6th IFAC Symposium Advances in Automotive Control
Munich, Germany, July 12-14, 2010

Set-Based Threat Assessment in Lane Guidance Applications

Paolo Falcone [*] **Mohammad Ali** [*,**] **Jonas Sjöberg** [*]

[*] *Chalmers University of Technology, Dept. of Signals and Systems, 412 96 Göteborg (e-mail: falcone@chalmers.se, jonas.sjoberg@chalmers.se).*
[**] *Volvo Car Corporation, Dept. of Vehicle Dynamics & Active Safety, 96250/PV4A, 405 31 Göteborg (e-mail: mali21@volvocars.com).*

Abstract: We present a model based threat assessment method for semi-autonomous vehicles. Based on the assumption that information about the surrounding environment is available over a future finite time horizon, we first introduce a set of constraints on the vehicle states, which are satisfied under "safe" driving conditions. Then, we use vehicle and driver mathematical models in order to predict future constraints violation, indicating the possibility of accident or loss of vehicle control.
The proposed method is demonstrated in a roadway departure application and validated through experimental data.

Keywords: Threat Assessment, Active Safety, Semi-Autonomous Vehicles, Invariant Sets Theory.

1. INTRODUCTION

In vehicles equipped with classical active safety systems like, e.g, yaw stability control, the vehicle motion within the environment is primarily determined by the driver, whereas the active safety systems merely affect the dynamical behavior of the vehicle.

Advanced Driver Assistance Systems (ADAS), instead, can implement complex accident prevention functions by influencing both the vehicle dynamical behavior and its motion within the surrounding environment. Such advanced active safety functions have been primarily enabled by recent advances in sensing technologies, which led to affordable onboard sensors providing the vehicle position and velocity in a global frame as well as information about the surrounding environment like, e.g., road geometry and relative position and velocity of moving objects. The current trend in the development of ADAS points in the direction of increased authority in controlling the vehicle motion in the environment Mellinghoff et al. (2009). Example of such trend are, e.g., the lane guidance systems assisting the driver in mantaining the vehicle within the lane boundaries, via autonomous braking and steering.

Early lane guidance systems, based on lateral vehicle control, were presented already in Pomerleau (1995). Lateral control for lane guidance and highway automation applications has then been recently further investigated in, among others, Hiraoka et al. (2009); Minoiu E. et al. (2009); Shin et al. (2008); Netto et al. (2004). In Hiraoka et al. (2009) a path tracking controller based on sliding mode control is proposed and demonstrated. In Minoiu E. et al. (2009) the lateral controller is instead derived using LMI and Lyapunov theory. In Shin et al. (2008), the authors implement a lateral controller using backstepping techniques while in Netto et al. (2004) the lateral control problem is solved through an adaptive controller. Most of the mentioned lane guidance approaches can be classified as autonomous driving systems, since they do not account for the presence of the driver. In active safety applications for passengers cars, instead, an intervention (or warning) should be issued if and only if a risk of lane departure (or, in general, accident) is detected, that the driver is not able to avoid. In particular, in an active safety problem, an autonomous driving intervention might be experienced as intrusive by the driver. It is thus essential that autonomous driving is initiated if and only if it is needed. The formulation of transition conditions, between the different modes (e.g., from manual to autonomous driving mode) of a safety system, is not trivial. Hence, active safety problems involve challenges which do not occur in completely autonomous driving problems.

In several lane guidance algorithms, the transition conditions to an autonomous driving mode are formulated based on the *"Time to Line Crossing"* (TLC). This is a tool for representing the threat level and it is among the most common threat assessment approaches in lane guidance applications. In TLC-based lane guidance applications, an intervention or warning is issued once the TLC passes a predefined threshold. An overview and assessment of methods for calculating the TLC is provided in Mammar et al. (2006). Artificial potential fields, instead, are used in the method presented in Rossetter and Gerdes (2002) where lane crossings are prevented, by minimizing cost functions whose value increase as the vehicle approaches the lane boundaries. An optimization based approach, for a semi-autonomous vehicle, is presented in Anderson et al. (2009). Every time step, based on current vehicle state and information about the surrounding environment, a Model

978-3-902661-72-2/10/$20.00 © 2010 IFAC

10.3182/20100712-3-DE-2013.00145

Predictive Controller is used to compute a vehicle trajectory over a future time horizon. An assisting intervention is issued if the computed trajectory is considered hazardous.

In the approaches in Rossetter and Gerdes (2002) and Anderson et al. (2009), the transition criteria, activating the autonomous driving interventions, are based on the evaluation of a controller behavior, rather than the limitations of the driver's ability in staying within the lane. This might lead to initiation of the autonomous intervention, in order to guarantee safe operation of the controller, in situations where the driver does not need assistance. On the other hand, if the controller is outperforming the driver, no intervention might be issued at all.

In this paper, we present a model based method for evaluating the driver's ability in safely performing a desired maneuver. We first introduce a set of constraints describing "safe" driving. Moreover, we assume the road geometry is available over a future finite time horizon and exploit the vehicle and driver modeling in order to predict future constraints violation, indicating the possibility of accident or loss of vehicle control. We demonstrate the proposed method in a roadway departure application, and validate it through experimental data. The paper is organized as follows. In Section 2, we provide basic definitions and results on reachability analysis and set invariance theory. In Section 3, we present the vehicle and driver modeling used next in Section 4, where the threat assessment algorithm is presented. In Section 5, we validate the proposed algorithm through experimental data, while Section 6 closes the paper with final remarks.

2. BACKGROUND ON REACHABILITY ANALYSIS AND SET INVARIANCE THEORY

In this section we introduce few definitions and recall basic results on set invariance theory and reachability analysis for constrained systems. A comprehensive survey of papers on set invariance theory can be found in Blanchini (1999). This section adopts the notation used in Grieder (2004); Rakovic (2005); Kerrigan (2000).

We will denote the set of all real numbers and positive integers by $\mathbb{R}$ and $\mathbb{N}^+$, respectively.

Denote by f_a the state update function of an autonomous system

$$x(t+1) = f_a(x(t), w(t)), \tag{1}$$

where $x(t)$ and $w(t)$ denote the state and disturbance vectors, respectively. System (1) is subject to the constraints

$$x(t) \in \mathcal{X} \subseteq \mathbb{R}^n, \; w(t) \in \mathcal{W} \subseteq \mathbb{R}^d, \tag{2}$$

where $\mathcal{X}$ and $\mathcal{W}$ are polyhedra containing the origin in their interior.

For the autonomous system (1)-(2), we will denote the one-step robust reachable set for initial states x contained in the set $\mathcal{S}$ as

$$\begin{aligned}\mathrm{Reach}_{f_a}(\mathcal{S}, \mathcal{W}) \triangleq \{x \in \mathbb{R}^n \mid \exists x(0) \in \mathcal{S}, \\ \exists w \in \mathcal{W} : x = f_a(x(0), w)\}.\end{aligned} \tag{3}$$

For the nominal system, i.e., $w(t) = 0, \; \forall t$ in (1), the one-step reachable set is defined as

$$\mathrm{Reach}_{f_a}(\mathcal{S}) \triangleq \{x \in \mathbb{R}^n \; |\exists x(0) \in \mathcal{S} : x = f_a(x(0))\}. \tag{4}$$

For the autonomous system (1)-(2), we define the dual of the reachable sets, i.e., the set of states that evolves to $\mathcal{S}$ in one step, as

$$\mathrm{Pre}_{f_a}(\mathcal{S}, \mathcal{W}) \triangleq \{x \in \mathcal{X} \mid f_a(x, w) \in \mathcal{S}, \; \forall w \in \mathcal{W}\}. \tag{5}$$

Similarly, for the nominal system

$$\mathrm{Pre}_{f_a}(\mathcal{S}) \triangleq \{x \in \mathcal{X} \mid f_a(x, 0) \in \mathcal{S}\}. \tag{6}$$

The following definitions are derived from Blanchini (1999); Kolmanovsky and Gilbert (1998).

Definition 1. (Robust positive Invariant Set). A set $\mathcal{O}$ is said to be a robust positive invariant set for the autonomous system (1) subject to the constraints in (2), if

$$x(0) \in \mathcal{O} \quad \Rightarrow \quad x(t) \in \mathcal{O}, \quad \forall t \in \mathbb{N}^+.$$

Definition 2. (Maximal Robust Positive Inv. Set). The set $\mathcal{O}_\infty$ is the maximal robust invariant set of the autonomous system (1) subject to the constraints in (2), if $0 \in \mathcal{O}_\infty$, $\mathcal{O}_\infty$ is a robust positive invariant set and $\mathcal{O}_\infty$ contains all the robust positive invariant sets contained in $\mathcal{X}$ that contain the origin.

3. MODELING

In this section, we present the vehicle and driver mathematical models used in Section 4, as basis of the threat assessment algorithm.

3.1 Vehicle Modeling

Consider the vehicle model sketched in Figure 1. The vehicle motion within the lane, subject to the lateral and yaw dynamics, is described by the following set of differential equations

$$m\dot{v}_y = -mv_x\dot{\psi} + 2\left[F_{y_f} + F_{y_r}\right], \tag{7a}$$
$$J_z\ddot{\psi} = 2[l_f F_{y_f} - l_r F_{y_r}], \tag{7b}$$
$$\dot{e}_\psi = \dot{\psi} - \dot{\psi}_d, \tag{7c}$$
$$\dot{e}_y = v_y + v_x e_\psi, \tag{7d}$$

where m and J_z denote the vehicle mass and yaw inertia, respectively, l_f and l_r are the distances of the vehicle center of gravity from the front and rear axles, respectively, v_x and v_y are the longitudinal and lateral velocities, respectively, in the vehicle body frame, $\dot{\psi}$ is the turning rate, where ψ denotes the vehicle orientation w.r.t. the fixed global frame (X, Y) in Figure 1(a). F_{y_f}, F_{y_r} are the lateral tire forces at the front and rear axles, respectively. In (7c) and (7d), e_ψ and e_y denote the vehicle orientation and position errors, respectively, w.r.t. the road centerline and ψ_d is the slope of the tangent to the curve Γ_d in the point O, i.e., the desired vehicle orientation.

The lateral tire forces in (7a) and (7b) are generated at the tire contact patch and are, in general, nonlinear functions of the vehicle states. Accurate physical modeling of tire forces is quite involving and several models have been