A PREDICTIVE APPROACH TO ROADWAY DEPARTURE PREVENTION

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In this paper, we investigate predictive control approaches to the problem of roadway departure prevention via steering and braking. We assume a sensing infrastructure detecting road geometry and consider a two layers architecture consisting of a threat assessment and an intervention layer. In particular, the upper threat assessment layer detects the risk of roadway departure or vehicle instability within a future time horizon. If a risk of roadway departure or vehicle instability is detected, the lower intervention layer is enabled. The latter is designed based on Model Predictive Control (MPC) approaches, where steering and braking interventions are the result of an optimization problem. This is formulated on the basis of vehicle state measurements and coming road information (e.g., road geometry, surface adhesion) and repeatedly solved over a moving future time horizon.

Simulation and experimental results are presented, showing that the proposed approach effectively exploits road preview capabilities in order to issue earlier and less intrusive interventions, compared to standard Electronic Stability Control (ESC) systems.

Keywords: Global Chassis Control, Vehicle Stability, Autonomous Vehicles, Threat Assessment, Active Safety, Model Predictive Control.

1. INTRODUCTION

Roadway departure related crashes account for a great share of all traffic related accidents. According to [1], in developed countries about half of all fatal and a third of all severe vehicle accidents are due to single vehicle crashes.

Over the last three decades, several research and technological advancements have contributed to the reduction of fatal roadway departures. Probably the first milestone in active safety dates back to the seventies, when Antilock Braking Systems (ABS) were put into production on passenger cars [2]. Successively, in the mid-1990s, car manufacturers began to equip vehicles with Electronic Stability Control (ESC) systems which have proven to be quite efficient in reducing the amount of fatal roadway departures that are caused by loss of vehicle control. Studies showed that ESC systems reduce the amount of fatal single vehicle crashes by 30-50% for cars and 50-70% for Sport Utility Vehicles (SUVs) [3].

A drastic increase of the overall vehicle safety is expected from future active safety systems, which are envisioned to rely on sophisticated sensing infrastructures providing preview of the coming road and information about the surrounding environment. Such preview capabilities are expected to enable early interventions, in order to prevent the vehicle from working in unsafe operating conditions where classical active safety systems are activated. Moreover, the possibility of partially or completely replacing the driver with an autonomous driving system will enable the possibility to recover vehicle control in critical scenarios, where the coordination of multiple vehicle actuators might lead to more effective evasive maneuvers.

Such vision of future active safety systems has motivated extensive research on control of autonomous vehicles. An important milestone in this field was achieved already in 1987 when Dickmanns and Zapp demonstrated a vehicle that drove autonomously over 20 km on the German Autobahn [4]. Despite the advances in the field of autonomous vehicles, vehicle manufacturers have shown little interest in developing new active safety systems based on autonomous driving, and autonomous vehicles have been rather confined to military applications. Instead, the main contribution to the automotive industry from initiatives like DARPA's *grand challenge* has been the development of sensor fusion algorithms [2].

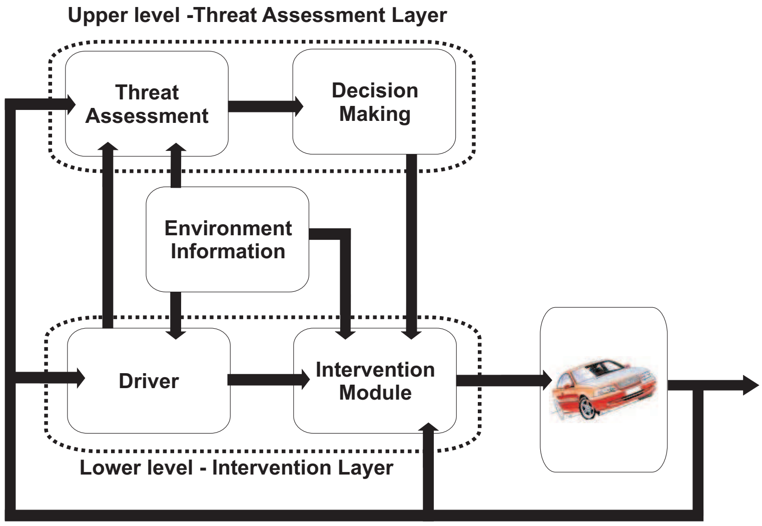

Figure 1. Overview of the suggested accident prevention architecture.

The development of these sensing systems has lead to a class of emerging active safety systems that have started to appear on the passenger cars market. These systems are usually referred to as Advanced Driver Assistance Systems (ADAS) and an example of such a system is the lane keeping system that warns or assists the driver when the vehicle might leave its lane. Contrary to ESC, lane keeping systems are effective in situations where the vehicle is about to leave its lane due to, e.g., driver distraction [2, 5].

In this paper, we assume the availability of advanced sensing systems, providing preview of the road geometry, and consider a general accident avoidance architecture. The two main components of such architecture are *a threat assessment* and *an intervention* layer. By using predictive approaches, both layers are designed in order to exploit the available preview capabilities. In particular, the threat assessment layer includes a decision making module that, based on threat level and type, decides the type of intervention that the intervention layer has to issue. For example, depending on the threat level, the decision making module might request an intervention ranging from a less intrusive warning to an autonomous driving intervention where steering, braking and accelerating are coordinated in order to perform high demanding evasive manoeuvres where a normally skilled driver would fail. In this paper we present a preliminary study of the considered architecture, focusing on the threat assessment and the intervention layers. The paper is structured as follows: in Section 2 we propose a general architecture for safety systems, in Section 3 we present the modeling the design of the threat assessment and the intervention layers are based on, Sections 4 and 5 describe the threat assessment and intervention layers, respectively, and in Section 6 we present simulation and experimental results from a roadway departure prevention system implemented using the proposed architecture.

2. ARCHITECTURE

The architecture underlying the roadway departure prevention algorithm proposed in this paper is sketched in Figure 1. This is a general architecture that, in principle, can be used for any accident prevention scenario, e.g., collision avoidance.

By using measurements of the vehicle state and road and environment information, e.g., road geometry and surface adhesion, the threat assessment layer evaluates the risk of accident or vehicle instability over a future finite time horizon. During normal, i.e., safe driving conditions the driver has full control of the vehicle. When the risk of accident or vehicle instability is detected, instead, the decision making layer is activated and, depending on the risk, the type of intervention is decided. In particular, in normal driving conditions the driver's commands are passed through the intervention module and sent directly to the vehicle. In unsafe driving conditions, instead, the driver can be either assisted by the intervention module correcting his or her commands, or completely excluded in an autonomous driving mode. In general, the type and intrusiveness of the intervention issued by the intervention module, depend on the detected risk of accident. For instance, if excessive speed is detected early in advance when approaching a curve, a simple warning might be issued to the driver. As the vehicle approaches the curve and the speed is not reduced, a slight braking might be issued in order to slow down the vehicle and safely perform the curve. In case of more severe risk of accidents, e.g., unexpected slippery road surface or obsta-

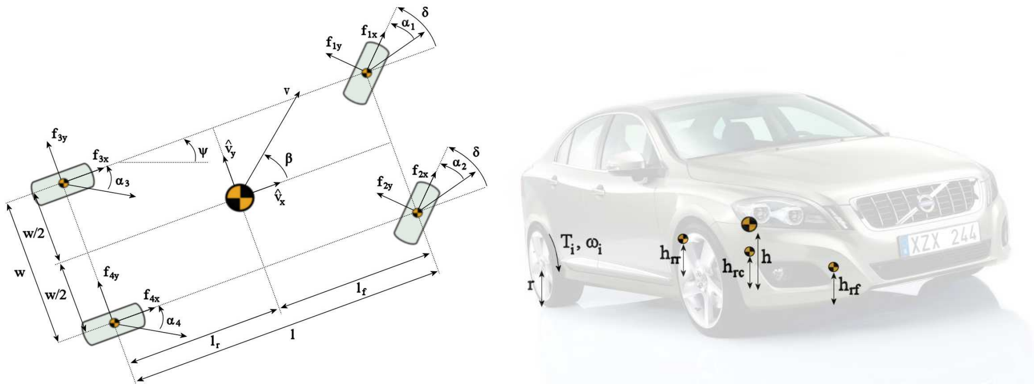

Figure 2. Notation for the double track vehicle model.

cles, a combined steering and differential braking intervention might be issued in order to autonomously compensate for a slippery surface or avoid an obstacle.

In the next sections, examples of threat assessment and intervention layers are presented for a roadway departure application. In this paper, the threat assessment layer is based on vehicle, driver and environment models. In particular, a driver model is used to generate the commands (i.e., steering, braking and accelerating) to the vehicle based on the road geometry and environment information. A vehicle mathematical model is then used to predict the vehicle behavior over a finite time horizon under the generated driver's commands. The vehicle behavior is then evaluated in order to detect the risk of accidents, e.g., lane departure, vehicle instability, collision with obstacles. Such evaluation might consist of either a simple set of rules or a complex function of the predicted vehicle state trajectory. For instance, the predicted vehicle motion along a coming curve might be evaluated in order to detect unsafe deviation from the road centerline.

Once the risk of accident is detected, the decision making module determines the type and intrusiveness of intervention to be issued by the lower intervention layer. Again, the decision making system might consist of either heuristic rules or complex functions designed based on the system model. The output of the decision making module, might be a selection of an appropriate low level controller for issuing an intervention, ranging from a warning to the driver to a full autonomous driving completely excluding the driver. In this paper, we design a low level steering and individual wheel braking controller based on MPC approaches and, according to the considered architecture, the decision making module might reconfigure the controller in order to steer, brake or do both. Moreover, the decision making system might also bound the steering and braking interventions in order to affect the intrusiveness of the intervention.

3. MODELING

In this section we briefly describe the driver and vehicle modeling used for designing the threat assessment and the intervention layers.

3.1. Vehicle modeling

The threat assessment layer presented in this work is based on the vehicle model in [6]. This is a standard four wheels vehicle model that captures the most relevant dynamics for the considered application. In particular, the considered vehicle model describes longitudinal, lateral and yaw dynamics, taking into account longitudinal and lateral load transfer and the nonlinear characteristics of the tyres. The interested reader is referred to [6] for further details.

We denote by ξ and u the state and input vectors, respectively, and describe the vehicle's motion in an inertial frame, subject to longitudinal, lateral and yaw dynamics, through a set of nonlinear differential equations that can be written in the following compact form

$$\dot{\xi}(t) = f_{veh}(\xi(t), u_d(t), u_\gamma(t), d(t)), \quad (1)$$

where $\xi = [v_y, v_x, \psi, \dot{\psi}, X, Y, \omega_1, \omega_2, \omega_3, \omega_4]^T$, with v_y and v_x the lateral and longitudinal vehicle velocities in the vehicle body frame, respectively, ψ the vehicle's heading angle in a global frame, $\dot{\psi}$ the yaw rate, X and Y the position of the vehicle's center of gravity in the global frame and $\omega_{(\cdot)}$ the wheels angular velocities, with the lower subscripts $(\cdot)_1$, $(\cdot)_2$, $(\cdot)_3$ and $(\cdot)_4$ indicating variables at the individual wheels as in Figure 2. Moreover $u_d = [\delta, T_1, T_2, T_3, T_4]^T$, where δ denotes the front wheel steering angle and $T_{(\cdot)}$ denote wheel torque, is the driver's command vector, $u_\gamma = \gamma_i\,(\xi, u_d, d)$ is a control signal vector computed through a low level feedback controller γ_i defined next in Section 5 and d is a vector of exogenous signals from the environment. f_{veh} is then a nonlinear function and is defined in, e.g, [6]

Remark 1 : The tyre forces are computed in this paper by using the Pacejka magic tyre formula [7]. This is a nonlinear static function whose parameters are calibrated on experimental data. We let α denote the tire slip angle, κ denote the longitudinal slip ratio, μ denote the friction coefficient, F_z denote the vertical load at each wheel respectively and write the tyre formula as

$$f_x = f_{x0} G_{x\alpha}(\alpha, \kappa, F_z) \tag{2}$$

$$f_y = f_{y0} G_{x\kappa}(\alpha, \kappa, F_z) + S_{Vy\kappa} \tag{3}$$

where f_{x0}, f_{y0} are the tyre forces under pure slip conditions, $G_{x\alpha}$, $G_{x\kappa}$ are weighting functions, $S_{Vy\kappa}$ the κ-induced side force and f_x, f_y are the longitudinal and lateral tyre forces under combined slip conditions. A thorough explanation of the magic tyre formula can be found in, e.g., [8].

Next we design a low level controller in the intervention layer, based on a simplified version of the vehicle model (1) where the lateral and longitudinal load transfers are omitted. We denote the simplified vehicle model as

$$\dot{\xi}(t) = f_{simpl}(\xi(t), u(t)). \tag{4}$$

3.2. Driver modeling

The threat assessment method considered in this paper is based on a mathematical model of the driver. Literature on driver modeling is enormous [9]. In our study we are interested in very simple model structures, enabling the design of a low complexity model based threat assessment algorithms.

In this paper the driver is described through a dynamical model, where the vehicle's state and the environment information (e.g., road geometry, obstacles position and speed) are exogenous signals:

$$\dot{x}(t) = f_{driver}(x(t), \xi(t), h_{dref}(d(t))). \tag{5}$$

In (5), x denotes the driver state vector, ξ is the vehicle state defined as in Section 3.1. $h_{dref}(d(t))$ is a map to extract a reference and might be a trajectory planner algorithm. We also define an output map

$$u_d(t) = h_{driver}(x(t), \xi(t), d(t)), \tag{6}$$

where the output u_d, depending on the application, can in general contain the steering angle, the deceleration request, the engine torque and the gear selection or any other command signal the driver might use to control a vehicle.

In general, the model (5), (6) can range from the very simple structure used in this paper to complex model structures accounting for a large amount of exogenous signals. For instance, the model (5), (6) could be a hybrid model, where different driver dynamics are selected depending on the vehicle operating regions and drowsiness estimated through, e.g., cameras in the rear-view mirror.

In our roadway departure prevention application, we describe the driver's steering and braking behavior through two decoupled controllers. In general, modeling of drivers braking behavior is complex, the drivers acceleration or deceleration commands depend on several factors like current velocity, road surface condition, road geometry and distance to preceding vehicle, to mention a few. For the sake of clearness and simplicity, in order to

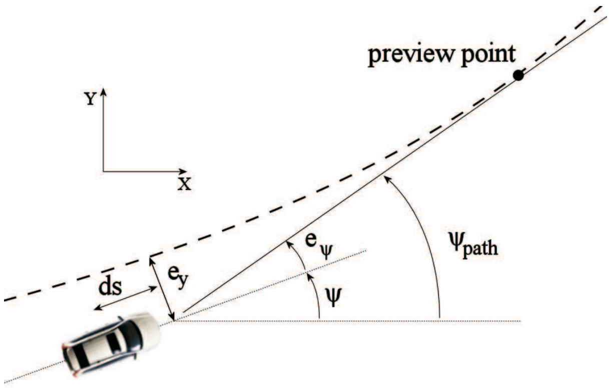

Figure 3. Definition of the control errors in (8), e_y denotes the vehicle's lateral displacement from the road at a distance ds ahead of the vehicle's center of gravity. ψ denotes the vehicle's heading angle and ψ_{path} denotes the roads heading angle at the preview point which is t_{prev} seconds ahead of the vehicle. Finally e_ψ denotes the difference between ψ_{path} and ψ.

demonstrate the proposed system architecture, in this study we assume that the driver is always trying to reduce speed. We model the braking behavior as a PI-controller

$$\begin{aligned} T_{tot} &= K_p(\kappa_{max} - \kappa_{ref}) + K_I \int(\kappa_{max} - \kappa_{ref})dt, \\ T_{1,2} &= 0.7T_{tot}, \quad T_{3,4} = 0.3T_{tot} \\ \kappa_{max} &= \max_{i\in\{1,2,3,4\}} \kappa_i \end{aligned} \tag{7}$$

where K_p and K_I are the proportional and integral gains, respectively and κ_{ref} denotes the slip reference.

The modeling of the driver's steering behavior is inspired by [10–12]. In [12], it is stated that the "pursuit" part of the human control system, using preview information about the oncoming road, generates the larger part of the steering commands while the closed loop portion only reduces the residue error. The driver's steering command is here modeled as the output of a proportional controller, with gains K_y and K_ψ

$$\delta = K_y e_y + K_\psi e_\psi(t_{prev}), \tag{8}$$

where e_y denotes the lateral displacement of the vehicle from the road centerline and $e_\psi(t_{prev})$ denotes the difference between the vehicles yaw angle and the tangent of the road centerline at a point t_{prev} seconds ahead. An illustration of the errors is provided in Figure 3. The time preview could alternatively be replaced by a distance preview as in [13]. A map of preview distances could then be defined for different velocities and environments (e.g. urban or highway) and the driver model would then be an hybrid model where different driver dynamics are selected depending on environment and vehicle operating region.

4. THREAT ASSESSMENT LAYER

Consider the closed loop system, obtained by combining the vehicle and driver models (1) and (5)-(6), respectively

$$\dot{x}_{aug}(t) = f_{aug}(x_{aug}(t), \gamma_i, d(t)), \tag{9}$$

where $x_{aug} = \begin{bmatrix} \xi \\ x \end{bmatrix}$ and γ_i denotes the active low level controller, i.e., the signal u_γ in (1) is computed through the feedback controller γ_i. We discretize the model (9) with a sampling time T_s

$$x_{aug}(t+1) = f^{DT}_{aug}(x_{aug}(t), \gamma_i, d(t)), \tag{10}$$

where, with an abuse of notation, the same symbols are used to denote the state and exogenous signal vectors of the system (9) and its discrete time version (10).

We denote by $\Phi_{\gamma_i}\left([t_i, t_f], x_{aug}(t_i), D_{[t_i,t_f]}\right)$, where $D_t^N = [d(t_i), \ldots, d(t_f)]$, a state trajectory over the time interval $[t_i, t_i + 1 \ldots, t_f]$ obtained as a solution of the, in general nonlinear, differences equation (10), with initial condition $\left[\xi^T(t_i), x^T(t_i)\right]^T$, when the feedback low level controller γ_i is active.

We introduce a threat assessment function $F_N\left(t, \Phi_{\gamma_i}\left([t_i, t_i + N], x_{aug}(t_i), D_{[t_i,t_i+N]}\right)\right)$ defined as follows

$$F_N : R^+ \times R^{Nn} \longrightarrow R^p,\ N,\ p \in N^+, \tag{11}$$

where n is the order of the closed loop system (9). Components of F_N are positive if the vehicle motion, predicted over a time horizon of N steps, through the autonomous system model (10), violates safety constraints, less than or equal to zero otherwise. The definition of the function $F_N(\cdot, \cdot)$ is crucial in the considered accident avoidance architecture. In particular, $F_N(\cdot, \cdot)$ can range from a simple time invariant function, e.g., evaluating the distance of the vehicle from the road centerline, to a complex time varying function detecting the collision with moving objects. Moreover, depending on the complexity of $F_N(\cdot, \cdot)$, the computation of the vector $D_{[t_i,t_f]}$, containing information about the surrounding environment, might require the use of complex sensor fusion algorithms [14]. The function F_N is repeatedly evaluated every time step, based on the predicted trajectory Φ_{γ_i} found as solution of (10) for the current state $x_{aug}(t)$ and active low level feedback controller γ_i.

We also define a set of k low level feedback controllers or intervention types $\Gamma = \{\gamma_1, ..., \gamma_k\}$ and let $\varrho(\gamma_i)$ denote the level of intrusiveness of the controller γ_i. We can then define a decision making function $\Xi(H(t))$ selecting the smallest element of the vector $H(t)$ defined as $H(t) = [h_1(t), \ldots, h_k(t)]$, with $h_i(t) = \varrho(\gamma_i) + \rho\varepsilon_i(t)$ and

$$\begin{aligned} \varepsilon_i(t) = \underset{\varepsilon \geq 0}{\operatorname{argmin}} \varepsilon \\ \text{subj.to } F_N(t, \Phi_{\gamma_i}) \leq \varepsilon \cdot \mathbf{1}, \end{aligned} \tag{12}$$

with $\mathbf{1}$ a vector of appropriate dimension of which each element is one and ρ a weight coefficient penalizing violation of the soft constraint. The decision making function will thus, depending on the output of F_N activate the least intrusive controller that can control the vehicle without violating the safety constraints reflected by the function F_N, which are soft in order to guarantee feasibility. A model based decision making procedure is currently the topic of ongoing research activities.

In our roadway departure application we define an output trajectory $\bar{\alpha} = h_\Phi(\Phi\left([t_i, t_f], x_{aug}(t_i), D_{[t_i,t_f]}\right))$ where $\bar{\alpha}$ denotes the trajectory of tyre slip angles over the time interval $[t_i, t_i + 1 \ldots, t_f]$ and let the threat assessment function be

$$F_N(t, \Phi) = |\bar{\alpha}| - \alpha_{bound} \cdot \mathbf{1} \tag{13}$$

where we remark that $|\cdot|$ in (13) denotes absolute value of each element in $\bar{\alpha}$, and $\mathbf{1}$ is, again, a vector of appropriate dimension of which each element is one. Elements of the function F_N will then be positive if the tyre slip angle at any of the four wheels exceeds the threshold α_{bound} during the time interval $[t_i, t_i + 1 \ldots, t_f]$.

The tyre slip angle is closely related to the stability of the vehicle since a large slip angle indicates that the vehicle is operated in the nonlinear region of the tyres. In the nonlinear region, the possibility to control the vehicle through the steering wheel will be greatly reduced thus compromising the stability of the vehicle, for further treatment of the effect of large slip angles the interested reader is referred to e.g. [8, 15].

5. INTERVENTION LAYER

In the lower level intervention layer the controllers in Γ are defined. In the roadway departure application, these can e.g. be a set of controllers, with different configurations, implemented using Model Predictive Control (MPC) approaches where the main concept is to use a *model* of the plant to *predict* the future evolution of the system [16–19]. An optimal control problem is repeatedly solved over a finite time horizon at each sampling time instant. The open-loop optimal control minimizes a predefined cost function and the computed optimal control 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 in order to take advantage of updated information about the road geometry and the vehicle states. For the roadway departure prevention system, we start from the results presented in [20–22] where a low complexity MPC algorithm is proposed in order to solve an autonomous path following problem via active front steering and independent braking.

We dicretize the system (4) with a fix sampling time T_s, and linearize the discretized system around the current operating point at each time sample to obtain

$$\begin{aligned} \xi_{k+1,t} &= \mathcal{A}_t \xi_{k,t} + \mathcal{B}_t u_{k,t} + \mathcal{E}_t \\ \alpha_{k,t} &= \mathcal{C}_t \xi_{k,t} + \mathcal{D}_t u_{k,t} \end{aligned} \tag{14}$$

Where $\mathcal{E}_t$ is an affine term, due to that the system is discretized in an operating point which in general is not an equilibrium point. Note also that the linear models $\mathcal{A}_t, \mathcal{B}_t, \mathcal{C}_t, \mathcal{D}_t, \mathcal{E}_t$ are recomputed at each time sample, but are nevertheless time invariant during each prediction. The variable $\alpha_{k,t}$ denotes the tyre slip angle variation and is constrained in the optimization problem in order to maintain vehicle stability. For the tracking variables we define the output map

$$\eta_{k,t} = \begin{bmatrix} 0\,0\,1\,0\,0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,1\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,1\,0\,0\,0\,0 \end{bmatrix} \xi_{k,t} = [\psi_{k,t}, X_{k,t}, Y_{k,t}]^T \tag{15}$$

We also formulate a cost function

$$J(\xi(t), \Delta\mathcal{U}_t, d(t)) = \sum_{i=1}^{H_p} ||\eta_{t+i,t} - \eta_{ref_{t+i,t}}||_Q^2 + \sum_{i=0}^{H_c-1} ||u_{t+i,t}||_R^2 + \rho\epsilon \tag{16}$$

where $\eta_{ref} = h_{ref}(d(t))$ denotes the reference, $\Delta\mathcal{U}_t$ denotes the optimization vector, H_p denotes the prediction horizon and H_c denotes the control horizon. H_p is chosen larger than H_c and the control is kept constant during the prediction time beyond H_c. ϵ is a slack variable used to induce soft constraints on α. ρ denotes the weight coefficient used in the term $\rho\epsilon$ that penalizes violation of the soft constraints. By introducing the soft constraints on α we penalize control inputs that causes the vehicle to operate in the nonlinear region of the tyres, while maintaining feasibility of the solution in case there are no control inputs that satisfies the constraint.

We are now ready to formulate the optimization problem to be solved at each time sample as

$$\begin{aligned} \min_{\Delta\mathcal{U}_t} \quad & J(\xi(t), \Delta\mathcal{U}_t, d(t)) \\ subj.to \quad & \xi_{k+1,t} = \mathcal{A}_t \xi_{k,t} + \mathcal{B}_t u_{k,t} + \mathcal{E}_t \\ & \alpha_{k,t} = \mathcal{C}_t \xi_{k,t} + \mathcal{D}_t \\ & \eta_{k,t} = \begin{bmatrix} 0\,0\,1\,0\,0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,1\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,1\,0\,0\,0\,0 \end{bmatrix} \xi_{k,t} \\ & -\alpha_{bound} - \epsilon \le \alpha_{k,t} \le \alpha_{bound} + \epsilon \\ & \epsilon \ge 0 \\ & \qquad\qquad k = t, ..., t + H_p \\ & u_{k,t} = \Delta u_{k,t} + u_{k-1,t} \\ & u_{min} \le u_{k,t} \le u_{max} \\ & \Delta u_{min} \le \Delta u_{k,t} \le \Delta u_{max} \\ & \qquad\qquad k = t, ..., t + H_c - 1 \\ & \Delta u_{k,t} = 0, \\ & \qquad\qquad k = t + H_c, ..., t + H_p \\ & \xi_{t,t} = \xi(t) \end{aligned} \tag{17}$$

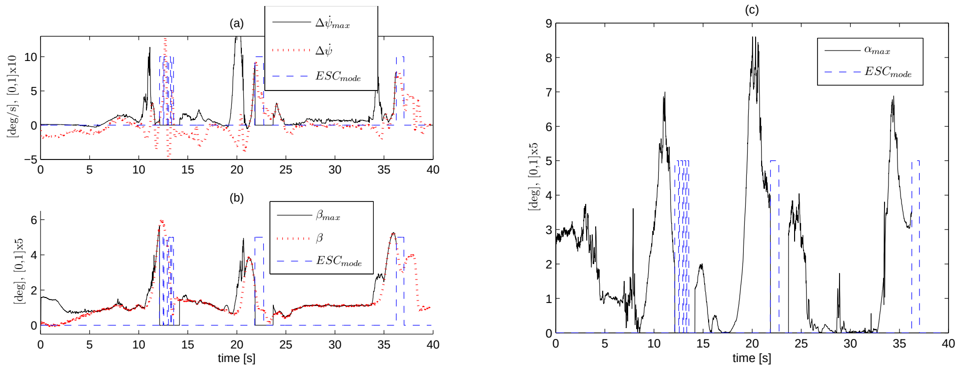

Figure 4. Shows the result of the proposed algorithm when applied on measured data. The parameter, ESC_{mode}, has the value one when the onboard ESC issues an intervention and zero otherwise. In (a) it can be seen that the maximum predicted yaw rate error (which ESC uses to issue interventions) $\Delta\dot{\psi}_{max}$ is increased and has a peak, before the onboard ESC decides to intervene. In (b) we see the results for β_{max}, while (c) shows the result for α_{max}, which is considered in the proposed threat assessment algorithm. Loss of control is thus well predicted by the algorithm, enabling the possibility to introduce an earlier intervention.

In addition to the soft constraints on α we have added a number of hard constraints. We constrain the values of the inputs i.e the steering angle and brake torques are only allowed within a certain interval. The last constraint specifies that the acquired solution starts at the current observed state $\xi(t)$.

6. RESULTS

For the purpose of evaluating the algorithm, experimental testing has been conducted on a test track. The track is short and wide with sharp curves and enables the possibility to adopt a rough driving style and provoke the ESC system without risking to end up in a major accident. The test vehicle was equipped with a differential GPS receiver, inertial measurement unit and a DSP. The DSP fuses the sensor information and gives accurate information about the vehicle's position and orientation in an inertial frame and other states needed in the algorithm. The DSP was also provided a digital map of the track which enabled the possibility to measure e.g. the distance to the lane markings. In addition we logged data from the onboard CAN-bus in the vehicle which gives information about e.g. whether the ESC system is active or not.

The test was conducted by a professional driver and in order to be able to test both positive (interventions issued when needed) and negative performance (no false interventions) the driver was asked to adopt a rough driving style in some laps and a normal driving style in other laps.

The threat assessment algorithm predicted all situations where the ESC system intervened to reduce understeer within the prediction horizon. In addition, the threat level was kept low when no loss of control was imminent. Figure 4 shows the result from one of the test drives. We can see that the threat level increases significantly right before the ESC system decides to intervene, enabling the possibility to assist the driver earlier.

In order to evaluate the complete system with the intervention layer included we chose one specific curve scenario from the measured data in which there's an intervention from the onboard ESC system recorded. The curve and the threat assessment predictions can be seen in Figure 5. We see that the threat level increases as the vehicle moves along the curve and passes the threshold in good time before the onboard ESC system intervenes. Imagine now that the vehicle would have been equipped with the proposed system and that the decision making module, at this point, commands the intervention module to switch to a completely autonomous mode. Figure 6 shows the simulation of such an intervention, $(a) - (d)$ shows the vehicle's state during the intervention lasting for 3 seconds, we can see that the controller follows pretty much the same trajectory as the driver did with the exception that it keeps a higher velocity. In Figure 6.e we can also see that the tyre slip angles are kept low throughout the whole simulation. The controller has no problem maintaining stability due to the availability of differential braking and the possibility to utilize the differential braking in a predictive manner. Since there is a penalty involved in braking, the controller chooses not to brake more than required to follow the path while maintaining stability.

In general, safety systems should only intervene when there's an actual threat. Issuing

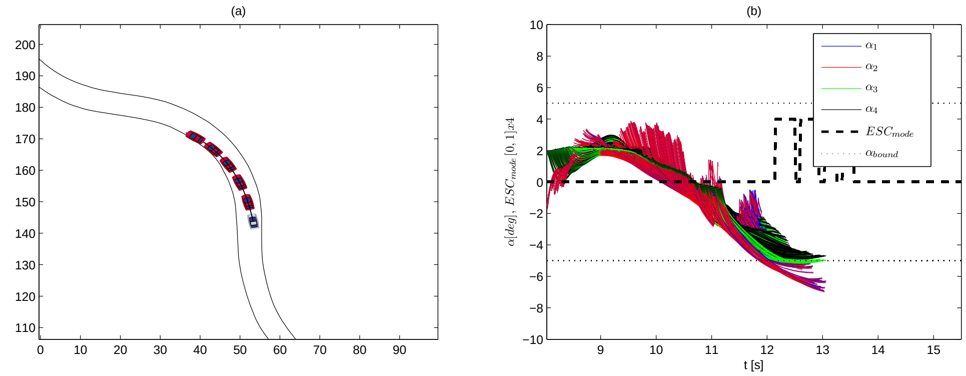

Figure 5. *(a) illustrates the situation when the algorithm has predicted imminent loss of control and handed over control to the autonomous controller in the intervention layer.(b) shows the predictions of tyre slip angles as the vehicle is approaching the curve scenario seen in (a). The black dashed line represents ESC_{mode} and shows when ESC intervened while the solid lines show the predictions at each time sample. We see that the predictions reveal an increase in the tyre slip angles well before the ESC decides to intervene.*

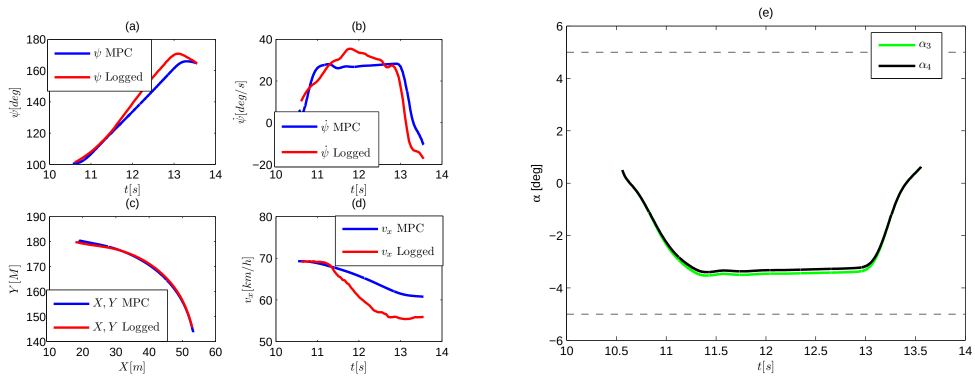

Figure 6. *(a)-(d) shows states of the vehicle during the autonomous intervention compared to the logged data, we see that the controller successfully negotiates the curve. (e) shows the tyre slip angles during the autonomous intervention, we can see that stability is maintained during the whole intervention.*

early interventions, might lead to an increase in the total amount of interventions issued by the safety system and it is thus important that the driver of the vehicle doesn't perceive these interventions as unnecessary and intrusive. There's therefore an interest in setting the thresholds of the safety system such that it intervenes at a stage where the driver also perceives that there is a threat, or can at least agree with the safety system after the intervention has been issued. There's however also a value in issuing interventions immediately when a threat has been identified since the control action can be kept smaller. Consider that the thresholds of the roadway departure system would have been set to $\alpha_{bound} = 6$, instead of $\alpha_{bound} = 5$, so that the autonomous intervention would have been issued 0.5 seconds later. In order to evaluate whether such a decision strategy would be more or less intrusive we consider Figure 7 which shows a simulation where the intervention has been postponed 0.5 seconds, in $(a) - (d)$ we see that it becomes more difficult to follow the same path while maintaining stability. In (e) we see that the vehicle's stability is maintained due to the soft constraint imposed on the tyre slip angles, however, in order to maintain stability the controller deviated from the path since the vehicle was in a state making it difficult for the controller to follow the path without activating constraints.

Considering the intrusiveness, the important thing is however that the control signals are greater in the postponed intervention. Figure 8 shows the applied control signals in both interventions. We clearly see that, in the postponed intervention, applied brake torque has a higher magnitude and that the variation in both torque and steering angle is more evident. It is thus not an unreasonable claim that the later intervention can be experienced as more intrusive by a driver.

A comparison between the control signals of the autonomous controller and the control signals issued by the onboard ESC in combination with the driver can also give a hint about the intrusiveness of an early predictive intervention. The driver's steering command is available in the logged data, however the wheel torques could not be recorded since they

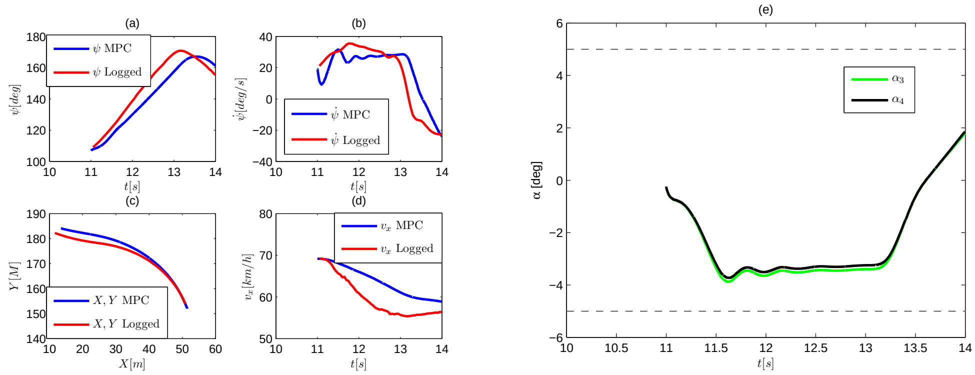

Figure 7. (a)-(d) shows states of the vehicle during the postponed intervention compared to the logged data, in this case it is more difficult for the controller to stay on track. (e) vehicle stability indicators during the postponed intervention, the vehicle's motion is still stable.

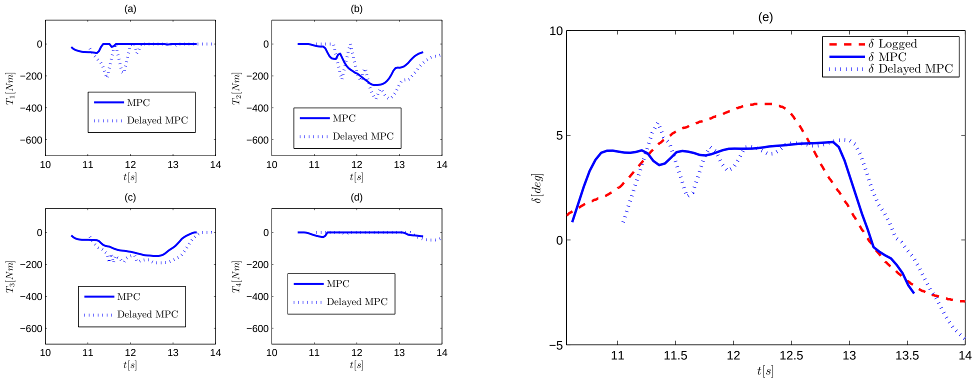

Figure 8. (a)-(d) shows the wheel torques applied during the autonomous interventions, we see that the required control action is increased when the intervention is delayed. (e) shows the steering angle, the delayed intervention has a higher change rate and is thus more intrusive.

are not available on the vehicle's CAN-bus. In order to make a comparison we therefore implemented a simple ESC controller. ESC systems are extensively treated in the literature and we refer the interested reader to e.g. [23–25]. We also assumed that the driver applied wheel torque according to the specific torque profile seen in Figure 9.(e)-(h). We applied the assumed open loop torque profile and the logged steering angle profile, and simulated the vehicle's motion, under the influence of the ESC controller. The result is seen in Figure 9, we see that the simulated vehicle states are very similar to those in the logged data. This implies that the assumed torque profile is comparable to the torque applied on the vehicle during the test drive. The simulation also serves as validation of the lateral and yaw dynamics of the vehicle model.

By comparing the torques applied on the vehicle using the ESC controller to those issued with the MPC controller we see that the torque magnitudes of the MPC controller are significantly lower. This is specially remarkable since the ESC controller operates in lower velocity. In addition we note that the MPC applies the torque more smoothly and has it's torque peaks earlier than the ESC controller. Since the ESC takes action only once the vehicle has already become unstable it applies more sudden and evasive control action to stabilize the vehicle. The speed reduction with the autonomous controller is very small and we can note that the controller almost only brakes wheels 2 and 3 to reduce speed with a slight overweight on wheel 2 to generate yaw moment.

To evaluate how well the ESC controller would have managed the situation if the driver wouldn't have braked we also simulated a case in which the driver's logged steering angle was fed to the vehicle model, but without any driver braking. In Figure 10.(a)-(d) we see the outcome of the simulation. As the vehicle approaches the curve and the steering angle is turned counterclockwise the vehicle builds up yaw rate, but when the steering angle starts moving in the opposite direction, the vehicle's speed is too high, and it is too difficult for the ESC controller to generate enough yaw moment to manage the situation. In Figure 10.(e) we see a comparison of applied brake torques in the different situations that has been considered in this section. We see that the magnitudes of the ESC systems control

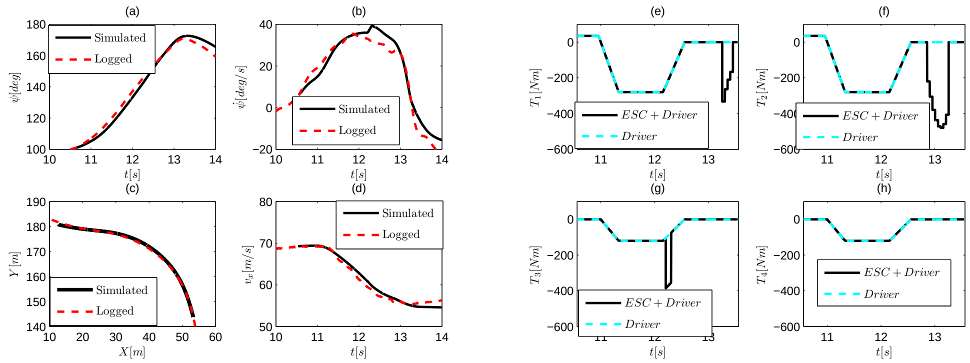

Figure 9. *(a)-(d) compares the states of the vehicle during the simulated motion of the vehicle to those logged during the test drive, we see that the simulated states are very similar to the logged states. (e)-(h) shows the wheel torques applied during the simulation with the ESC controller. The dashed lines show torques originating from the driver's pedal commands, they are distributed with a fix ratio between front and rear and doesn't contribute to the vehicle's yaw moment. The black solid line shows the total torque applied at each wheel including the ESC commands, we see that the ESC applies brake torque at individual wheels in order to generate additional yaw moment and assist the driver. By comparing the torques applied by ESC to those applied by the MPC controller in Figure 8.(a)-(d) we see that the ESC intervenes with higher magnitude and less smoothness than the MPC controller.*

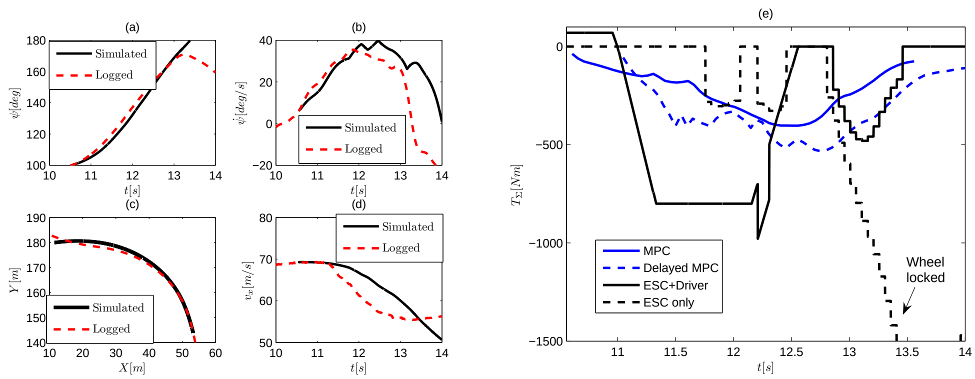

Figure 10. *(a)-(d) shows vehicle states in the case when ESC acts without the braking from the driver. We see that without the speed reduction that was previously provided by the driver, there's no possibility for ESC to recover the situation. (e) shows a comparison of applied brake torque in the different cases that has been demonstrated, we see that the MPC intervention, issued at the correct time, has smoother and smaller control action than the rest.*

action increases rapidly in the case where there was no braking provided by the driver, in fact the magnitude becomes so high that one of the wheels lock since we didn't implement any ABS controller. An ABS controller, wouldn't however have made any difference since the vehicle has strayed too far from the path at the point where the wheel locks.

By comparing the torque profiles in Figure 10.(e) we see that the MPC controller is superior. The preview capability of the MPC controller enables the possibility to build up yaw moment in advance, thus enabling smaller and smoother control action than the ESC controller. The smaller control action of the MPC controller leads us to assume that the predictive intervention is less intrusive than the ESC intervention which is accepted by drivers already. This in combination with that the vehicle's motion was actually stable during the whole maneuver, while the ESC intervened only once the vehicle had already become unstable promises great advantage to the predictive approach.

7. CONCLUDING REMARKS

We have considered a general architecture for accident prevention systems and implemented a roadway departure prevention system based on it. The architecture enables exploiting preview capabilities in order to intervene earlier than traditional safety systems. Simulation and experimental results confirm that such an architecture enables earlier, less intrusive interventions with greater capability to keep the vehicle within stable operating regions. This opens up for interesting research activities. Topics which are currently subject of ongoing investigation are on threat assessment, decision making and efficient and non intrusive control design that, in addition, has low computational burden.

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