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Whole-Body Model Predictive Control for Biped Locomotion on a Torque-Controlled Humanoid Robot

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Abstract—In this paper, we present a whole-body Model Predictive Control framework for locomotion and validate it on the humanoid robot Talos. Using a time horizon of 1.5 second and a 20 Degree of Freedom model, the proposed controller outputs the optimal feedforward torque and Riccati-based feedback policy at a frequency of 100 Hz and the optimal feedback torque at 2 kHz. Contact constraints are handled through wrench regularization following a normal force reference in order to hint smooth force transitions to the solver. Contact locations and timings are user-defined, and Bezier curves are implemented as reference feet trajectories. Experimental validation includes dynamic locomotion at different gaits as well as 10 cm height stairstep crossing. To the best of the authors' knowledge, this experimental result marks the first achievement of locomotion on non-flat terrain for an electric torque-controlled humanoid robot using a full-dynamics Model Predictive Control scheme.

I. INTRODUCTION

A. Context

Generalized locomotion for legged robot is a complex problem that requires predicting the future in order to cope with the effects of inertia. Consider the prediction of the motion of a 36 Degree of Freedom (DoF) humanoid robot along its next walking cycles, ie 1.6s, corresponding to 160 integration nodes: this corresponds to solving a problem with about 108000 decision variables at a control frequency of 2 kHz for a humanoid like Talos.

The first approach consists in decoupling the centroidal part of the dynamics and the whole-body control [1], [2]. In practice it boils down to predict the future with a reduced model around the center of mass and then using an instantaneous controller to produce a whole-body trajectory following the desired centroidal dynamics. Early works assumed that robots were controlled in position and therefore used inverse kinematics to compute the whole-body control [3], [4], [5]. However, this approach is limited as inverse kinematics does not account for the inertia of the limbs which matters for robots with heavy arms and legs (e.g. Talos [6], [7]); moreover, the compliance is not intrinsic to the controller and needs to be actively designed. As a consequence, using torque control offers the best solution to produce compliant behaviour for heavy robots. Researchers started to use inverse dynamics as a whole-body instantaneous controller [8], [9], [10] despite its lack of kinematic precision. In order to

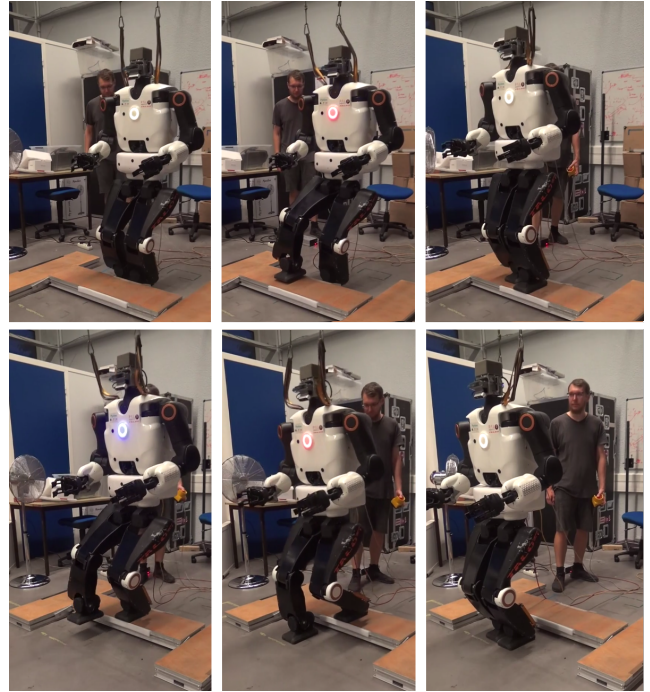


Fig. 1. Snapshots of the stairstep crossing experiment.

tackle this issue, combinations between inverse kinematics and inverse dynamics were also studied [11], [12].

The second approach involves coupling the centroidal dynamics over a preview horizon while only using the whole-body dynamics for the first timesteps [13]. This has the advantage to propagate the terminal cost or constraint of the dynamics into the whole-body motion.

Recent efficient solvers [14], [15] allow for a third approach which consists in implementing complete whole-body Model Predictive Control (MPC). Particular implementations involve solving iteratively the centroidal dynamics and whole-body kinematics over a preview horizon until both solutions are consistent [16], [17], [18]. The other possibility is to optimize the full motion directly [14] through a direct shooting approach [19], either by using iterative Linear Quadratic Regulator (iLQR) [20], [21] methods or Differential Dynamics Programming (DDP) [22], [23]. These algorithms feature a linear complexity in the time horizon, which make them especially efficient for large horizon and complex models; moreover, they produce a reliable state-feedback policy at no extra cost through the Riccati gains [23], [24].

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B. Contributions

In this work, a DDP-based MPC scheme taking into account the whole-body model of the robot is used to achieve dynamic locomotion and stairstep crossing. Given the current state of the robot measured at 2 kHz, the control block directly computes the optimal torque and feedback policy to be played on the robot, without any other refinement or estimation needed. The details of the formulation of the resulting MPC are given in Sec. III. We demonstrate the validity of the framework on the torque-controlled humanoid robot Talos [25] through a series of locomotion experiments, presented in Sec. IV. The method is fully generic, open-source and can be applied to any legged robots on various terrains. It corresponds to the first demonstration of the capabilities of whole-body MPC for the locomotion of a torque-controlled humanoid robot on flat and non-flat environments.

II. WHOLE BODY TRAJECTORY OPTIMISATION PROBLEM

A. Problem formulation

Given a floating-base robot with n_j actuated joints and n_p contacts with the environment, we consider the usual formulation where the robot state is described by $\mathbf{x} = (\mathbf{q}, \dot{\mathbf{q}}) \in \mathbb{R}^{n_x}$, $\dot{\mathbf{x}} = (\dot{\mathbf{q}}, \ddot{\mathbf{q}}) \in \mathbb{R}^{n_{dx}}$, with $\mathbf{q} \in SE(3) \times \mathbb{R}^{n_j}$ the configuration vector composed of the free-flyer joint position and the actuated joint positions. In this context, we consider $\mathbf{u} = \boldsymbol{\tau} \in \mathbb{R}^{n_j}$ to be the vector of joint torques, and $\boldsymbol{\lambda} = (\boldsymbol{\lambda}_1 \dots \boldsymbol{\lambda}_{n_p}) \in \mathbb{R}^{6 \times n_p}$ to be the concatenation of spatial forces for every end effector in contact.

Using a multiple-shooting formulation, we describe our problem as a discretized Optimal Control Problem (OCP) which optimizes the state and control trajectories over a given time horizon T :

$$\begin{aligned} \min_{\underline{\mathbf{x}}, \underline{\mathbf{u}}} \quad & \sum_{t=0}^{T-1} \ell(\mathbf{x}_t, \mathbf{u}_t, t) + \ell_T(\mathbf{x}_T) \\ \text{s.t.} \quad & \mathbf{x}_0 = \mathbf{f}_0 \\ & \forall t = 0..T, \quad \mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t) \end{aligned} \quad (1)$$

where $\underline{\mathbf{x}} = (\mathbf{x}_t)_{t=0..T}$ and $\underline{\mathbf{u}} = (\mathbf{u}_t)_{t=0..T-1}$ are the state and control trajectories, T is the number of knots, ℓ and ℓ_T are the running and terminal cost functions which will define the locomotion tasks, and \mathbf{f}_0 is the initial state. In order to be able to solve this problem in real time, we don't consider any other state and control constraints, but instead choose to use penalty costs.

B. Whole-body dynamics modelling

Similarly to [26], we consider a rigid body system with n_j joints and n_p rigid contacts with the environment and model the dynamics of this constrained multi-body system through the following equation [27]:

$$\begin{bmatrix} \mathbf{M} & \mathbf{J}_c^\top \\ \mathbf{J}_c & \mathbf{0} \end{bmatrix} \begin{bmatrix} \ddot{\mathbf{q}} \\ -\boldsymbol{\lambda} \end{bmatrix} = \begin{bmatrix} \mathbf{S}^\top \boldsymbol{\tau} - \mathbf{b} \\ -\mathbf{J}_c \dot{\mathbf{q}} \end{bmatrix} \quad (2)$$

where \mathbf{M} is the inertia matrix, \mathbf{b} the generalized Coriolis, centripetal and gravity terms, \mathbf{S} a selection matrix mapping

over the actuated joints, $\mathbf{J}_c = (\mathbf{J}_1 \dots \mathbf{J}_{n_p})$ the concatenation of contact Jacobian matrices. In [28], it has been shown that the contact-constrained rigid body dynamics of the robot can be expressed through an equation where contact forces directly depend on the state \mathbf{x} . This leads to a simple, explicit next-state integration scheme written as a dynamics constraint at time t : $\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t)$.

C. Solving the OCP with DDP

DDP is a very efficient tool to solve (1) based on Bellman's principle [29]. The algorithm leverages the sparsity of the Markovian nature of the dynamics constraints and provides a descent step $((\Delta \mathbf{x}_t, \Delta \mathbf{u}_t)_{t=0..T})$ through a backward-forward pass formulation followed by a line search heuristics. Moreover, it naturally computes the optimal state feedback gains \mathbf{K}_t , also known as Riccati gains, such that $\Delta \mathbf{u}_t = \mathbf{K}_t \Delta \mathbf{x}_t + \mathbf{k}_t$. We demonstrated before that these gains can be used to produce a first order approximation of the optimal torque at the frequency of the low-level control [24]. In classical DDP scheme [30], [31], the second-order term of the Taylor approximation of the quality function is taken into account; here we neglect this term to keep the computation load of the backward pass low, and to be able to solve the OCP in real time. Such an approach is classically called iLQR [32]. Note that this approximation does not affect the computation of the optimal feedback gains.

D. Formulation of the costs

The walking task is described in our OCP through 6 different costs:

- a state regularization cost:
 $\ell_1(\mathbf{x}) = (\mathbf{x} - \mathbf{x}_d)^T \mathbf{R}_x (\mathbf{x} - \mathbf{x}_d)$ with \mathbf{R}_x a positive definite weight matrix and \mathbf{x}_d the initial state of the robot, usually half-sitting position with null velocity. This cost prevents the optimized state trajectory from being too far away from the default position of the robot.
- a control regularization cost:
 $\ell_2(\mathbf{u}) = (\mathbf{u} - \mathbf{u}_d)^T \mathbf{R}_u (\mathbf{u} - \mathbf{u}_d)$ with \mathbf{R}_u a positive definite weight matrix and \mathbf{u}_d the gravity-compensating torque in default state. This cost prevents the solver to cross torque limits, although it does only act as a penalization.
- a goal-tracking cost:
 $\ell_3(\mathbf{x}, t) = a(\mathbf{p}(\mathbf{x}) - \mathbf{p}_d(t))$ with $a : \mathbf{r} \mapsto \log(1 + \frac{\|\mathbf{r}\|}{\alpha})$ a logarithmic activation function, $\mathbf{p}(\mathbf{x})$ and $\mathbf{p}_d(t)$ current and desired foot placement in $SE(3)$, and $\alpha = 0.2$. This cost, associated with an user-tuned desired foot trajectory $\mathbf{p}_d(t)_{t=0..T}$, ensures that the foot in swing phase goes to the next pre-defined contact. It is only active during swing phases.
- a kinematic limit cost:
 $\ell_4(\mathbf{x}) = \|\max(\mathbf{x} - \mathbf{x}_u, \mathbf{0}) + \min(\mathbf{x} - \mathbf{x}_l, \mathbf{0})\|^2$ with \mathbf{x}_u the upper bound and \mathbf{x}_l the lower bound of the joints positions and velocities. This cost prevents the solver from crossing the kinematics bounds of the robot, and although it takes the form of a penalization associated

with a high weight, it efficiently rejects unfeasible trajectories.

The two last costs are a local Center of Pressure (CoP) regularization and a wrench tracking cost. They ensure that the contact forces remain dynamically consistent during the motion, and that the robot weight efficiently switches from one contact to the next. In the following, we only consider contacts between two rigid bodies. Given a foot in contact, the 6-dimension wrench it applies on its environment can be written $\mathbf{w} = (\mathbf{f}, \boldsymbol{\tau}) = (f_x, f_y, f_z, \tau_x, \tau_y, \tau_z)$, being respectively the linear and angular part of the wrench. Let us note L, W the half-length and half-width of the foot, and μ a friction coefficient. Ideally, we want \mathbf{w} to remain inside the wrench cone [33], [34] defined by the following inequalities:

$$f_z > 0 \quad (3a)$$

$$|f_x| \leq \mu f_z \quad (3b)$$

$$|f_y| \leq \mu f_z \quad (3c)$$

$$|\tau_x| \leq W f_z \quad (3d)$$

$$|\tau_y| \leq L f_z \quad (3e)$$

$$\tau_{min} \leq \tau_z \leq \tau_{max} \quad (3f)$$

with

$$\tau_{min} = -\mu(W + L)f_z + |Wf_x - \mu\tau_x| + |Lf_y - \mu\tau_y|$$

$$\tau_{max} = \mu(W + L)f_z - |Wf_x + \mu\tau_x| - |Lf_y + \mu\tau_y|$$

These inequalities describe a linearized wrench cone with 4 facets. While one can opt for a better approximation of the true wrench cone by adding more facets, we choose to use a simple model for the sake of time computation. As already mentioned, DDP does not allow yet to take into account such inequality constraints, although some recent works may solve this issue in the near future [35], [36]. Interestingly, using penalization costs to approximate those constraints make the problem too hard to solve in real time, as the solver struggles to discover the optimal contact forces in just one iteration. For this reason, we introduce a reference wrench trajectory $\mathbf{w}_d(t) = (0, 0, f_d(t), 0, 0, 0)$ where $f_d(t)$ is a simple normal force reference equal to $M_r g$, the weight of the robot during single support phase, and switching continuously from $M_r g - f_{min}$ to f_{min} during double support phase. Here, $f_{min} = 150$ N is a security margin and should be read as the minimum force reference at contact just before take-off. This margin should be implemented because the DDP solver doesn't handle well near-zero predicted forces.

The contact wrench constraints are summarized in the matrix $\mathbf{A} \in \mathbb{R}^{17 \times 6}$ such that $\mathbf{A}\mathbf{w}_c < 0$ is an exact rewriting of (3). The final wrench tracking cost is then defined by:

$$\ell_5(\mathbf{x}, \mathbf{u}, t) = \|\mathbf{A}(\mathbf{w} - \mathbf{w}_d(t))\|^2 \quad (4)$$

with every wrench expressed in the local frame of the contact foot.

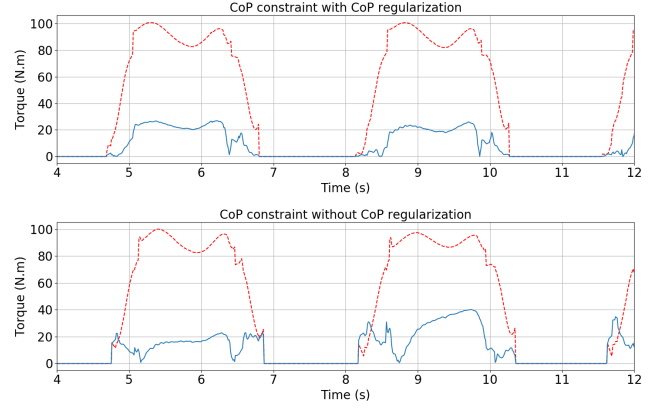


Fig. 2. Left foot CoP constraint $|\tau_y| \leq Lf_z$ for simulated walk with and without CoP regularization. Blue plain line is $|\tau_y|$, red dotted line is Lf_z . Bottom plot shows violations of the constraint during contact switch, which translate into oscillating ankles in simulation. On the real robot, those constraints violations lead to falling.

Unfortunately, this formulation alone does not prevent occasional breaking of the wrench constraints during contact transition. Practically speaking, it has been observed in simulation and on the robot that the local CoP constraints described by inequalities 3d and 3e are violated during contact switches, although the wrench tracking cost ℓ_5 should regularize the contact torque to zero. To address this behaviour, a local CoP regularization cost has been added to the formulation:

$$\ell_6(\mathbf{x}, \mathbf{u}) = \frac{1}{2W^2} \left(\left| \frac{\tau_y}{f_z} \right|^2 + \left| \frac{\tau_x}{f_z} \right|^2 \right) \quad (5)$$

The idea behind this cost is to force the inequalities $\left| \frac{\tau_y}{Lf_z} \right| < 1$ and $\left| \frac{\tau_x}{Wf_z} \right| < 1$ by penalizing the corresponding quantities. In order to be more conservative, W can be set smaller than the half-width of the foot, which is equivalent to increasing the CoP cost weight.

The effect of this cost is illustrated in Fig. 2, where a walking motion was performed in simulation with and without the CoP regularization.

III. MODEL PREDICTIVE CONTROL SCHEME

A. Timings and model

In order to cut the computation load as much as possible, a reduced robot model including a total of 14 torque-controlled joints is used: 6 for each leg and 2 for torso. The arm joints are controlled in position and remain fixed during the walking motion. It has been demonstrated that including the arms in the model allows for a better control of the centroidal angular momentum of the robot [11]; using only a half-body model is thus penalizing to the walking motion. Nevertheless, our scheme is able to handle this issue. As for the contact phases and timings, they are decided offline by the user, which could be replaced in the future by a high-level pattern generator in order to perform step adaptation. The DDP problem is formulated using the open-source Crocoddyl library [15], which is based on Pinocchio [37], a state-of-the-art rigid body algorithms library.

The horizon of our OCP has 150 knots separated by a 10ms time step, allowing the solver to predict the behaviour of the robot 1.5s into the future. Before starting the motion, the OCP is first solved until convergence with a horizon only composed of double support models; then, at each control cycle, the previous optimal trajectory is used as a warm-start to bootstrap the problem and one DDP iteration is performed. As the time goes by, contact switches and desired wrench trajectory are gradually inserted at the end of the horizon. This scheme allows us to solve the whole-body problem online in about 10ms.

B. Reference foot trajectory

During double support phase, at each control cycle, the desired swing foot trajectories are updated over the entire horizon using a minimum jerk Bezier curve, as in [38]. The final placement of the swing foot is set to be the placement of the support foot, plus a desired 2D translation $(\delta x, \delta y)$. These curves are tuned so that during landing and take-off, foot velocity and acceleration are colinear to the normal of the contact surface; as a consequence, the entire foot area is making contact with the ground at the same time.

C. Cost parametrization

The following weight distribution has been used on the robot to make it walk.

State	Control	Foot pose	Limits	Wrench	CoP
1	0.005	1000	1000	0.001	10

Additionally, the weight matrix R_x in the state regularization cost has been carefully tuned to penalize critical behaviors like tilting torso or swinging base. Here are the weights used on the robot.

	Base pose	Base angle	Leg	Torso
Position	0	10000	10	100
Velocity	10	10	10	10

D. Robotic Operating System (ROS) architecture

Our MPC is embedded inside a ROS node which subscribes to the actual state of the robot measured at 2 kHz, and which publishes a feedforward optimal torque u_0 , Riccati gains K_0 and last computed initial state x_0 at 100 Hz (see Fig. ??). The final torque sent to the low-level control combines the feedforward control with a state feedback based on the Riccati gains (see [24] for more details):

$$u = u_0 + K_0(x_0 - x_m) \quad (6)$$

At last, the desired motor current for each controlled joint is computed through a proportional-derivative feedback on the joint torque measurement. Because the actuator dynamics (motor inertia, frictions, flexibility...) are not considered in the whole-body model, a feedforward term on the current is added to compensate for the model discrepancy. As a consequence, from the point of view of the high-level MPC, every joint is behaving as an ideal joint. The architecture is separated in two parallel processes running on different

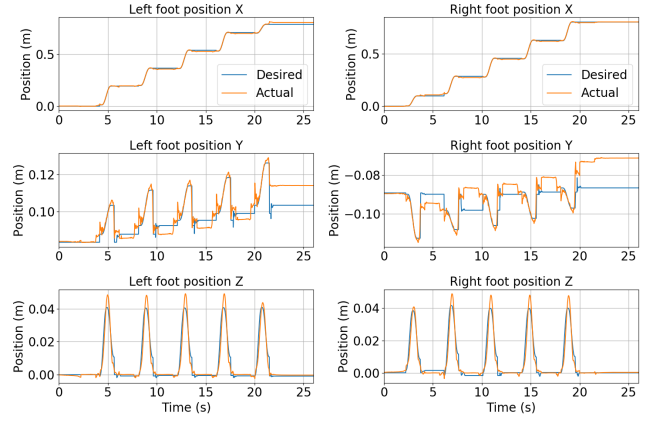


Fig. 3. Measured and desired feet position during locomotion on flat floor.

CPUs. This publisher-subscriber architecture has been successfully tested in previous works [24], [39].

IV. EXPERIMENTAL RESULTS

In this section are presented the experimental results obtained with our whole-body MPC framework applied to the humanoid robot Talos [25]. Due to the critical problem of computation time, the MPC runs on a powerful external computer (AMD Ryzen 5950X, 32 cores and 4.9GHz with 64 Go of RAM), whereas the low-level control runs on the embedded CPU of the robot.

The proposed control scheme has been evaluated in two locomotion scenarios: in the first one, the robot performed a straight walk on flat floor with two sets of gait timings; in the second one, the robot successfully climbed up and down a 10cm-high step. In both experiments, the exact same cost weights have been used on the robot, and the only varying parameters were the feet trajectory and gait timings. This demonstrates the adaptability of the MPC framework which can produce relevant stable trajectories over a wide range of dynamic motions. The videos of the experiments, as well as the associated raw data are available at <https://gettoweb.laas.fr/articles/dantechumanoid22.html>. The following table presents the different gait parameters used during experimental validation.

	Gait 1	Gait 2	Stairstep
Forward step length δx	10cm	20cm	30cm
Width btw. feet δy	20cm	20cm	20cm
Single support time	1.1s	1.5s	3s
Double support time	0.3s	0.75s	2s

A. Walking on flat floor

For the sake of conciseness, only the first gait tested on the robot will be discussed in this paper. Both gaits are nonetheless displayed in the attached video.

The results of the walking experiment are presented in figures 3 to 7. Fig. 3 shows the tracking of the desired feet trajectories over time. The Bezier curves used to generate the reference in position are only followed during swing phases,

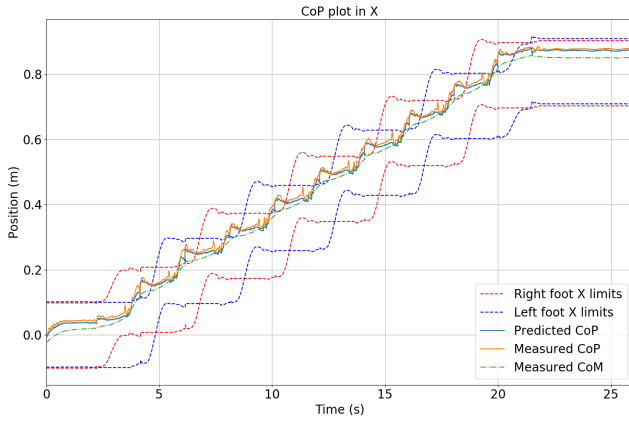


Fig. 4. CoP trajectory in X axis compared to actual feet position during locomotion on flat floor. The foot of the robot is 10 cm long.

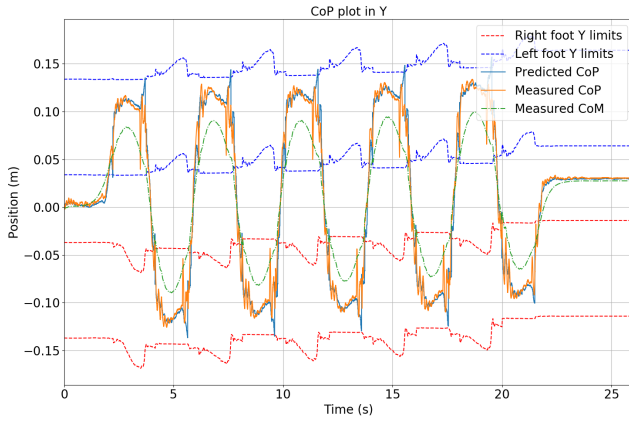


Fig. 5. CoP trajectory in Y axis compared to actual feet position during locomotion on flat floor. The foot of the robot is 5 cm wide.

hence are not relevant during support phases. Although the reference in X-axis is precisely tracked, the actual foot roll and position in Y-axis suffer from noisy oscillations at take-off and landing. Empirically, we found out that the walking motion improves when the contact switch happens while the foot reference is 1cm above ground. Doing this makes the robot force the contact into the ground with non-zero forces, creating a stable contact and an impact. Because the control scheme is intrinsically compliant, it damps the impact and limits the resulting forces, preventing hardware damage.

Additionally, Fig. 6 shows that a normal force is measured just before contact switch, which means that the foot impacted the ground before the solver predicted it. As no step or timing adaptation has been introduced in our framework yet, such behaviour is for now unavoidable; nevertheless, the MPC is able to cope with such unknown disturbances and produce a stable walking trajectory.

Figures 4 and 5 shows that the predicted CoP, computed from the forces computed by the solver, matches the CoP based on the sensor's forces. During the motion, the solver defines its own CoP trajectory so as to minimize the user-tuned cost function. It is interesting to notice that when the

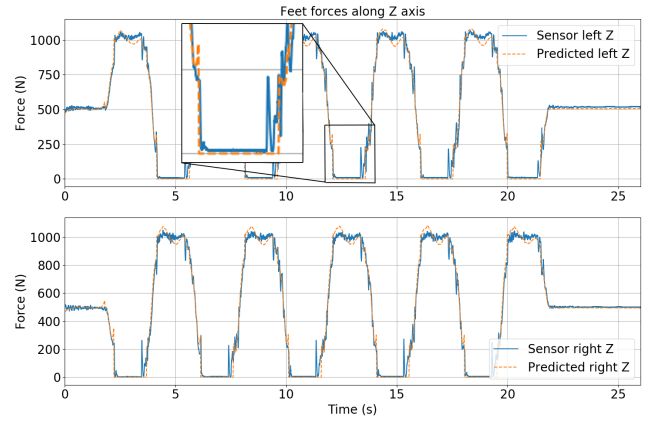


Fig. 6. Predicted vs measured normal forces in left and right feet during locomotion on flat floor. The foot is touching the ground before landing as can be seen in the zoomed window.

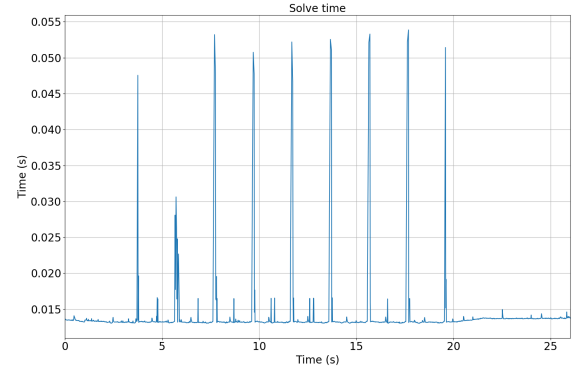


Fig. 7. Time computation of one DDP iteration during locomotion on flat floor.

foot lands, the predicted CoP in Y axis may sometimes go outside the feet support area, although the real CoP remains inside. In this case, the low-level torque feedback loop is acting as a low-pass filter which smooths the control's sharp edges.

Finally, Fig. 7 indicates that the MPC is computed in a little bit less than 15ms, but features brutal peaks of 50ms mainly due to random processing delay inside the CPU. Despite these unexpected time overflows, the motions produced by our framework remain stable because the approximated Riccati policy takes over while the high-level control is computing.

B. Stair up and down

The main objective of the stair experiment is to demonstrate the versatility of the proposed framework. Compared to the walking experiment, only the feet trajectories and contact timings have been modified, while the wrench trajectory remains the same. Figures 8 to 11 illustrate the results of this experiment.

Fig. 8 highlights an essential issue caused by a bad estimation of the base of the robot: during the last 5 seconds of the motion, whereas the right foot is in support phase

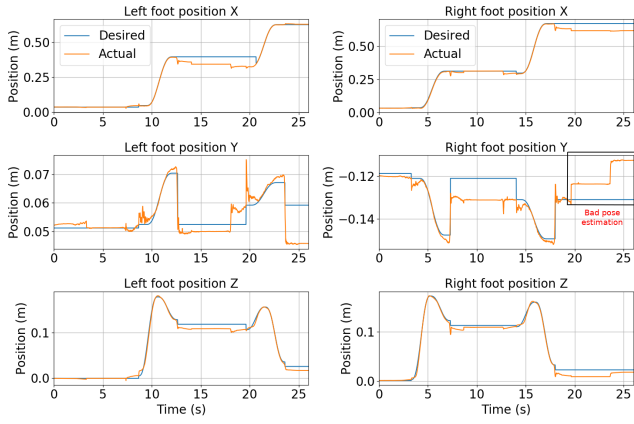


Fig. 8. Measured and desired feet position during stairstep crossing. Bad pose estimation is highlighted at the end of the right foot trajectory.

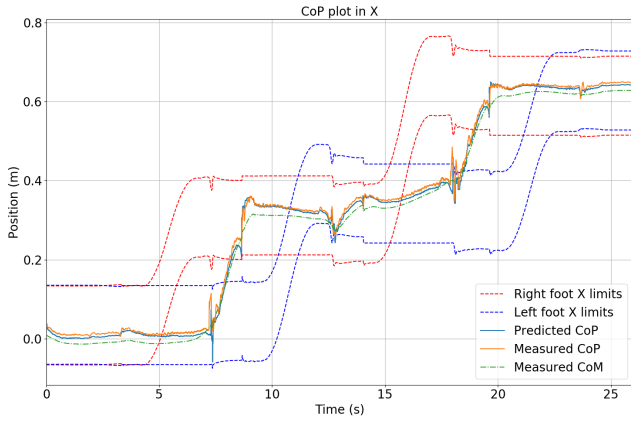


Fig. 9. CoP trajectory in X axis compared to actual feet position during stairstep crossing. The foot of the robot is 10 cm long.

and not moving, the actual foot position in Y shows brutal discontinuities of 1cm when the left foot is creating and breaking contact. The estimated base of the robot shows the exact same discontinuities at the same time. Fortunately, the solver is robust enough to handle such disturbances.

Similarly to the flat floor experiment, the predicted CoP trajectory briefly goes outside of the foot area when landing occurs, as seen in Fig. 10. This issue is also noticeable in Fig. 11 where the lateral forces during contact switches feature several peaks corresponding to contact mismatches caused by blind time-scheduled transitions and model uncertainties.

V. CONCLUSION

This paper shows the first application of whole-body MPC applied to the locomotion of an industrial biped robot. The proposed framework can be adapted to cross obstacles like stairstep by simply adjusting the feet reference trajectories and locomotion gaits. It has proven to be robust against model uncertainties, imprecise state estimation and unexpected latency in data transmission. The key to implementing this MPC on a real platform lies in the approximation of the wrench cone constraints treated as regularization costs and

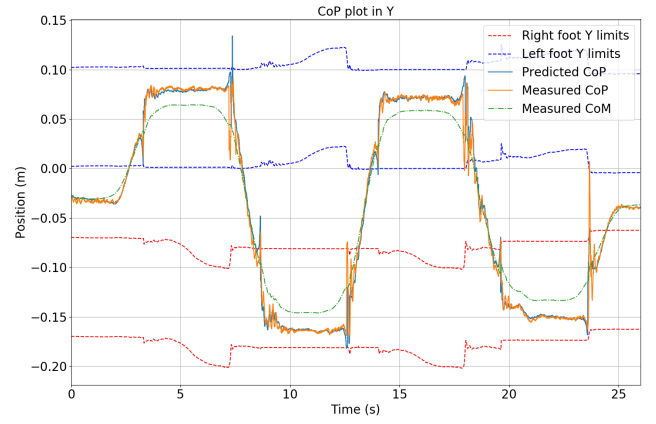


Fig. 10. CoP trajectory in Y axis compared to actual feet position during stairstep crossing. The foot of the robot is 5 cm wide.

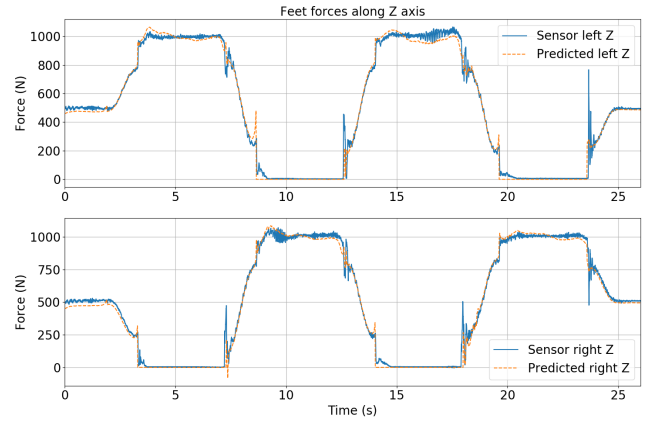


Fig. 11. Predicted vs measured normal forces in left and right feet during stairstep crossing.

the use of Riccati-based feedback policy inside the low-level control of the robot. The latter improvement allows us to increase the frequency of the control scheme to 2 kHz. Our single-block framework can be extended to any given task at the (small) price of designing and tuning specific costs adapted to the goal.

Although this whole-body MPC architecture produces promising results, we still need to prove that it can outperform state-of-the-art centroidal walking controllers. The proposed method used to cope with wrench cone constraints resulting in dynamically unfeasible predicted CoP trajectories, even if the filtering effect of the low-level control allows for such solutions to be executed on the robot. The behaviour of the robot at contact transitions needs to be studied more thoroughly, so as to eliminate those brutal discontinuities in torques and forces. Our main perspective of work is to get rid of the feet reference trajectories in order to make the solver able to perform push recovery. Following this logic, we plan to introduce step adaptation and online optimization of the contact timings, with the goal of increasing control smoothness, walk speed and step length.

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