Semi-Autonomous Vehicle Control for Road Departure and Obstacle Avoidance

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Abstract: This paper presents a semi-autonomous controller for integrated design of an active safety system. A model of the driver's nominal behavior is estimated based on observed behavior. A nonlinear model of the vehicle is developed that utilizes a coordinate transformation which allows for obstacles and road bounds to be modeled as constraints while still allowing the controller full steering and braking authority. A Nonlinear Model Predictive Controller (NMPC) is designed that utilizes the vehicle and driver models to predict a future threat of collision or roadway departure. Simulations are presented which demonstrate the ability of the suggested approach to successfully avoid multiple obstacles while staying safely within the road bounds.

1. INTRODUCTION

Modern passenger vehicles are increasingly equipped with computational, sensing and actuating capabilities which enable the design of systems that can autonomously control the vehicle motion in order to assist the driver, Mellinghoff et al. (2009). In this paper, we develop a safety system which lets the driver remain in control of the vehicle while intervening to ensure that the vehicle remains in the lane, operates in a stable region of the state space and, in addition, avoids stationary obstacles, only if necessary. This is a combined lane keeping, Cerone et al. (2009), stability control, Van Zanten (2000), and collision avoidance problem, Distner et al. (2009).

A challenging aspect in the design of such a safety system is that the system needs to autonomously determine when the driver needs assistance. An assisting autonomous driving intervention should be issued if and only if a risk of accident is detected, that is assessed unavoidable for the driver. In lane keeping systems, it has been proposed that this problem is tackled by activating steering interventions when the *time to line crossing* passes a certain threshold, Mammar et al. (2006). Equivalently, the *time to collision* has been used to activate braking interventions in collision avoidance systems, Jansson (2005), and in stability control systems interventions are activated once the vehicle deviates from a nominal behavior, Van Zanten (2000).

In some approaches, several safety requirements are accounted for simultaneously. In e.g. Anderson et al. (2010), Model Predictive Control (MPC) is utilized in order to form a heuristic function that determines whether the driver should be assisted. An MPC problem is solved at each time step and the heuristic function then determines the level of assistance based on the aggressiveness of the optimal trajectory obtained as a solution to the MPC problem. The underlying idea is that, if an aggressive maneuver is needed to meet the safety requirements which are imposed as constraints in the MPC problem, it is likely that the driver is in need of assistance. In Falcone et al. (2011), an alternative approach is adopted. A solution to the problem of evaluating whether a steering maneuver exists that is the output of a considered driver model and accomplishes the driving task while maintaining the vehicle state within a prescribed set is proposed. Vehicle and driver models are used to compute sets of safe states from which the vehicle can safely evolve and assisting interventions are activated once the vehicle state is outside. By including a model of the driver behavior, interventions can be activated based on limitations of the estimated behavior of the driver rather than just the limitations set by the vehicle dynamics.

Nonetheless, the main use of MPC in driver assistance applications has been for generation and tracking of feasible trajectories rather than for determining whether a driver is in need of assistance. In the approach presented in e.g. Anderson et al. (2010) the solution to the MPC problem is used to guide the vehicle through a *safe corridor* which is constructed based on the road boundaries and obstacles. The MPC problem is formulated as a quadratic program by restricting the intervention to steering only, linearizing the vehicle dynamics around a constant vehicle speed and assuming linear tyre characteristics. Nonlinear MPC has also been used for combined steering and braking Falcone et al. (2008). However incorporating obstacle avoidance constraints while allowing the MPC controller to control the vehicle speed requires the online solution of a mixed-integer program or the offline computation of a large look-up table.

This paper focuses both on improving the performance of safety systems for avoiding roadway departures and increasing the scope of such technology to avoid or mitigate collisions with obstacles by combined braking and steering maneuvers. Rather than introducing heuristics and switching logics to activate interventions and separately designing a safety controller, we formulate a single combined optimization problem that handles both prob-

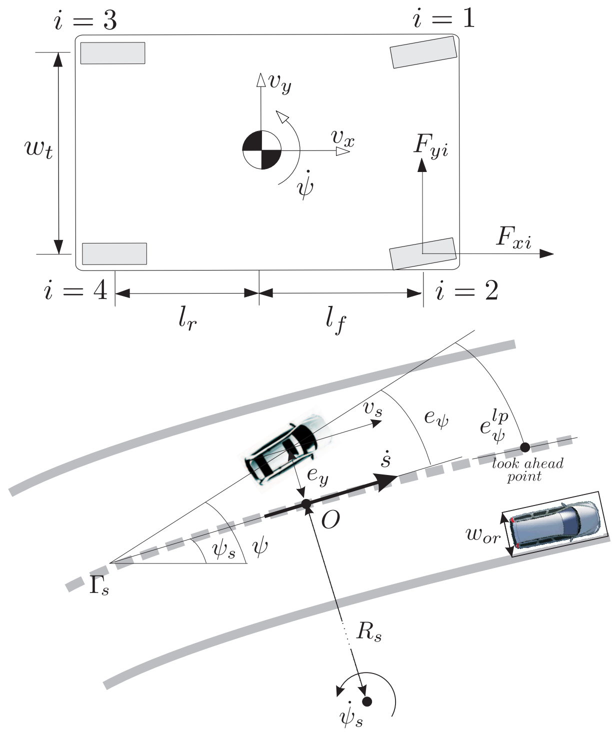

Fig. 1. Modeling notation.

lems. In particular, a predictive optimal control problem is formulated which simultaneously uses predicted driver behavior and determines the least intrusive intervention that will keep the vehicle in a region of the state space where the driver is deemed safe. We also introduce a transformation which transforms the time-dependent vehicle dynamics into spatial-dependent dynamics. This transformation leverages the incorporation of the obstacle avoidance constraints while maintaining the MPC controller's authority to influence both steering and braking. The resulting controller is always active and only applies the correcting control action that is necessary to avoid violation of the safety constraints.

The rest of the paper is organized as follows: in Section 2 we introduce the vehicle dynamics and driver models. In Section 3 we introduce the safety constraints as requirements that the vehicle stays in a collision free path in the lane while operating in a region of the state space where the driver is deemed capable of maneuvering the vehicle. In Section 4, the proposed predictive controller is presented and in Section 5 we present validation results of the proposed method. Finally, in Section 6 we provide some concluding remarks and outline future work.

2. MODELING

In this section, we present the mathematical models used for the combined threat assessment and control design.

2.1 Vehicle model

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

$$m\dot{v}_x = mv_y\dot{\psi} + \sum_{i=1}^{4} F_{xi}, \tag{1a}$$

$$m\dot{v}_y = -mv_x\dot{\psi} + \sum_{i=1}^{4} F_{yi}, \tag{1b}$$

$$J_z\ddot{\psi} = l_f(F_{y1} + F_{y2}) - l_r(F_{y3} + F_{y4}) + \tag{1c}$$

$$\frac{w_t}{2}(-F_{x1} + F_{x2} - F_{x3} + F_{x4}), \tag{1d}$$

$$\dot{e}_\psi = \dot{\psi} - \dot{\psi}_s, \tag{1e}$$

$$\dot{e}_y = v_y\cos(e_\psi) + v_x\sin(e_\psi), \tag{1f}$$

where m and J_z denote the vehicle mass and yaw inertia, respectively, l_f and l_r denote the distances from the vehicle center of gravity to the front and rear axles, respectively, and w_t denotes the track width. v_x and v_y denote the vehicle longitudinal and lateral velocities, respectively, and $\dot{\psi}$ is the turning rate around a vertical axis at the vehicle's center of gravity. e_ψ and e_y in Figure 1 denote the vehicle orientation and lateral position, respectively, in a road aligned coordinate frame and ψ_s is the angle of the tangent to the road centerline in a fix coordinate frame. F_{yi} and F_{xi} are tire forces acting along the vehicle lateral and longitudinal axis, respectively, and $f_{yi},\ f_{xi}$ are forces acting along the tire lateral and longitudinal axis, respectively.

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

$$F_{xi} = f_{xi}\cos(\delta_i) - f_{yi}\sin(\delta_i), \tag{2a}$$

$$F_{yi} = f_{xi}\sin(\delta_i) + f_{yi}\cos(\delta_i), \qquad i \in \{1,2,3,4\}, \tag{2b}$$

where δ_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 which corrects the driver commanded steering angle, such that $\delta = \delta_d + \delta_c$, is available, where δ_d is the driver commanded steering angle and δ_c is the correcting steering angle component. This can be realized by means of, e.g., a planetary gear and electric motor.

We introduce the following assumption on the braking forces,

Assumption 2. Pedal braking, distributes braking forces according to the following relation,

$$f_{x1} = f_{x2} = \sigma\frac{F_b}{2},\ f_{x3} = f_{x4} = (1-\sigma)\frac{F_b}{2}, \tag{3}$$

where σ is a constant (vehicle dependant) distribution parameter and F_b is the total braking force. An actuator capable of augmenting the braking of the driver is assumed available.

f_{yi} is computed using a simplified version of the Pacejka magic tire formula Pacejka (2005). We let α_i denote the tire slip angle, μ_i denote the friction coefficient, F_{zi} denote the vertical load at each wheel and write the tire formula as

$$f_{y_i} = \sqrt{(\mu_i F_{z_i})^2 - f_{x_i}^2}\,\sin\left(C_i \arctan\left(B_i\alpha_i\right)\right), \tag{4}$$

where C_i, B_i are tire parameters calibrated using experimental data.

The tire slip angles α_i in (4) are approximated as,

$$\alpha_1 = \frac{v_y + l_f\dot{\psi}}{v_x - \frac{w_t}{2}\dot{\psi}} - \delta, \qquad \alpha_2 = \frac{v_y + l_f\dot{\psi}}{v_x + \frac{w_t}{2}\dot{\psi}} - \delta, \tag{5a}$$

$$\alpha_3 = \frac{v_y - l_r\dot{\psi}}{v_x - \frac{w_t}{2}\dot{\psi}}, \qquad \alpha_4 = \frac{v_y - l_r\dot{\psi}}{v_x + \frac{w_t}{2}\dot{\psi}}. \tag{5b}$$

We make use of the following assumptions,

Assumption 3. In equation (4) the vertical forces F_{zi} are assumed constant and determined by the vehicle's steady state weight distribution when no lateral or longitudinal accelerations act at the vehicle center of gravity.

Assumption 4. The friction coefficient is treated as an exogenous disturbance signal. It is assumed to be 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 μ is assumed available. See, e.g., Yamazaki et al. (1997); Shim and Margolis (2004); Pasterkamp and Pacejka (1997); Tsunashima et al. (2006) for an overview on friction estimation techniques.

Assumption 5. The signal $\dot{\psi}_s$ is treated as an exogenous disturbance signal. Every time instant, an estimate of $\dot{\psi}_s$ is available over a finite time horizon. See, e.g., Jansson (2005); Bertozzi et al. (2000); Eidehall et al. (2007) for sensing technologies that can be used to obtain this signal.

2.2 Driver model

We will utilize 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 Cacciabue (2007). 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.

Define the orientation error e_{ψ}^{lp}, w.r.t. a look-ahead point as in Figure 1,

$$e_{\psi}^{lp} = \psi - \psi_s^{lp} = e_{\psi} + \Delta\psi_s, \tag{6}$$

where ψ_s^{lp} is the heading of the lane centerline at time $t + t_{lp}$, with t the current time, $\Delta\psi_s = \psi_s - \psi_s^{lp}$ and t_{lp} the preview time that can be mapped into the preview distance s_{lp}.

Denote by $w_{or}, \ w_{ol}$, the width of an obstacle located at the right and left lane borders, respectively, which are zero in case no obstacle is present. We introduce the position error,

$$e_y^{lp} = e_y - \frac{1}{2}w_{or} + \frac{1}{2}w_{ol}, \tag{7}$$

which is the distance of the vehicle's center of gravity from the center of the free portion of the lane.

We compute an estimate of the driver commanded steering angle $\hat{\delta}_d$ as,

$$\hat{\delta}_d = K_y e_y^{lp} + K_{\psi} e_{\psi}^{lp}, \tag{8}$$

with K_y and K_{ψ} as gains that are, in general, time varying and are updated online. Clearly, $\Delta\psi_d$ in (6) and $w_{or}, \ w_{ol}$ in (7) depend on the preview time t_{lp} that, in our modeling framework, is considered as a parameter of the driver model. We also remark that the steering model (8) is velocity dependant since $\Delta\psi_s$ also depends on the vehicle speed v_x.

Remark 1. The obstacle widths $w_{or}, \ w_{ol}$ are included in (7) to model that the driver tries to avoid road side obstacles, which is a realistic assumption when the driver is attentive. Nevertheless, if it can be established that the driver is distracted, this can be accounted for by setting the widths $w_{or}, \ w_{ol}$ to zero.

Estimation results of driver model parameters, obtained using a nonlinear recursive least squares algorithm, are presented in Falcone et al. (2011) for both normal and aggressive driving styles.

We write the model (1)-(8) in the following compact form,

$$\dot{\xi}(t) = f(\xi(t), u(t), w(t)), \tag{9}$$

where $\xi = \left[v_x, \ v_y, \ \dot{\psi}, \ e_{\psi}, \ e_y\right]^T$, $u = [\delta_c, \ F_b]^T$ and $w = \left[\mu, \ \dot{\psi}_d, \ \Delta\psi_d, \ w_{ol}, \ w_{or}\right]^T$ are the state, input and disturbance vectors, respectively.

2.3 Spatial Model

The semi-autonomous controller derived in Section 4 utilizes both braking and steering to keep the vehicle on a collision free path. In order to formulate the safety constraints on the vehicle's position, as in Section 3, while maintaining the ability to control both steering and braking, we introduce a spatial-vehicle model where the independent variable, with respect to which the system states are differentiated, is the traveled distance along the lane centerline s.

The following kinematic equations can be derived from Figure 1,

$$v_s = (R_s - e_y)\cdot\dot{\psi}_s = v_x \cdot cos(e_{\psi}) - v_y \cdot sin(e_{\psi}), \tag{10}$$

where v_s is the projected vehicle speed along direction of the lane center line and R_s is the radius of curvature. The vehicle's velocity along the path $\dot{s} = \frac{ds}{dt}$ is then given by

$$\dot{s} = R_s \cdot \dot{\psi}_s = \frac{R_s}{R_s - e_y}\cdot(v_x \cdot cos(e_{\psi}) - v_y \cdot sin(e_{\psi})). \tag{11}$$

Using the fact that $\frac{d\xi}{ds} = \frac{d\xi}{dt}\cdot\frac{dt}{ds}$ we write the spatial model in the following compact form,

$$\xi' = f(\xi, u, w)\cdot\frac{1}{\dot{s}} = f^s(\xi, u, w), \tag{12}$$

where $(\cdot)'$ denotes a variable's derivative with respect to s.

Remark 2. The time as a function of s, $t(s)$, can be retrieved by integrating t', $t(s_f) = \int_{s_0}^{s_f}\frac{1}{\dot{s}}\,ds$.

3. SAFETY CONSTRAINTS

We recall that the overall aim of the safety system proposed in this paper is to keep the vehicle on a collision free path within the safety of the lane while maintaining a stable vehicle motion. In this section we express the requirements that the vehicle stays in the lane and avoids obstacles, while operating in a stable operating region, as constraints on the vehicle state, input and disturbance variables.

Let $e_{y_i},\ i \in \{1,2,3,4\}$ be the distances of the four vehicle corners from the lane centerline. e_{y_i} can be written as

$$e_{y_1} = e_y + \frac{c}{2} + a\sin(e_\psi), \quad e_{y_2} = e_y - \frac{c}{2} + a\sin(e_\psi), \tag{13a}$$

$$e_{y_3} = e_y + \frac{c}{2} - b\sin(e_\psi), \quad e_{y_4} = e_y - \frac{c}{2} - b\sin(e_\psi), \tag{13b}$$

where c is the vehicle width, a and b are the distances of the center of gravity from the front and rear vehicle bumpers, respectively.

The requirement that the vehicle stays in the free portion of the lane is then expressed,

$$-e_{y_{\max}} + w_{or} \leq e_{y_i} \leq e_{y_{\max}} - w_{ol},\ i \in \{1,2,3,4\}. \tag{14}$$

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. This requirement can be ensured by limiting the tire slip angles α_i as,

$$\alpha_{i_{\min}} \leq \alpha_i \leq \alpha_{i_{\max}},\ i \in \{1,2,3,4\}. \tag{15}$$

For limited slip angles the vehicle behavior is predictable by most drivers and Electronic Stability Control (ESC) systems are inactive Gillespie (1992); Tseng et al. (1999).

The constraints (14)-(15) can be compactly written as,

$$h(\xi, u, w) \leq \mathbf{0}, \tag{16}$$

where $\mathbf{0}$ is a vector of zeros with appropriate dimension

4. PREDICTIVE CONTROL PROBLEM

In this section we formulate the threat assessment and control problems as a Model Predictive Control Problem (MPC). At each sampling time instant an optimal input sequence is calculated by solving a constrained finite *distance* optimal control problem for the transformed system (12). 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 the system (12) with a fixed sampling distance ds to obtain,

$$\xi_{k+1} = f^{ds}(\xi_k, u_k, w_k), \tag{17}$$

and formulate the optimization problem, to be solved at each step, as

$$\min_{\mathcal{U}_s,\epsilon} \sum_{k=0}^{H_c-1} ||u_{s+k,s}||_R^2 + \rho\epsilon \tag{18a}$$

$$\begin{aligned}
s.t.\ & \xi_{s+k+1,s} = f^{ds}(\xi_{s+k,s}, u_{s+k,s}, w_{s+k,s}), && \text{(18b)}\\
& \qquad\qquad\qquad\qquad k = 0, ..., H_p - 1 && \\
& h_t(\xi_{s+k,s}, u_{s+k,s}, w_{s+k,s}) \leq \mathbf{1}\epsilon, && \text{(18c)}\\
& \epsilon \geq 0, \qquad\qquad k = 0, ..., H_p && \text{(18d)}\\
& u_{s+k,s} = \Delta u_{s+k,s} + u_{s+k-1,s}, && \text{(18e)}\\
& u_{\min} \leq u_{s+k,s} \leq u_{\max}, && \text{(18f)}\\
& \Delta u_{\min} \leq \Delta u_{s+k,s} \leq \Delta u_{\max}, && \text{(18g)}\\
& \qquad\qquad\qquad\qquad k = 0, ..., H_c - 1 && \\
& \Delta u_{s+k,s} = 0, \qquad k = H_c, ..., H_p && \text{(18h)}\\
& u_{s-1,s} = u(s-1), && \text{(18i)}\\
& \xi_{s,s} = \xi(s), && \text{(18j)}
\end{aligned}$$

where s denotes the current position along the curve and $\xi_{s+k,s}$ denotes the predicted state at step $s+k$ obtained by applying the control sequence $\mathcal{U}_s = [u_{s,s}, \ldots, u_{s+k,s}]$ to the system (17) with $\xi_{s,s} = \xi(s)$. H_p denotes the prediction horizon and H_c denotes the control horizon. The safety constraints (16) have been imposed as soft constraints, by introducing the slack variable ϵ in (18a) and (18d). R and ρ are weights of appropriate dimension penalizing control action and violation of the soft constraints.

We note that no penalty on deviation from a tracking reference is imposed in the cost function (18a). The objective here is to ensure that the safety constraints (16) are not violated, while utilizing minimal control action. If the driver steering model (8) is alone capable of steering the vehicle without violating the safety constraints (16), no control action will be applied and the optimal cost will thus be zero.

In addition to the soft constraints we have imposed hard constraints. (18e)-(18g) reflect limitations set by the actuators. The constraint (18h) 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.

5. RESULTS

In this section we validate the behavior of the proposed active safety system. In Section 5.1 we first show a situation where the driver is attentive and capable of avoiding an obstacle . In this situation, the safety system correctly detects that the driver is capable of performing the driving task and does not intervene. Next, in Section 5.2, we demonstrate the ability of the adopted approach to detect critical situations and adequately assist the driver in avoiding accidents. We also demonstrate how the performance of the safety system can potentially be influenced if the system is complemented with a driver monitoring system that is capable of assessing whether the driver is distracted. Finally, in Section 5.3, we consider a scenario with multiple obstacles and demonstrate the ability of the controller to avoid collisions in such challenging situations.

For the results presented next, the estimation algorithm used in Falcone et al. (2011) is implemented to estimate parameters of the driver model (8) and the vehicle and design parameters in Tables 1 and 2 are used to implement the predictive controller (18).

Table 1. Vehicle parameters

$m =$ 2050 kg	$\sigma =$ 0.7	$w_t =$ 1.63 m	$B_1, B_2 =$ -10.5	$C_1, C_2 =$ 0.5
$J_z =$ 3344 kgm^2	$l_f =$ 1.43 m	$l_r =$ 1.47 m	$B_3, B_4 =$ -12.7	$C_3, C_4 =$ 0.5
μ	a	b	c	
1.0	2.12 m	2.66 m	1.77 m	

Table 2. Design parameters

$u_{\max} =$ $[0.7 \text{ rad}, 0 \ N]^T$	$H_p = H_c =$ 21	$\alpha_{\max} =$ $4°$
$u_{\min} =$ $[-0.7 \text{ rad}, -\mu m g \ N]^T$	$ds =$ 1 m	$\alpha_{\min} =$ $-4°$
$\Delta u_{\max} =$ $[1.4 \text{ rad}, \mu m g \ N]^T$	$\rho =$ 10^4	$e_{y_{\max}} =$ 2.5 m
$\Delta u_{\min} =$ $[-1.4 \text{ rad}, -\mu m g \ N]^T$	$R =$ $diag(1, 10)$	$e_{y_{\min}} =$ -2.5 m

The driver estimation algorithm adapts and updates the parameters of the driver model as new data becomes 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 next, as the behavior of the suggested predictive controller is analyzed for the considered scenarios.

5.1 Attentive Driver

We first show a situation where the driver is attentive. Consider Figure 2 which shows a situation where an attentive driver is negotiating a curve and encounters an obstacle in the path. The dashed line shows the path

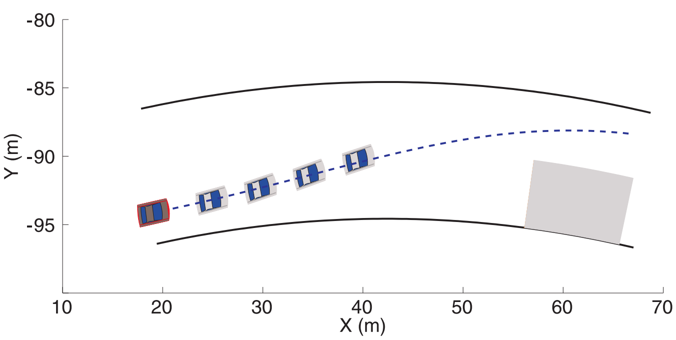

Fig. 2. A situation where an attentive driver encounters an obstacle in the path. The driver is capable of avoiding the obstacle and for this reason, the MPC controller doesn't intervene.

traversed by the driver. Clearly, the driver has no problems avoiding the obstacle. The shaded vehicles illustrate the trajectory that is predicted by the MPC controller when the vehicle is in the position shown with a darker color. In this situation the driver behavior, modeled by (8), is capable of avoiding the obstacle without assistance from the MPC controller. The MPC controller correctly predicts that the driver can maintain a safe trajectory and the decision to not intervene in this situation is correct.

5.2 Distracted Driver

In this section we consider a scenario where the driver is distracted. Consider Figure 3 where the vehicle is ap-

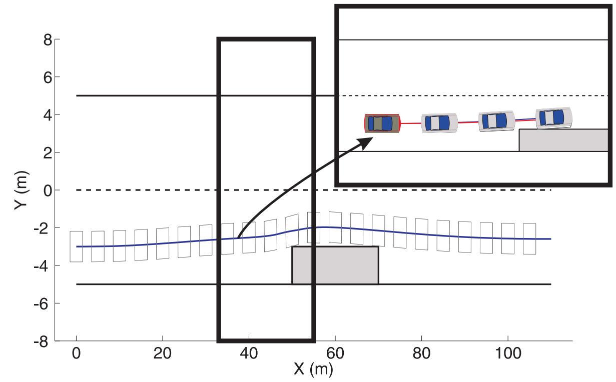

Fig. 3. The closed-loop vehicle trajectory where the driver is assisted by the MPC controller. The controller detects that the nominal driver behavior is no longer sufficient to maintain a safe vehicle trajectory and intervenes in order to avoid the road side obstacle.

proaching an obstacle and the driver is distracted. In this situation the driver doesn't account for the obstacle and instead just drives as if the object wasn't present. The inset in Figure 3 shows a comparison between the predicted trajectory obtained with the driver model (8) and the trajectory obtained when the driver is assisted by the MPC controller. These predictions are initiated at the position where the MPC controller first starts assisting the driver, i.e., when the two predicted trajectories no longer overlap. We note that, at this position, even though the driver is assumed attentive and will try to avoid the obstacle, the vehicle is already in a state where the driver would have to deviate from the nominal behavior, described by the model (8), in order to avoid the obstacle. The MPC controller, therefore, assists the driver with as much control action as necessary to avoid the obstacle while minimizing the cost function (18a). Figure 4 shows the steering angle of the distracted driver and the controller's corrective steering angle and braking force. We note that the controller

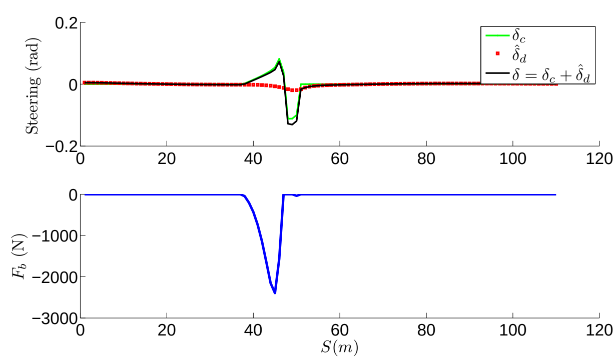

Fig. 4. The inputs required from the safety system, the controller slightly steers and brakes the vehicle to avoid the roadside obstacle and smoothly gives back control to the driver once the obstacle has been avoided.

slightly steers and brakes the vehicle to avoid the roadside obstacle and smoothly gives back control to the driver once the obstacle has been avoided and the vehicle is again in a state where the driver is expected to be capable of avoiding violation of the safety constraints.

Figure 3 demonstrates the ability of the adopted MPC approach to intervene and avoid roadside objects without utilizing any information about driver's distraction. Consider the scenario shown in Figure 5 where the driver model in the MPC controller has been modified to account for a distracted driver, as suggested in Remark 1. Information about driver distraction might be obtained

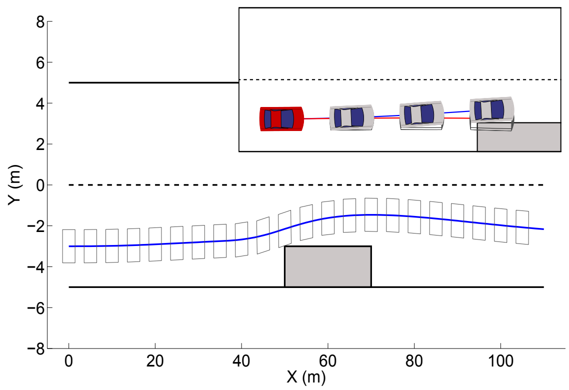

Fig. 5. The closed-loop trajectory of the vehicle. The inset shows a snapshot of the time instant an intervention was required. In this case a driver monitoring system has detected that the driver is distracted and consequently, we note that the intervention is activated earlier.

through a driver monitoring system like e.g. the monitoring system suggested in ?. Figure 5 shows that the MPC controller is capable of avoiding the obstacle in this case and the inset shows how the distracted driver is expected to hit the obstacle. Nonetheless, we note in Figure 6 that the intervention is activated earlier in this case than in Figure 4 and that consequently the control signals are kept smaller.

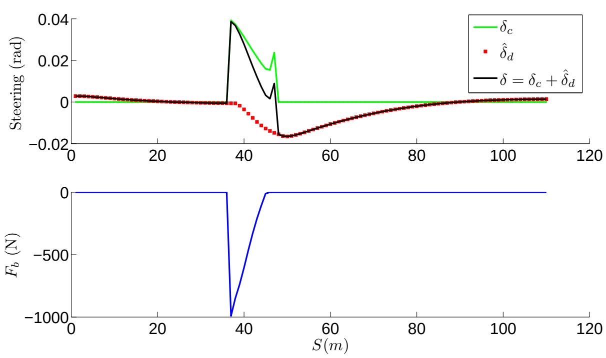

Fig. 6. The input signals in the scenario shown in Figure 5. Since the intervention is issued early, the control action is smaller when compared to the input signals shown in Figure 4 .

5.3 *Multiple Obstacles*

Next we show a scenario that is more challenging. In Figures 7-8, a distracted driver is approaching multiple obstacles. The inset in Figure 7 shows a snapshot of the moment the second obstacle is encountered. A driver monitoring system has detected that the driver is distracted and the driver model in the MPC algorithm has been modified accordingly. Again we note that the controller intervenes to satisfy the constraints in order to minimize the control action, as prescribed by the cost function (18a). The results show the ability of the active safety system to successfully navigate around multiple obstacles while minimizing the interference to the driver.

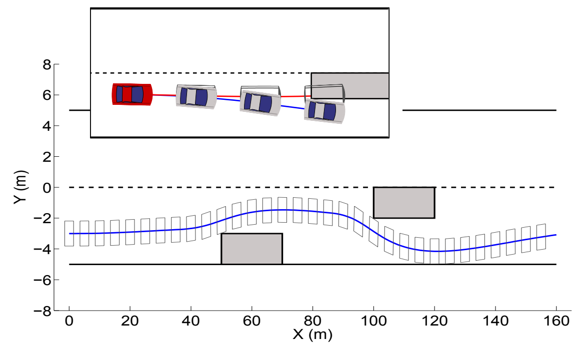

Fig. 7. The closed-loop trajectory of the vehicle in a situation with multiple obstacles. The inset shows a snapshot of the moment the second obstacle was encountered and intervention was required.

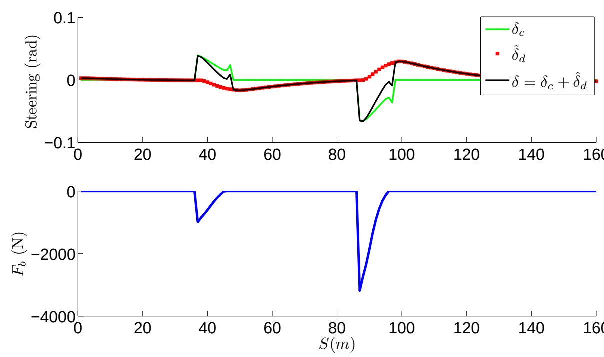

Fig. 8. The inputs showing the corrective action, $[\delta_c, F_b]$, of the safety system required to keep the driver safe while navigating through multiple obstacles.

6. CONCLUSIONS

This paper presents the integrated design of an active safety system for prevention of collisions with roadside obstacles and roadway departures. The resulting predictive controller is constrained to stay within the safe region of the road while allowing full control of braking and steering. The system accounts for the predicted nominal driver behavior in an effort to reduce interventions when they are not necessary. Even though the proposed system doesn't rely on driver monitoring systems, it is demonstrated how such systems can be integrated to further reduce the intrusiveness of the interventions. The studied simulations presented demonstrate the controller's ability to detect and avoid collisions by applying the minimum corrective action to keep the driver safe. The results further motivate efforts towards a real-time implementation to evaluate the system in real world scenarios.

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