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Autonomous Driving of a Mobile Robot Using a Combined Multiple-Shooting and Collocation Method

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Abstract: A nonlinear model predictive control (NMPC) approach for steering an autonomous mobile robot is presented. The vehicle dynamics with a counter steering system is described by a nonlinear bicycle model. The NMPC problem is formulated taking into account the obstacles description as inequality constraints which will be updated at each sampling time based on a laser scanner detection. The nonlinear optimal control problem (NOCP) is efficiently solved by a combined multiple-shooting and collocation method. Experimentation results illustrate the viability of our approach for active autonomous steering in avoiding spontaneous obstacles.

Keywords: Autonomous mobile robot, bicycle model, obstacle detection and avoidance, nonlinear model predictive control.

1. INTRODUCTION

In recent years, obstacle detection and avoidance as well as lane-keeping have become major issues in studies on autonomous vehicle driving. Model predictive control (MPC) has been proved as a promising control strategy with many desired features. Unlike pre-mission planning and offline design of nominal references, MPC provides adaptive control strategies based on the actual and spontaneous traffic situation, leading to a higher level of system autonomy and robustness. There is a variety of MPC approaches to autonomous vehicle steering, differing in models used, application purposes, optimization problems formulated, numerical solution techniques, applied software, etc.

A predictive control approach was reported by Keviczky et al. (2006) where a nonlinear bicycle model with constant tire forces and a tire model considering the interaction between tractive force and cornering force in combined braking and steering were used. An Euler method was employed to discretize the optimal control problem where the steer angle was used as the control variable. The problem was solved with commercial software in different simulation scenarios.

Kim et al. (2014) proposed an MPC-based path tracking algorithm including steering actuator dynamics. The problem was solved by a quadratic programming method. Various scenarios of simulation results concerning prediction and control horizon lengths, model order of the steering system, and speed were reported.

A tube-based robust nonlinear MPC (NMPC) approach was suggested by Gao et al. (2014) for lane-keeping and obstacle avoidance. The approach is based on a control law where nominal states and controls are gained from a nominal NMPC and an offline calculated robust invariant set. Both simulation and experimentation results were given for obstacle avoidance.

Using an extended bicycle model with lagged tire force for better prediction accuracy, the work of Choi and Choi (2014) addressed electronic stability control relying on MPC. Based on the nonlinear model, a reference trajectory is generated to maintain the vehicle yaw stability. To avoid the computational burden in satisfying state inequalities, the reference strategy is followed applying a linear MPC which can easily be obtained in a closed form.

Further references concerning the ground traffic of autonomous vehicles and also using MPC techniques are e.g. Kim and Kumar (2014), Schildbach and Borelli (2015).

The basic idea of an NMPC problem is to transfer the optimal control problem using a discretization method into a nonlinear program (NLP). It is well known that an essential limitation of applying NMPC is due to its long computation time taken to solve the NLP at each sampling time. In general, the computation time should be much less than the sampling interval of the NMPC scheme. Therefore, it is highly desired to enhance the computation efficiency for solving the NLP. To this end, the method used for discretization plays an essential role. However, the simplest Euler method was employed in almost all previous studies on MPC-based autonomous steering vehicles. But this method has been known as being inefficient for discretizing dynamic systems, Aktas and Stetter (1977), Ascher et al. (1979).

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Therefore, the aim of this study is to implement a highly efficient numerical approach for online solving the NMPC problem and to experimentally verify it on a mobile robot. The mobile robot is modeled by a nonlinear bicycle model. Obstacles are occurring spontaneously from the robot's viewpoint. Using a laser scanner, the obstacles are detected and a description of obstacles is formulated as inequalities updated at each sampling time based on the real-time situation. An NMPC problem with these inequality constraints is formulated and solved by means of a combined multiple-shooting and collocation method. Results of real-time experiments in different scenarios will be presented.

2. MODELING

2.1 System description

The system under investigation is a mobile robot SUMMIT for research applications amongst other ones, Robotnik (2015), see Fig. 1. The mobile robot is equipped with a

Fig. 1. Mobile robot SUMMIT

symmetric two-axles counter steering system. The symmetric property means that the distances between both the front and the rear axle to the mass center of the rigid body are equal. The planar positioning is achieved by steer angle and driving velocity control of the four wheels. The wheels are manipulated axle-wise. The angular velocity of the rear wheels is measured by an encoder. It is assumed that the front wheels behave like the rear wheels because the control input is the same. One brushless DC motor per axle drives the wheels with no differential. Two servo motors, one at each axle, serve for adjusting the steer angle. The mobile robot is not equipped with a braking system. It stops by blocking the wheels. A Hokuyo laser scanner is used as a sensor for the detection of obstacles. A pan-tilt-zoom camera is also attached and will be used for sensor fusion in the future.

The communication is set up by an external notebook, a WiFi TCP/IP network, and an internal processing unit (IPU). The notebook receives the sensor data via the TCP/IP network, calculates the optimal controls by means of C++ code including libraries from Player/Stage (2010) and an optimization solver, and sends the control signals back to the IPU. The IPU realizes the actuation of the servo and driving motor as well as the sensor data reading.

2.2 State-space model

According to the vehicle dynamics, the steering system, and the relatively low driving velocity and steer angles the following nonlinear dynamic model is formulated, Jazar (2009), Müller (2014), Thieme (2014), Drozdova (2015):

$$\dot{\boldsymbol{x}} = \begin{bmatrix} \dfrac{c_\alpha \cos(u_2)[-2x_1 + \frac{x_3}{u_1}(l_h - l_v)]}{m_{rob} u_1 \cos(x_1)} - x_3 \\ x_3 \\ \dfrac{c_\alpha \cos(u_2)[u_2(l_h + l_v) + x_1(l_h - l_v) - \frac{x_3}{u_1}(l_h^2 + l_v^2)]}{J_{rob}} \\ u_1 \cos(x_1 + x_2) \\ u_1 \sin(x_1 + x_2) \end{bmatrix} \tag{1}$$

where $\boldsymbol{x} = [x_1\, x_2\, x_3\, x_4\, x_5]^T = \left[\beta\, \psi\, \dot{\psi}\, s_x\, s_y\right]^T$ is the time-dependent state vector consisting of five states with side slip angle β, yaw angle ψ, yaw rate $\dot{\psi}$, xy-coordinates in global coordinate frame s_x and s_y, respectively. The two controls are summarized in the control vector $\boldsymbol{u} = [u_1\, u_2]^T = [v\, \delta]^T$ with v - driving velocity and δ - steer angle. Model parameters are: c_α - side slip coefficient, l_h, l_v - distances of tire point from rear and front axle to the rigid-body plane, respectively, m_{rob} - mass and J_{rob} - rotational mass moment of inertia of the robot. The behavior of the actuators is not modeled because our NMPC delivers setpoints for the underlaying controllers.

2.3 Obstacle detection and description

The laser scanner attached at the mobile robot has a range of 5.60 m and a scan angle of 240°. But due to the forward movement, the reduction of the unnecessary complexity of measurement information, and the corresponding CPU time for evaluation, the scan angle is set to 120°. The sensor data at each sample time instant include the angle and the distance of obstacles. A graphical illustration of the scanned field is shown in Fig. 2. Relevant marginal

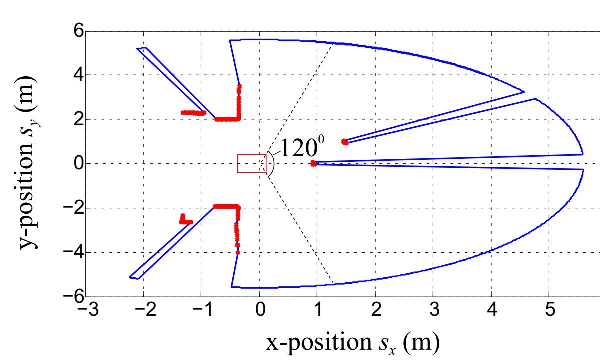

Fig. 2. Scanned field

obstacle points are indicated red. Subsequently, the outer points of an obstacle will be used, firstly, to decide if a single or multiple obstacles are detected. Secondly, it has to be decided if close to each other situated obstacles are summarized to a single obstacle if passing of the robot in between the obstacles is impossible.

Outgoing from the distance of outer obstacle coordinates and taking into account technical facts and safety aspects,