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Distributed nonlinear model predictive control of an autonomous tractor–trailer system

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ABSTRACT

This paper addresses the trajectory tracking problem of an autonomous tractor–trailer system by using a fast distributed nonlinear model predictive control algorithm in combination with nonlinear moving horizon estimation for the state and parameter estimation in which constraints on the inputs and the states can be incorporated. The proposed control algorithm is capable of driving the tractor–trailer system to any desired trajectory ensuring high control accuracy and robustness against environmental disturbances.

1. Introduction

The basic idea behind automating agricultural production machines, *e.g.* an autonomous tractor–trailer system, is not only the fact that energy and labor costs are increasing day by day but also farmers need durable accurate and reliable production machines. However, the steering accuracy of these machines decreases when the operator gets tired or has to perform other tasks apart from driving the tractor like operating mounted trailers. In such cases, advanced control algorithms are more than welcome. This has resulted in several automatic guidance systems, of which some are already available on the market.

Today's fast moving technology allows us the application of real time kinematic (RTK)–global positioning systems (GPSs) which can provide an accurate positioning accuracy of a few cm. Nonetheless the performance of the currently available machine guidance systems is rather limited due to the poor performance of the automatic control systems used for this purpose. The main reasons for this poor performance are the complex vehicle dynamics and the large variation in soil conditions which make that the conventional (*e.g.* PID) controllers for machine guidance have to be tuned very conservatively. By conservative tuning, robustness of the controller is obtained at the price of performance. Moreover, the constraints of the mechanical system cannot be taken into account directly in these controllers, such that the ad hoc implementation of these constraints can lead to suboptimal behavior of the system. In such cases, advanced control algorithms which can deal with constraints on the states and the inputs are coherent preferences for the control of complex outdoor vehicles.

Applied to agricultural machinery, model predictive control (MPC) has several advantages over conventional controllers, *e.g.* they can deal with the constraints on the system and actuator saturation. The main goal of MPC is to minimize a performance criterion with respect to constraints of a system's inputs and outputs. The MPC caught the attention of researchers in the 1980s, and the first MPC controllers were implemented in the process industry which has less stringent real-time requirements due to large sampling periods in the order of seconds or minutes [1]. The reason for a such a preference is that MPC depends upon repetitive online solution of an optimal control problem.

Large scale complex systems can be divided into a finite number of subsystems. Real-life applications may be continuous (power networks, sewer networks, water networks, canal and river networks for agriculture, etc.) or discrete (traffic control, railway control, etc.) [2]. The common approach to control these systems is the use of a decentralized control approach, *e.g.* decentralized MPC in which the interactions between the subsystems are considered as disturbances to each subsystem. As these controllers are not aware of the interactions with other subsystems, they will

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exhibit selfish behavior leading to suboptimal performance of the global system. An alternative solution is the use of a centralized control approach, *e.g.* centralized MPC. However, centralized MPC design for such a complex large scale system may not be practical due to the computational requirements or to the impossibility of obtaining a centralized model of the whole system including all the subsystem interactions. Besides, the computational complexity, another disadvantage of the centralized control approach is that all subsystems have to trust one central controller which is difficult to coordinate and maintain [3]. One way of addressing such problems is to use of distributed MPC in which the overall system is controlled by local MPCs based on a limited information about the system to be controlled or a partial state information [4]. Roughly speaking, whereas this type of control approach consisting of several local agents requires less computational power when compared to its centralized counterpart, the overall control accuracy of the system highly depends on the cooperation and communication between the local agents.

As an agricultural production machine, a tractor–trailer is a complex mechatronic system which consists of several subsystems that interact with each other as a result of energy flows. For instance, the diesel engine, the steering system of the tractor and the steering system of the trailer share the same hydraulic oil. As a result, once an input is applied to one of the subsystems, it always affects the others. Considering the disadvantages of decentralized and centralized control approaches mentioned above, complex mechatronic systems, such as a tractor–trailer, are the worthwhile considering distributed control approach since the design of robust and accurate controllers for such systems is not a straightforward task due to their highly nonlinear dynamics [5].

Researchers have recently been focussing on distributed control in which some limited information is transmitted among local agents. In distributed MPC, the optimization problem is broken into smaller pieces under the assumption of solving many small problems is faster and more scalable than solving one large problem [6]. A detailed survey about the architectures for distributed and hierarchical MPC can be found in [7]. There are two main approaches to distributed control: Independent distributed control [8,9] and cooperative distributed control [10,11]. While in the former, each subsystem agent considers network interactions only locally resulting into a Nash equilibrium for the performance of the system, in the latter, all local control actions actions are considered on all subsystems resulting into a Pareto optimum [12]. So, in independent distributed NMPC (iDiNMPC), the cost function of each subsystem consists of only the states of the local subsystem. On the other hand, in cooperative distributed NMPC (cDiNMPC), the cost function of each subsystem consist of the states of the overall system dynamics. An iterative cooperative distributed case was proposed in [3]. It has been shown in [3] that the communication between subsystems and using the global cost function result converging to the one of the corresponding centralized control case as the iterations number increases. Since the trajectory following accuracies of both the tractor and the trailer are essential in an agricultural operation, the latter approach is followed in this paper.

In this paper, a DiNMPC with the *ACADO* code generation tool [13,14] for the trajectory tracking problem of an autonomous tractor–trailer system has been developed and tested in real-time in the presence of several uncertainties, nonlinearities and biological variabilities. Although a tractor–trailer system is relatively less complex when compared to other large-scale systems (power networks, etc.), short times for optimization are crucial for such a mechatronic system. Since the optimization problem of NMPC is a complex problem and it is time-consuming, the main goal of this study is to design a fast NMPC for the tractor–trailer system. To succeed, the following selections have been made:

1. The use of a kinematic model instead of a dynamic model.
2. The use of C++ source files to realize the control algorithm in real-time.
3. The use of the distributed control algorithm instead of a centralized one.

Thanks to the selection above, the feedback times of the cDiNMPC and iDiNMPC are around 7 ms and 3 ms, respectively.

This paper has been organized as follows: The kinematic model of the system is presented in Section 2. The basics of the implemented DiNMPC and the learning process by using a nonlinear moving horizon estimation (NMHE) method have been explained in Section 3. The experimental set-up and the experimental results are described in Section 4. Finally, some conclusions have been drawn from this study in Section 5.

2. Kinematic tricycle model of a tractor–trailer system

The schematic diagram of an autonomous tractor–trailer system is presented in Fig. 1.

The model for the autonomous tractor–trailer system is *a kinematic model* neglecting the dynamic force balances in the equations of motion. A dynamic model would, of course, represent the system behavior with a better accuracy, but then a system identification and multibody modeling techniques would be needed for obtaining an accurate dynamic model of the system. Moreover, a dynamic model would increase the computational burden in the optimization process in DiNMPC. Thus, an extension of a simpler well-known tricycle kinematic model in [15,16] has been used for the DiNMPC design in this paper. The extensions are the additional three slip parameters (μ, κ and η) and the definition of the yaw angle difference between the tractor and the trailer by using two angle measurements (δ^i and β) instead of one angle measurement.

The equations of motion of the system to be controlled are as follows:

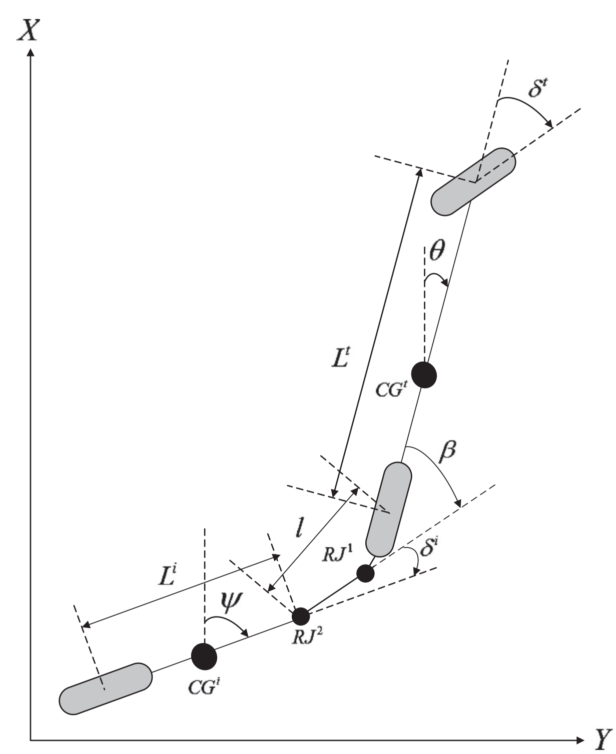

Fig. 1. Schematic illustration of tricycle model for an autonomous tractor–trailer system.