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MPC-based control architecture of an autonomous wheelchair for indoor environments

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ABSTRACT

In this paper a linear MPC control scheme is proposed to address the motion problems of an autonomous wheelchair in a realistic environment. Thanks to an inner feedback-linearizing loop, the formulation of the model predictive control problem is simplified, allowing for a real-time computationally-efficient implementation. Thanks to the MPC framework, constraints like obstacle avoidance, actuator limitations, and passenger comfort have been included in the optimization problem. Experimental results show the effectiveness of the proposed scheme.

1. Introduction

In many application domains, autonomous and semi-autonomous vehicles play a fundamental role, e.g., in air (Alexis, Nikolakopoulos, & Tzes, 2012; Dydek, Annaswamy, & Lavretsky, 2013; Ryll, Bülthoff, & Robuffo Giordano, 2015), sea (Cervantes, Yu, Salazar, Chairez, & Lozano, 2016; Millán, Orihuela, Jurado, & Rubio, 2014), land (Hu, Wang, Yan, & Chen, 2016; Wang, Jing, Hu, Yan, & Chen, 2016), and space (Truszkowski, Hinchey, Rash, & Rouff, 2006) explorations, in operations in dangerous and/or unknown environments, in mine detection, in agricultural applications (Liu, Wang, & Zhou, 2008), in the Ambient-Assisted Living (AAL) field (Celeste, Filho, Filho, & Carelli, 2008; Sinyukov & Padir, 2015), and they are also envisaged as promising solutions for enhancing road safety (Cavanini, Benetazzo, Freddi, Longhi, & Monteriù, 2014; Guo, Hu, & Wang, 2016; Lefèvre, Carvalho, & Borrelli, 2016). In particular, control in AAL is crucial to improve the life quality of – especially elderly and physically impaired – people, e.g., in home and hospital environments (Cavanini et al., 2014; He et al., 2017; Leaman & La, 2017; Li et al., 2017; Parikh, Grassi, Kumar, & Okamoto, 2007; Zhang et al., 2016).

Autonomous vehicles are sophisticated systems, endowed with advanced sensing, actuation, processing, and data transmission capabilities. As far as the software is concerned, a large number of algorithms must run in parallel and in real-time (including, e.g., localization, object and obstacle recognition, and a complex hierarchical control structure including a number of different planning and control layers) to provide efficient, reliable, robust, and safe operation. At the core of these complex systems lies a control algorithm, that aims at conferring to the vehicle robust stability and suitable performance levels in different control tasks, e.g., parking, trajectory tracking, obstacle avoidance, etc.

The approaches traditionally used by the robotics community for trajectory tracking and collision avoidance of mobile robots and autonomous vehicles are based on the Dynamic Window Approach (DWA) (Fox, Burgard, & Thrun, 1997) and on the Timed Elastic Band (TEB) (Rösmann, Feiten, Wösch, Hoffmann, & Bertram, 2012, 2013; Rösmann, Hoffmann, & Bertram, 2015) algorithms. DWA is based on the online definition of an optimal control action by sampling the control space, generating feasible paths and choosing the best one between them based on an optimality criteria. TEB, instead, takes the initial trajectory generated by a planning algorithm and performs and online optimization minimizing the trajectory execution time, separation from obstacles and compliance with kinodynamic constraints such as satisfying maximum velocities and accelerations.

Besides usual control tasks, like trajectory tracking or parking, other control specifications, e.g., smooth acceleration and deceleration profiles and collision avoidance requirements, must be properly formulated to guarantee safety and comfort. Model Predictive Control (MPC) (Rawlings & Mayne, 2009) has gained interest, in the past decade, in the

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field of autonomous vehicle control, in view of the possibility to cast the motion problems into optimization ones, where operational constraints can be enforced and where predictions can be included. Indeed, MPC allows to develop modular control strategies, where the aforementioned requirements can be formulated in terms of constraints or elements of the cost function, that can even support different operating scenarios, e.g., wheelchair indoor navigation and sidewalk or road driving, by changing on the fly constraints or cost function elements. It is worth noting also that robust MPC implementations are also available, to account for disturbances and model inaccuracies (Rawlings & Mayne, 2009).

In the context of MPC-based autonomous vehicle control, in many works a hierarchical scheme is proposed, consisting of (i) a (event based or slow timescale) local planner that guarantees obstacle avoidance features, possibly based on a rough vehicle mathematical model and (ii) a low-level (path-following) controller, based on a high-fidelity mathematical model. For example, in Falcone, Borrelli, Asgari, Tseng, and Hrovat (2007) this scheme is applied to a 6-states bicycle model with constant wheel angular speed. For numerical complexity reduction, the model is linearized at each time step around the current operating point, leading to a LTV system. Related works (Gao et al., 2012; Gao, Lin, Borrelli, Tseng, & Hrovat, 2010; Gray et al., 2012) propose different solutions for local planning. In Bernardini, Cairano, Bemporad, and Tseng (2009) and Palmieri, Barbarisi, Scala, and Glielmo (2009) dynamic path following layers, similar to the one developed in Falcone et al. (2007), are developed also for lateral dynamics, side-slip control, or yaw rate reference tracking, based on full vehicle models. Also in Katriniok and Abel (2011), a similar low-level stabilizing controller is proposed, to work at the limits of the model dynamics, and where the linearized prediction model proposed in Falcone et al. (2007) is performed, at each time step, not about the current operating point, but about future estimated trajectories, resulting in a time-varying prediction model. A robust low-level MPC implementation is proposed in Bahadorian, Savkovic, Eaton, and Hesketh (2012) using a bicycle model, linearized about the reference trajectory to be tracked. In Raffo, Gomes, Normey-Rico, Kelber, and Becker (2009) a similar hierarchical scheme is proposed: a linear MPC-based local planning (called vehicle guidance) level is devised using the linearized kinematic model of the Ackermann steered vehicle, controlling position and orientation using the desired steering angle as control variable; the dynamic control layer aims to control the yaw rate and the chassis side-slip.

In later works the two levels (i.e., local planner and path follower) are fused together. In Frasch et al. (2013) a nonlinear MPC (NMPC) algorithm solved online with advanced numerical optimization allows to account for obstacle and road traffic constraints, modeled as bounds on the state vector. Here a four-wheel vehicle dynamical model with wheel dynamics and load transfer is used, transformed to a position-dependent one, which is also the approach taken in Plessen, Bernardini, Esen, and Bemporad (2018). In Gao, Gray, Carvalho, Tseng, and Borrelli (2014), a robust tube-based MPC strategy is used considering LTV models, while in Lenz, Kessler, and Knoll (2015) chance constraints are used for comfortable and safe driving. In Ji, Khajepour, Melek, and Huang (2017) and Rasekhipour, Khajepour, Chen, and Litkouhi (2017), the reference trajectory is defined based on a potential field, considering both the goal and the obstacles. General theoretical grounds for trajectory-tracking and path-following controllers are established in Alessandretti, Aguiar, and Jones (2013) and Faulwasser and Findeisen (2016).

Note that distributed MPC-based schemes have also been developed for vehicle formation stabilization (Chen, Sun, Yang, & Chen, 2010; Dunbar & Murray, 2006; Keviczky, Borrelli, Fregene, Godbole, & Balas, 2008), multi-vehicle guidance (Kuwata, Richards, Schouwenaars, & How, 2007), multiple vehicle coordination (Farina, Perizzato, & Scattolini, 2015; Xie & Fierro, 2007).

With specific reference to control of the unicycle-type model, which is the one considered in this paper, two main approaches are taken. For reference trajectory tracking, the most common approach consists of linearizing the tracking error model around the reference trajectory. This approach is taken, e.g., in Kühne, Lages, and Gomes Da Silva (2004) and in Bahadorian et al. (2012) and Gonzalez, Fiacchini, Guzman, and Alamo (2009), where robust MPC is used. On the other hand, the NMPC is adopted for point stabilization (Kühne, Lages, & Gomes Da Silva, 2005; Xie & Fierro, 2008) and for general problems (Gu & Hu, 2006; Maniatopoulos, Panagou, & Kyriakopoulos, 2013). In these papers, collision avoidance constraints are not addressed, but only state convex regions are admitted, including the field-of-view state constraints defined in Maniatopoulos et al. (2013).

In this work we rely on linear models thanks to a standard feedback linearization procedure, similar to the one adopted in Oriolo, De Luca, and Vendittelli (2002) and in Farina et al. (2015); this approach allows to formulate operational, comfort, and collision avoidance requirements as linear constraints: the MPC optimization problem can be thus greatly simplified, allowing for real-time efficient implementation, as witnessed by the experimental results.

Note, however, that in Farina et al. (2015) the proposed control approach is a distributed one, tailored for completing multi-agent tasks (e.g., formation control and coverage), and that it is applied to a team of small-scale educational unicycle robots, with no real realization problems (e.g., localization, real-time implementation in the ROS platform, actuation).

A preliminary control scheme for wheelchair control based on this approach and preliminary results can be found in Ceravolo, Gabellone, Farina, Bascetta, and Matteucci (2017). The present work, however, besides including more thorough discussions, presents the overall control scheme (including localization, planning, and obstacle detection functionalities) in a more rigorous and comprehensive fashion, as well as the implementation/realization choices. Also, it essentially differs from the preliminary paper (Ceravolo et al., 2017) in many respects. For example, the control scheme has been implemented in C++ and embedded, in the form of a local planner, in the Robot Operating System (ROS) (Quigley et al., 2009) standard navigation stack. Also, in this work we have performed a number of new, more comprehensive, and more realistic experimental tests, including a test where two persons are moving in the working area.

The paper is organized as follows. Section 2 describes the model of the system under control, the actuator dynamics, the feedback linearization procedure, and the main regulator structure. Section 3 focuses on the MPC control problem, including the definition of the cost function and of the constraints, while Section 4 introduces some implementation details. Section 5 shows significant experimental tests, while conclusions are drawn in Section 6. Finally, in Appendix, some technical details on the feedback linearization procedure are given.

2. Feedback linearization and control-oriented model of the wheelchair dynamics

In this section we first introduce the nonlinear kinematic model of the wheelchair, showing the results of the actuator identification phase. Moreover, we describe how an internal control loop for the wheelchair is designed, based on the feedback linearization technique, to obtain a versatile discrete-time linear control-oriented model, to be used by a suitable MPC control algorithm.

2.1. Unicycle model

From a kinematic point of view, the motion of a wheelchair can be represented using the *unicycle* nonlinear model, i.e.,

$$\begin{cases} \dot{x}(t) = v_{\text{long}}(t)\ \cos\theta(t) \\ \dot{y}(t) = v_{\text{long}}(t)\ \sin\theta(t) \\ \dot{\theta}(t) = \omega(t) \end{cases} \tag{1}$$

where $x(t)$, $y(t)$ and $\theta(t)$ are the state variables representing the wheel axle center position and orientation in the global reference system (see Fig. 1). The input variables are commonly the longitudinal and angular velocities $v_{\text{long}}(t)$ and $\omega(t)$, respectively.