})</td>
<td>([0.4, 1])</td>
<td>rad, [−]</td>
<td>(H_i)</td>
<td>3</td>
<td>-</td>
</tr>
<tr>
<td>(\Delta u_{\text{min}})</td>
<td>([-0.4, 1])</td>
<td>rad, [−]</td>
<td>(T_a)</td>
<td>200 ms</td>
<td></td>
</tr>
<tr>
<td>(Q)</td>
<td>(1, 100)</td>
<td>-</td>
<td>(e_{y,\text{max}})</td>
<td>0.7 m</td>
<td></td>
</tr>
<tr>
<td>(R)</td>
<td>(1, 1)</td>
<td>-</td>
<td>(e_{y,\text{min}})</td>
<td>−0.7 m</td>
<td></td>
</tr>
</tbody>
</table>

A. Test 1: Distracted Driver Approaching a Curve

The intent of this experiment was to capture the controller’s performance for a scenario in which the driver is distracted while approaching a curve. The driver brought the car to an initial velocity of 50 km/h and maintained steady driving in the center of the lane. The driver then let go of the steering wheel and approached a curve. The resulting performance follows.

Fig. 12 shows the paths predicted by the controller at each time instant. As the vehicle approaches the curve, it begins to stray out of the lane. As the lane constraints become active, the controller adds corrective steering to keep the predicted trajectory within the lane, as can be seen by the curved paths at the lower lane constraint.

The associated states and inputs corresponding to Test 1 are shown in Figs. 13 and 14, respectively. In Fig. 13, a time history of the states of the vehicle is shown. The lateral offset, i.e., \(e_y\), is seen to approach the lower bound of the road as the controller intervenes. A jump in yaw angle \(e_\psi\) and yaw rate \(\dot{\psi}\) and a decrease in velocity are seen, as the controller acts to keep the vehicle within the lane. The inputs calculated by the controller, both steering, \(\delta_c\), and braking, \(\beta_r\), are shown in Fig. 14. As the road boundary is approached, the controller adds corrective steering and braking. The moment the vehicle is no longer threatened to depart the road, the corrective action returns to zero. Videos of the experiments can be found online in [23].

B. Test 2: Unintentional Drifting

In this experiment, we emulate a distracted driver by leaving the steering wheel unattended. The vehicle starts to stray off the road to the left into oncoming traffic. As the road boundary is approached, the controller adds corrective steering and braking to keep the vehicle within the lane. The states are shown in Fig. 15, and the inputs are shown in Fig. 16. The intervention during this experiment is more subtle than the experiment in
Fig. 13. Plot of four vehicle states, i.e., \( e_y, e_\psi, \dot{x}, \dot{\psi} \), during the experiment in Section VI-A. This plot details the moment the controller intervenes at approximately 6 s, as shown in Fig. 12. The velocity is slightly reduced and the lateral offset is corrected to keep the vehicle inside the lane. The associated inputs are shown in Fig. 14.

Fig. 14. Corrective steering and braking action induced by the controller during the intervention shown in Figs. 12 and 13 during the experiment in Section VI-A. The cost is also shown where the spike at approximately 6 s coincides with the soft constraint, i.e., \( \epsilon \), taking a small value. The inputs are shown correcting the constraint violation.

Section VI-A because the vehicle approached the upper bound at a shallower angle.

It is important to note here that the soft constraint is violated (\( e_y \) exceeds 0.7 m). This is attributed to the time delay in the system. The controller itself has a sample time of 200 ms, as noted in Table III. The vision system also has a time delay that is estimated to be approximately 200 ms. This additive delay limits our vehicle speed to around 50 km/h for effective interventions.

Fig. 15. Plot of four vehicle states, i.e., \( e_y, e_\psi, \dot{x}, \dot{\psi} \), during the experiment in Section VI-B. The vehicle approaches the upper bound on \( e_y \) and the controller corrects the steering and braking to remain inside the lane. The associated inputs are shown in Fig. 16.

Fig. 16. Corrective steering and braking action induced by the controller during the intervention shown in Fig. 15 during the experiment in Section VI-B.

VII. CONCLUSION

This paper has presented a predictive controller for prevention of unintended roadway departures. The predictive controller is persistent and mode switching is not necessary. Driver simulator experiments demonstrated the capability of the suggested controller to detect and avoid roadway departures while avoiding unnecessary interventions in a wide range of scenarios. The promising results from the simulations motivated an effort to implement the proposed active safety system. Experimental tests were performed at Volvo Car Corporation in Gothenburg, Sweden. The results collected show that the approach can effectively use driver models in closed-loop to predict road departures and is capable of augmenting the
driver’s steering and braking to ensure safety. The approach can be easily generalized to incorporate vehicle and driver models that are more advanced than the models suggested in this paper.

REFERENCES


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