Machine learning-assisted state estimation-based controller design

Supervisors: Thach N. Dinh, Tarek Raïssi (LAETITIA) and Kamel Barkaoui (SYS)

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Contacts: ngoc-thach.dinh@lecnam.net, tarek.raissi@cnam.fr and kamel.barkaoui@lecnam.net

Introduction: The race to develop autonomous vehicles (AV) and advanced driver assistance systems (ADAS) is on. Public institutions and the industry are accelerating AV and ADAS development efforts to get ahead in the race. The design of advanced, intelligent, and efficient ADAS's such as lane keeping assist (LKA), adaptive cruise control (ACC), collision avoidance (CA) and so on has been carried out in many works and successfully implemented. Despite the results already available in the literature, much remains to be done to complete the theory as well as experiments of ADAS. Indeed, the successful integration of these systems in the control design while considering cooperative control between human driver and ADAS together with uncertainties such as state and measurement disturbances remains a challenging issue.

Context: This PhD is a collaborative project between two teams (LAETITIA and SYS) of CEDRIC-Lab and aims to design advanced control and estimation algorithms for ADAS, which can guarantee not only the real-time capability, but also the robustness of the system against external disturbances (e.g. slope, road edge, road/tire fiction, driver reaction etc.), unmeasured states (e.g. sideslip angle) and noisy sensor data. In contrast to the state feedback controller which is frequently used, we focus on dynamic output feedback controller since in almost all practical control applications, a full access to the state of the physical system is neither available for measurements nor practical to measure all of them (e.g., it is too expensive to measure all state variables), see for instance (Sadabadi and Peaucelle, 2016). An observer-based control scheme is a dynamic feedback controller with a two-stage structure (Trentelman and Antsaklis, 2014). First, a virtual sensor (called an observer) of the state variable of the system to be controlled is designed, using the measured output, and known input of the system. This observer generates an estimate of the system state. Next, the state estimate is treated as if it were equal to the exact state of the system, and it is used by a static state feedback controller. Dynamic feedback controllers with this two-stage structure appear in various control synthesis problems for dynamical systems.

Mission: Observer-based Controller

The first objective of the mission is to develop robust estimation algorithms, called set-membership estimators, based on the concepts of guaranteed state estimation. Two main approaches will be considered: interval observers (Dinh et al., 2014; Wang et al., 2018; Dinh et al., 2020) and zonotope estimators (Combastel, 2015). They can be applied to dynamical systems that can be subject to sensor and actuator faults in the presence of noises and disturbances. The second objective of this mission is to develop control methods based on guaranteed state estimation (Dinh and Ito, 2017) to manage the conflict between the human driver and the ADAS. Inspired by (Sentouh et al., 2019), the driver dynamics will be incorporated into the vehicle system for driver-in-the-loop control purposes. Next, the driver-vehicle system can be represented in the form of Takagi-Sugeno (also called quasi-LPV) models (Takagi and Sugeno, 1985). These models represent exactly the dynamics of a given nonlinear system within a compact set of the state space. Using Lyapunov functions, rigorous proofs on stability and performance of nonlinear systems can be demonstrated. The control and observer design can be reformulated as a convex optimization problem. Then, the control law with the feedback gains are computed by solving Linear Matrix Inequality (LMI). Another technical challenge has to be considered in this mission is to include the saturation (magnitude/rate) of input into the control design. Although there exist in the literature solutions using advanced anti-windup design (Tarbouriech and Turner, 2007) and observer-based controller (Liu et al., 2018) to tackle this problem, to the best of our knowledge, this problem is hardly taken into account in robust control design for ADAS and in particular, the guaranteed state estimation-based controller has not been fully investigated. Together with solving LMI, a more updated technique in tuning parameters for above-mentioned guaranteed state estimation-based controller is to employ machine learning in control design to improve the performance and drivability of the system. Employing machine leaning helps to update the feedback gains, control law adaptively over driving styles and measured performance changes using reinforcement learning (Kuderer et al., 2015). This tuning method is a new trend in automatic control and will be a possibly considerable research for the next generation of semi and full-autonomous systems (Sutton and Barto, 2018). The scenarios for full-autonomous vehicles can be modelled with an appropriate formalism. This formalism should be expressive enough for quantifying risks and describing various situations. High-level stochastic Petri nets or multi-agent systems (see for instance Duplouy, 2018) are such candidates.

Application: Safety and Application to V2V

The usefulness of interval estimates is evident for monitoring purposes when large disturbances or uncertainties are present. Monitoring problems will be also carried out when there is not intervention of the human driver, which can be extended to autonomous vehicles. The knowledge of localization uncertainties is of prime importance when the navigation of autonomous vehicles must deal with safety issues (Drevelle and Bonnifait, 2013). This PhD presents a robust estimation method that can quantify the localization confidence based on interval analysis and can open an application to vehicle-to-vehicle (V2V) systems in which vehicles are providing each other with information, such as safety warnings and traffic information. The tradeoff between monitoring, disturbance rejection, robustness with respect to the modeling uncertainties and the vehicle fuel consumption will be studied. The developed control and estimation algorithms will be tested under various driving situations (i.e., highway driving, urban obstacles avoidances, etc.) in simulation.

Timeline: The procedure to arrive at our goals is divided into four work-stages.

- Stage 1 (4 months): Literature review. Study on structural properties of systems to find suitable ones for which interval techniques can be constructed and observer-based controller can be designed.
- Stage 2 (21 months): Accomplish the main mission.
- Stage 3 (6 months): Test the theoretical developments in real-life applications.
- Stage 4 (5 months): Write PhD thesis and prepare for the defence.

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