Abstract

In this thesis, we present novel model predictive control (MPC) formulations based on a convex open-loop optimal control problem to tackle the problem setup of *trajectory tracking* and *path following* as well as the control of *systems with unknown system dynamic*. In particular, we consider the framework of relaxed barrier function based MPC (rbMPC). We extend the existing stability theory to the trajectory tracking and the path following problem. We establish important system theoretic properties like closed-loop stability and exact constraint satisfaction under suitable assumptions. Moreover, we evaluate the developed MPC algorithms by comparing it with a standard controller in the area of automated driving in simulations as well as in real-world for an automated driving scenario. Further, we consider the control of completely unknown systems based on online optimization. We divide the overall problem into the design of an estimation algorithm and a control algorithm. The proposed estimation algorithm does not belong to the class of identification algorithms but can rather be seen as an asymptotically accurate *signal predictor algorithm* of the closed-loop trajectory. The control algorithm is a model-independent receding horizon control algorithm in which important system theoretic properties like convergence to the origin are guaranteed without the knowledge of the true system parameters. The estimation and control algorithm are combined together and convergence to the origin of the closed-loop system for fully unknown linear time-invariant discrete-time systems is shown.

Deutsche Kurzfassung

In der vorliegenden Arbeit werden neue, auf konvexen Optimierungsproblemen basierende modellprädiktive Regelungsverfahren (engl. model predictive control, MPC) untersucht. Ziel ist die Entwicklung von Algorithmen für das *Trajektorienfolgeproblem* und *Pfadverfolgungsproblem* sowie der Regelung von Systemen ohne Kenntnis eines Systemmodells. Dabei erweitern wir die existierende MPC Theorie, basierend auf relaxierten Barrierefunktionen, auf die Problemstellung des Trajektorien- und Pfadverfolgungsproblems. Hier weisen wir wichtige systemtheoretische Eigenschaften wie die Stabilität des geschlossenen Kreises und die exakte Einhaltung von Beschränkungen unter bestimmten Annahmen nach. Zudem vergleichen wir die entwickelten MPC Algorithmen simulativ mit einem Standardregler im Bereich des automatisierten Fahrens und werten Daten einer experimentellen Erprobung aus. Außerdem betrachten wir die optimierungsbasierte Regelung von Systemen ohne Kenntnis eines Systemmodells. Der Lösungsansatz basiert auf dem Entwurf eines Schätzalgorithmus und eines Regelalgorithmus. Dabei gehört der Schätzalgorithmus nicht zur Klasse der Systemidentifikationsalgorithmen, sondern kann als asymptotisch korrekter Signalprädiktor der Trajektorie des geschlossenen Kreises aufgefasst werden. Der Regelalgorithmus gehört zur Klasse der MPC Algorithmen, welcher Konvergenz des geschlossenen Kreis zum Ursprung ohne genaue Kenntnis der Systemparameter garantiert. Schließlich kombinieren wir den Schätz- und den Regelalgorithmus und weisen Konvergenz des geschlossenen Kreis zum Ursprung für linear zeitinvariante Systeme nach.

1
Introduction

1.1 Motivation

Autonomously driving vehicles are one of the main scientific and technological challenges of our time. Basically, there exist different automation levels, starting from no automation to full automation of the vehicle in which the surveillance of the driver is not needed anymore, see E. Yurtserver et al. (2020). From a conceptual point of view, the architecture of autonomous driving consists of three steps: *Sense*, *understand and plan*, and *act*. Sensing refers to the first step and deals with the transfer of environmental data into a digital map based on the available vehicle sensors, e.g., cameras, radars or lidars. Understanding and planning depicts the second step and mainly takes care about the calculation of a safe trajectory based on the digital map. Finally, the acting step considers the control of a vehicle by steering, braking and accelerating commands such that the deviation to the trajectory, calculated in the sensing step, is minimal. The topic addressed in this thesis is motivated by automated driving on test tracks. In particular, we like to focus on the development process of a vehicle. There, the vehicle has to successfully pass several tests, e.g., endurance tests, high speed tests or braking tests before it is delivered to the customer. These tests are carried out by trained drivers on either public streets or non-public proofing grounds to ensure public safety. In case of non-public proofing ground tests, the driver typically aims to drive a given driving line as reproducible as possible in a repetetive manner. However, given that the driver only remembers the most important points of the test run, he or she will make non-reproducible errors. Hence, it is difficult to locate the error source that originates from either the test driver or a defective part of the vehicle. Thus, it is desirable to tackle this problem by replacing the driver by an algorithm tailored for automated driving to ensure reproducability between the different test runs.

In this thesis, we apply MPC to certain tasks in an automated driving scenario. We will use here the term automated driving and not autonomous driving, given that we only deal with the acting step of the autonomous driving architecture. MPC, also referred to as *receding horizon control*, is a model-based control method in which a suitable control input is obtained by solving online an open-loop optimal control problem. Herein, a user-defined cost criterion along a specific prediction horizon is minimized under the explicit consideration of certain state and input constraints. Owing to the flexibility of the user-defined cost criterion, many industrial control tasks have been so far addressed using an MPC formulation such as the control of an industrial servo machine tool drive, see M. Stephens and M. Good (2013), the control of a chemical reactor, see M. Bakosova and J. Oravec (2014), or the control of an automated driving vehicle, see B. Gutjahr, L. Gröll and M. Werling (2017). For a survey paper about the challenges and opportunities of MPC in industrial applications, we refer to M. Forbes et al. (2015). A driver acts in many ways similar to MPC. Not only does MPC naturally provide a prediction horizon, it also enables us to include the vehicle dynamics as well as physical constraints such as acceleration constraints. Thus, it is a natural choice to use MPC in auomated driving scenarios. Nevertheless, standard MPC formulations have two disadvantages. On the one hand, the online solution of the open-loop optimal control problem requires high computational effort but at the same time has to satisfy hard real-time requirements. This might be problematic implementing the algorithm on low-cost ECUs (electronic control unit). On the other hand, consider a real system in which, in almost any case, the prediction model of the MPC formulation is not exactly capturing the real system behaviour. Operating at the limit of the imposed constraints, the mismatch between the prediction model and the actual system behaviour may lead to constraint violation and thus to an infeasible optimization problem and instabilities. One promising approach to overcome these issues is *relaxed barrier function* MPC (rbMPC), which enjoys desirable properties like convergence guarantees under suboptimal inputs, robustness properties, exact constraint satisfaction under certain initial conditions, and feasibility even if the constraints are violated. For an overview of this topic, we refer the reader to C. Feller and C. Ebenbauer (2016, 2017, 2020) and C. Feller (2017). However, so far, a proper control and systems theoretic investigation of an rbMPC setup tailored for the problem class of automated driving is not available in literature. Hence, we will investigate rbMPC formulations which can be used for automated driving. In particular, we focus on two main problem formulations to follow a desired driving line at a specific velocity profile. One is the so-called *trajectory tracking* problem, and the other one refers to the so-called *path following* problem. In a trajectory tracking problem setup, one tries to track a time-varying trajectory in which the timing of the trajectory is implicitly predefined by the trajectory itself. In the path following problem, one likes to track a geometric path where the timing on this geometric path is left an additional degree of freedom to the controller. Path following allows, e.g., to overcome certain performance limitations, see A. Aguiar, J. Hespanha and P. Kokotovic (2005) for nonminimum phase systems in case of unstable zero dynamics. Due to the fact that some of the applied control energy must be used for its stabilization.

The control performance of an MPC algorithm is highly depending on the used prediction model, or, in terms of the driver, directly corresponds to how well he or she knows the vehicle dynamics. The better the prediction model fits the actual system behavior, the better the transient behavior of the closed loop will be. However, models are never exact and become often uncertain where modeling of the decisive effects is hard or expensive in time and cost. This is true for a wide range of industrial applications. In the case of an automated driving vehicle, this is important for the high dynamics area, where for example, the tire slip curve is located in its nonlinear region, see for example H. Pacejka (2012) and thus the tire model becomes inaccurate. Hence, this motivates us to investigate an MPC formulation where the prediction model is learned online via input and output data. Many different approaches exist in the adaptive control and learning literature consisting of model-free approaches and model-based ones, see G. Goodwin and K. Sin (2009); G. Tao (2014); M. Benosman (2016). A quite common procedure in the control of unknown systems is to divide the overall control task into a control scheme and an estimation scheme. This strategy is also pursued in this thesis. However, in contrast to the existing literature, see P. Tabuada and L. Fraile (2020); T. Nguyen et al. (2020); V. Adetola, D. DeHaan and M. Guay (2009), we develop a fully online optimization-based solution for the estimation and control scheme with provable convergence to the origin of the closed-loop system for completely unknown linear time-invariant discrete-time systems.

1.2 Contribution and outline

In this section, we will summarize the main contributions of the thesis and we will give a brief outline of the thesis's structure. The main contributions consist of two parts. In the first part, in Chapter 2, we extend the theory of relaxed barrier functions to the *trajectory tracking* and *path following* problem. We exploit the properties of relaxed barrier functions to guarantee important system-theoretic properties like *closed-loop stability* and *exact constraint satisfaction* for a certain set of initial conditions under rather mild assumptions for linear time-invariant discrete-time systems. Further, we apply both algorithms to numerical examples to illustrate the theoretical results. In the second part, in Chapter 3, we consider the stabilization of the origin of fully unknown linear time-invariant discrete-time systems. We divide the problem into an *estimation problem* and a *control problem*. For the estimation algorithm, we design an optimization algorithm based on a proximal minimization algorithm. The estimates do not necessarily converge to the true system parameters and thus the estimator does not belong to the class of model identification algorithms but can rather be seen as an asymptotically accurate *signal predictor algorithm* of the closed-loop trajectory. For the control algorithm, we design a new model-independent receding horizon control scheme. We prove convergence to the origin for a certain class of prediction models without the knowledge of a system model. Therefore, we refer to the control algorithm as a *modeling-free* receding horizon control policy. Further, we combine both schemes into a full online optimization control scheme and show convergence to the origin of the closed loop under certain assumptions. We provide a strict convergence analysis to the origin for unknown linear time-invariant discrete-time systems. Finally, we show the potential of the proposed algorithm for nonlinear systems.