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Hierarchical Model Predictive Control for Autonomous Vehicle Area Coverage

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Abstract: Area coverage using autonomous vehicles receives increasing attention due to a widespread range of possible applications. Examples are surveillance and monitoring tasks or search and rescue missions. Efficient and safe area coverage in dynamic environments, however, is challenging. It requires tight integration of the planning and control task to guarantee collision avoidance and optimal coverage. We propose a combination of two coupled model predictive controllers for optimal area coverage with dynamic obstacle avoidance. The planning is based on a mixed integer programming formulation of the predictive controller. It allows to take dynamic objects, such as other autonomous vehicles into account and considers a simplified dynamic model of the autonomous vehicle. The autonomous vehicle itself is controlled by a continuous time nonlinear model predictive path following controller, which obeys detailed dynamic and kinematic constraints and follows the provided path. The design of the controllers takes the interconnections in terms of dynamic constraints and reference definitions between them into account. Simulation results for a quadcopter illustrate the performance and real-time feasibility of the proposed hierarchical predictive control strategy.

Keywords: Area coverage, Autonomous Vehicles, Model Predictive Control, Path Planning, Path Following Control, UAV.

1. INTRODUCTION

Area coverage performed by autonomous vehicles such as quadcopters or mobile robots receives increasing attention. It makes dangerous tasks safer for the humans, decreases cost of operation and can lead to an increase in flexibility. Applications span from agriculture (Richards, 2018), to cleaning robots (Miao et al., 2018) and search and rescue missions (Liu and Nejat, 2013). Coverage path planning

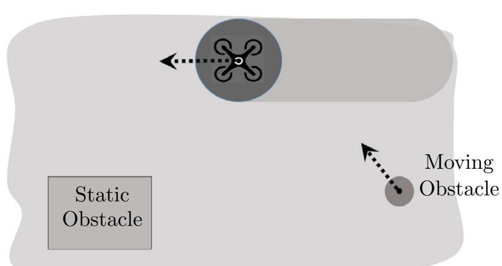

Fig. 1. Considered coverage problem: An area (light grey) should be covered by the sensors of an autonomous vehicle avoiding static and dynamic objects.

and control aims (c.f. Fig. 1) to find a suitable path and corresponding autonomous vehicle inputs to completely cover an area while minimizing a cost, such as energy (due to limited battery capacities) or time needed to cover an area. Furthermore, constraints such as maximum vehicle acceleration or representations of dynamic obstacles to avoid collisions should be considered. Increasing performance demands and increasingly dynamic environments require the path planning and control to be closely interwoven, taking all available information, such as preview data from sensors and detailed dynamic models into account.

Much research has been done in the field of path planning for area coverage, see e.g. (Galceran and Carreras, 2013; Bormann et al., 2018). However, often the system dynamics of the autonomous vehicle or of the dynamically changing environments are not or only indirectly considered. Rather it is often assumed that the lower level controller will take care of the dynamics and keep the autonomous vehicle close to the planned path and that the path can be re-planned sufficiently fast if the environment changes. As speed and performance demands increase, this separation of planning and control becomes challenging, leading to possibly unsafe overall behavior of the autonomous vehicle. Area coverage path planning considering static obstacle avoidance was considered in e.g. (Xu et al., 2011), and (Broderick et al., 2014), using hierarchical and optimization based approaches. Online coverage path planning and control subject to moving obstacles was considered in (Hsu et al., 2014), while the system dynamics were only considered in the control layer (not planning). Model predictive control (MPC) using Mixed Integer Linear Programming

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(MILP) for optimal trajectory generation was investigated in (Trodden and Richards, 2008; Pinto and Afonso, 2017; Richards and How, 2003; Culligan et al., 2007).

The main contribution of this paper is a strategy for combined, optimization-based, reactive online planning and control for area coverage in dynamic environments. We propose to combine MILP based path generation with model predictive path following (Matschek et al., 2019). This allows to adjust the speed of the vehicle along the path in the control layer instead of pre-defining it in the planner as was done in the mentioned previous works. Doing so leads to an optimized online area coverage planning and control conglomeration allowing to handle dynamic obstacle and thus collision avoidance. More specifically (c.f. Fig. 2), we utilize a linear MPC with discrete decision variables to obtain a collision free path. This path is provided to a Nonlinear MPC (NMPC) which can exploit a detailed, continuous time model of the autonomous vehicle to follow the derived path. This hierarchical separation allows to meet real time requirements. However the contribution of the paper is to outline this new combined concept rather than performing hardware experiments or giving detailed stability proofs.

The remainder of the paper is structured as follows: MPC path planning using MILP is presented in Section 2.1. Section 2.2 outlines the continuous time NMPC path following. The overall approach is illustrated with an unmanned aerial vehicle example in Section 3. Conclusions and directions for future work are given in Section 4.

2. HIERARCHICAL PREDICTIVE CONTROL

Model predictive control (MPC) is a control strategy that, by taking into account a model of the system to be controlled, solves repeatedly a finite horizon optimization problem subject to state and input constraints (see e.g. (Findeisen and Allgöwer, 2002; Grüne and Pannek, 2017)). We exploit MPC formulations on both, the planning and

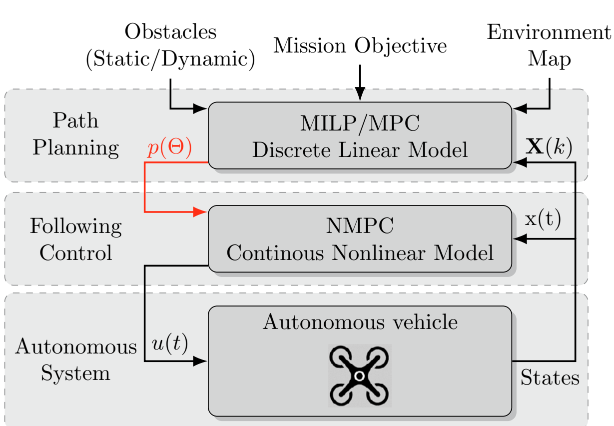

Fig. 2. Proposed hierarchical MPC strategy.

the control layer, c.f. Fig. 2, providing real-time feasible area coverage while avoiding collisions in dynamic environments. On the planning level a linear MPC formulation with a sampling time T_{d} for repeated path planning is designed, which includes continuous and discrete decision variables. The discrete decisions “schedule” waypoints which should be visited thereby constructing the path,

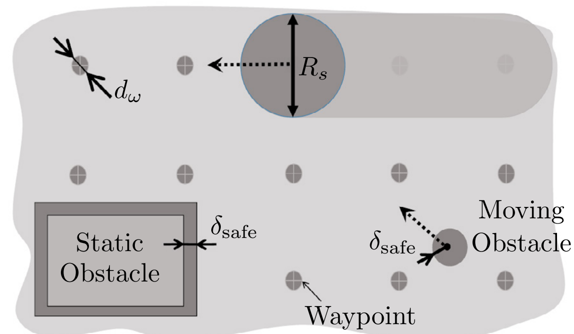

Fig. 3. The area to be covered is divided in cells, each containing a waypoint which should be visited. d_w defines a relaxation threshold, allowing deviation from these waypoints for the visit of the autonomous vehicle, which has a sensor range R_s. Static and dynamic obstacles should be avoided with safety margin δ_{safe}.

which should be followed. Based on the planned path, a nonlinear continuous time MPC, with a sufficiently small sampling time T_{s}, is used to achieve path following of the derived path and stabilization of the autonomous vehicle.

2.1 MPC based Path Planning using MILP

As often done in path planning, see e.g. (Galceran and Carreras, 2013), we divide the area to be covered in cells, each containing a waypoint, c.f. Fig. 3.

The number of the waypoints is a function of the sensors range of the autonomous vehicle and the desired precision. Based on the defined waypoints the planning algorithm finds a path which covers a maximum number of waypoints online. We propose to use an optimization-based planner, in which the visited waypoints are represented by discrete decision variables. The movement between the waypoints is parametrized by continuous decision variables taking simplified vehicle dynamics into account. Consequently, the path planning problem becomes a mixed-integer problem. To obtain a computationally feasible optimization problem, we consider simplified, discretized vehicle and moving obstacle dynamics. The objective of the planner is to find a plausible, i.e flyable/moveable path that minimizes the uncovered area by solving (in real-time) an optimization problem subject to a cost function (such as energy consumption) while satisfying constraints that represent the capability of the autonomous vehicle. Overall the resulting optimization problem can be formulated as:

$$\min_{\mathbf{X},\mathbf{U},\mathbf{D},\mathbf{C}} J(\mathbf{U}(k), \Phi(k)) \tag{1a}$$

subject to ($\forall k \in \{1, \ldots, N\}, \forall i \in \{1, \ldots, N_p\}$)

$$\mathbf{X}(k+1) = A\mathbf{X}(k) + B\mathbf{U}(k), \tag{1b}$$

$$\mathbf{X}(k) \in \bar{\mathbf{X}}(k), \quad \mathbf{U}(k) \in \bar{\mathbf{U}}(k), \tag{1c}$$

$$\Phi_i(k+1) = \Phi_i(k) - c_i(k) \tag{1d}$$

$$c_i(k) \leq d_i(k) \tag{1e}$$

$$0 \leq \Phi_i(k) \leq 1 \quad 0 \leq c_i(k) \leq 1 \tag{1f}$$

$$d_i(k) = 1 \Rightarrow \|r^i - r(k)\| \leq d_w. \tag{1g}$$

Here, J denotes the cost function, N denotes the planning horizon and N_p is the number of waypoints. We assume that the autonomous vehicle dynamics, i.e. the coupling of the states $\mathbf{X}$ and inputs $\mathbf{U}$ at current time k to the