Developments in Nonlinear Model Predictive Control for Telescopic-Wheeled-Legged Robot Tachyon 3

Sotaro Katayama¹, Noriaki Takasugi¹, Mitsuhisa Kaneko², and Masaya Kinoshita¹

Abstract— This work presents advancements in nonlinear model predictive control (NMPC) for the telescopic-wheeledlegged robot, Tachyon 3. Our NMPC is based on the fullcentroidal NMPC formulation to accurately capture the complex constraints of Tachyon 3. Furthermore, we introduce a stochastic NMPC to ensure safety-related constraints even in the presence of contact uncertainties. The proposed NMPC is implemented with a real-time CBF-QP controller to ensure strict safety and an internal state integrator to adapt the NMPC with actuators that employ high-gain position control. The effectiveness of our NMPC is demonstrated through hardware experiments with limited on-board computation.

I. INTRODUCTION

Wheeled-legged robots are promising robotic platforms that amalgamate the strengths of both mobile ground robots and legged robots: energy efficiency and terrain traversability [1], [2], [3]. In the same sprit, but to further enhance the hardware capabilities, we have developed a six-telescopic-wheeled-legged robot named Tachyon 3¹², which is depicted in Figs. 1 and 2. Each leg of Tachyon 3 comprises a revolute joint at the hip, a telescopic joint at the knee, and a driven/passive wheel at the tip. Remarkably, the knee joint is designed to support the entire mass of the robot without any energy consumption at a specific joint posture. Furthermore, its center of mass (COM) is by design positioned much lower than that of typical legged robots, potentially minimizing damage from accidents.

Despite the aforementioned advantages, wheeled-legged robots generally face challenges in motion planning and control due to complexities such as additional degrees of freedom (DOF) and non-holonomic constraints from the wheels [1]. Furthermore, the novel hardware configuration of Tachyon 3 introduces the following distinctive features:

- Each foot of Tachyon 3 has only two degrees of freedom (DOF) relative to the body (x and z directions), whereas typical legged robots have more than three DOF.
- The joint ranges of Tachyon 3 are severely limited (e.g., 50 deg in middle and hip joints and 90 deg in the other hip joints) to prevent self-collisions, while typical robots possess larger joint ranges (e.g., 180 deg).
- Knee joints are designed to operate near their positional limits to maintain a lower COM, in contrast to typical

¹Website: https://www.sony.com/en/SonyInfo/research/technologies/new_mobility

²Video: https://youtu.be/sorw7o73ydc



Fig. 1: Perceptive locomotion of Tachyon 3 utilizing the proposed nonlinear predictive control

quadruped robots, which are designed with sufficient joint margins in their nominal configurations.

• Each joint of Tachyon 3 is governed by high-gain position control, as opposed to the torque control commonly used in legged robots.

In this study, to achieve versatile locomotion under the aforementioned hardware specifications, we have developed a nonlinear model predictive control (NMPC) framework for Tachyon 3. Our NMPC is based on the full-centroidal NMPC formulation [4], [5], [6], [7] to comprehensively address a variety of constraints of Tachyon 3 [7]. To augment safety such as collision avoidance even in the presence of contact uncertainties, we have implemented stochastic NMPC using Saltation matrices [8]. We further ensure safety by hierarchically integrating NMPC with the real-time CBF-QP controller [9]. Additionally, to adapt NMPC for Tachyon 3, whose joints utilize high-gain position control, we propose the incorporation of an internal state integrator for state feedback within the NMPC to prevent oscillations in the resultant joint position commands [7]. We have implemented our NMPC on the onboard computer of Tachyon 3 and demonstrated its practical feasibility through hardware experiments.

II. NONLINEAR MODEL PREDICTIVE CONTROL FOR TACHYON 3

A. Full-Centroidal NMPC

Tachyon 3 is modeled utilizing the full-kinematics and centroidal dynamics model, akin to [4], which is termed a *full-centroidal model*. The full-kinematics encapsulates the precise constraints, while the centroidal dynamics articulates the accurate dynamics for position-controlled robots [10]. The precise constraint evaluation is particularly pivotal for Tachyon 3, which possesses severe joint range limits, limited foot-wise DOF, and non-holonomic wheel contact

¹Sony Group Corporation, Minato-ku, Tokyo, Japan, 108-0075 sotaro.katayama@sony.com

 $^{^2 \}mathrm{Sony}$ Global Manufacturing and Operations Corporation, Minato-ku, Tokyo, Japan, 108-0075



Fig. 2: Tachyon 3 consists of 16 active joints including 6 prismatic joints, 6 hip joints and 4 drive wheels, and additional two passive omni wheels.



Fig. 3: Control pipeline of Tachyon 3 including NMPC

constraints. We imposed joint position, velocity, and torque limits, friction cone, and foot placement constraints as inequality constraints. Additionally, we incorporated collision avoidance constraints between Tachyon 3's feet and the environment, modeled by a finite number of cuboids.

B. Stochastic NMPC for Contact Uncertainties

Exteroceptive sensors such as RGB-D cameras or LiDAR inevitably encompass perception uncertainties due to factors such as sensor noises, limited resolution, occlusions, etc. This poses a challenge for NMPC that is consistently based on environment perception. For instance, if the estimated terrain height is greater than the actual height, a swinging foot may fail to establish contact, leading to the robot's instability and potential falls. To mitigate this issue, in [8], we have developed a zero-order stochastic NMPC [11], [12], [13], [14] using Saltation Matrices [15] and output-feedback stochastic NMPC methodology [16]. With the method, the constraint margins can be adaptively updated online according to the predicted motions, as benchmarked in [8].

C. Control Pipleine and Software Implementation

Fig. 3 illustrates the overall pipeline of Tachyon 3. Tachyon 3 is equipped with two on-board PCs: a perception PC and a control PC. The perception PC is utilized for environment perception (e.g., extracting terrain surfaces and obstacles) based on exteroceptive sensors such as LiDAR. The control PC is employed for motion planning and control based on the proprioceptive sensors and the environment information extracted from the perception pipeline. The main thread (real-time thread) of the control PC runs at 1 kHz and includes the contact planner, CBF-QP [9], internal state integrator, and state estimator. NMPC is implemented on another thread of the control PC. The NMPC thread asynchronously receives state and contact plans from the real-time thread and dispatches the optimal trajectory to the real-time thread. The CBF-QP guarantees real-time safety whereas the internal state integrator enables a NMPC application to a high-gain position controlled robot without joint oscillations [7]. The implementation of NMPC optimization is similar to [17], e.g., internally using efficient software such as [18], [19].

III. EXPERIMENTS

To validate the practical feasibility of the proposed method, we conducted hardware experiments on the per-



Fig. 4: Time histories of the base linear velocity and joint positions over the hardware experiment. RF and RR legs behaved almost the same as LF and LR legs. The dotted gray lines show the joint position limits.

ceptive locomotion of Tachyon 3. The horizon length was set to 1.5 s and the discretization time step was set to 0.02 s. We have applied the proposed stochastic NMPC. Figs. 1 and 4 display snapshots and plots of Tachyon 3's perceptive locomotion using the proposed stochastic NMPC. Tachyon 3 successfully ascended and descended a series of two steps via the proposed stochastic NMPC, even when joints moved close to its boundaries as we can see from Fig. 4. The average computational time of the stochastic NMPC was 29 ms while that of the nominal NMPC (i.e., NMPC without covariance propagation) was 26 ms measured on the on-board PC (CPU: Intel(R) Core(TM) i7-8850 H CPU @ 2.606 GHz).

IV. CONCLUSION

In this study, we have presented NMPC for our wheeledlegged robot Tachyon 3. It effectively achieved perceptive locomotion online even with limited on-board computation. Our future work is to explore the capabilities of the proposed NMPC in a wider variety of settings, such as narrow spaces, cluttered environments, and curved surfaces.

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