Proceedings Paper:

Castano, JA, Zhou, C orcid.org/0000-0002-6677-0855, Kryczka, P et al. (1 more author) (2018) MPC strategy for dynamic stabilization of preplanned walking gaits. In: Proceedings of the IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids). 2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids), 15-17 Nov 2017, Birmingham, UK. , pp. 618-623. ISBN 978-1-5386-4679-3

https://doi.org/10.1109/HUMANOIDS.2017.8246936

MPC Strategy for dynamic stabilization of preplanned walking gaits

Juan A. Castano, Chengxu Zhou, Przemyslaw Kryczka and Nikos Tsagarakis

***Abstract*— In this paper, we report the implementation and the experimental validation of a balancing controller of bipedal robots during the execution of predefined walking patterns. The proposed controller is a cascade controller that uses the actual centre of mass (CoM) states at each sampling time and the desired CoM trajectory within a defined time window. The purpose of this controller is to generate at each sampling time a corrective term at the pelvis that allows a better tracking of the CoM and Zero Moment Point trajectories. Therefore, the overall stability is increased during the gait execution. The method permits to minimize tracking errors due to small disturbances and control errors. The effectiveness of the proposed controller is validated in simulation and in real implementation on the full-body humanoid robot Walk-Man.**

I. Introduction

The development of bipedal locomotion that is adaptable to external disturbances such as external forces and terrain uncertainties is a fundamental prerequisite to introduce these technologies in environments originally designed for humans. Nowadays, many of the existing walking methodologies for bipedal robots consider known trajectories that permit a stable motion of the robot [1]–[3]. However, given the model discrepancies, errors during the execution, and small disturbances due to contact interactions, it is necessary to include additional stability strategies as referred in different works [4]–[7]. The aim of such controllers, is to permit the robot to converge towards the desired gait allowing the biped to continue the gait execution. Different works re-plan the walking patterns according to the new robot states [8]–[10] changing continuously the step time and/or the step position allowing the robot to continue the walking. In order to further increase the stability, the use of local feedback controllers is a common practice in locomotion, these controllers reduce the effect of factors that increase the tracking errors and affect the gait execution in general.

The stabilizer presented in [11] develops a compliant behavior which is achieved using an admittance control that takes the six-axis force/torque measurements in the feet as feedback and generates a deviation in the CoM reference that makes the measured Center of Pressure to converge towards the desired one for the increasing of the stability. The approach in [7] used the full state feedback of the CoM, and applied the CoM/ZMP regulator presented in [12] to modify the Zero Moment Point (ZMP) reference. The new ZMP trajectory is the reference to a lower layer ZMP controller that tracks the ZMP distributed in each foot. By following the new ZMP reference, the robot is stabilized and the gait executed successfully.

Another feedback based balancing strategy is given in [8]. In that work, the authors presented a two-stage controller using for both layers PID controllers. The first layer uses the CoM position error to modify the ZMP reference. The modified reference will permit to track better the pre-computed CoM trajectory which implies a proper track of the ZMP reference as well. To track the modified ZMP reference, the second layer of the controller provides a modification in the pelvis reference. Modifying the pelvis reference instead of the CoM is because of a direct modification of the CoM is not trivial and might move the ZMP to the edge of the support polygon which will destabilize the robot. By applying the modification to the pelvis, the modified ZMP is tracked and the CoM converges towards the desired trajectory recovering the pre-computed gait.

Even though the proposed controller could provide a stable walking gait, it is desired to increase the robustness of the balancing strategy with the use of a predictive controller that takes advantage on the fact that the trajectories are pre-computed and predictive models of the system dynamics can be found. This will permit a proper performance of the robot while executing different walking gaits increasing the robustness of the walk.

In this paper, we present a modification to the first control layer of the controller presented in [8]. In our approach, the first control stage uses a Model based Predictive Control (MPC) strategy such that the future CoM trajectory is considered and the future error is estimated based on the present CoM states. This way, the controller reduces the tracking error taking into account the CoM behaviour and known reference within a time window. This will reduce strong behaviors, glitches and increases the bandwidth response of the system given the controller properties. The output of the first control layer is the modified ZMP reference which is constrained within the support polygon. The modified ZMP reference is used by the second control layer which tracks the generated ZMP reference adjusting the pelvis as done by [8]. As second layer controller we used a PID controller considering the fast rate of change of the ZMP and the drawbacks that a predictions of the ZMP might have [13]. Using a PID implies that there is no future known trajectory. The control method was tested in simulation and on the real bipedal robot Walk-Man developed by the Italian Institute of Technology.

Humanoids & Human Centered Mechatronics Research Line, Istituto Italiano di Tecnologia, via Morego, 30, 16163 Genova, Italy.

Tel.: +39-010-71781407. Fax: +39-010-71781232. name.surname@iit.it

This work is supported by the FP7 European project WALK-MAN (ICT-2013-10).

II. MPC Overview

An MPC controller uses a model of the system such that the obtained control effort minimizes an objective function over a time horizon given the model dynamics. In our work, we used the Extended Prediction Self-Adaptive control (EPSAC) algorithm presented in [14]. This controller has a simple representation of the system and includes a noise observer which increases the performance of the closed loop. The noise estimation is consider in control effort calculation and includes the known disturbances sources such as low frequencies errors given the walking dynamics. For a complete description of the method the reader is encouraged to read [14], [15].

The generic model of the process within the EPSAC algorithm is given by

$$y(t) = \Psi(t) + n(t)\,, \tag{1}$$

where $y(t)$ is the measured output of the process, $\Psi(t)$ is the model output and $n(t)$ is the process disturbance at discrete time index t. The noise is described as a filter with transfer function

$$n(t) = \frac{C(q^{-1})}{D(q^{-1})}e(t)\,, \tag{2}$$

where $e(t)$ is uncorrelated (white) noise with zero mean and C, D are monic polynomials in the backward shift operator q^{-1}. Choosing properly the filter model will increase the performance of the controller. For this aim, resonance frequencies and known noise sources should be consider.

Given (1), the predicted values of the output are

$$\mathbf{y}(t+k|t) = \mathbf{y_{base}}(t+k|t) + \mathbf{y_{opt}}(t+k|t)\,, \tag{3}$$

the contribution of each terms is:

- $\mathbf{y_{base}}(t+k|t)$ Is the base response, this term reflects the estimation of the output given the effect of the past inputs $\mathbf{u}(t-1), \mathbf{u}(t-2)\ldots$, the future base control sequence $\mathbf{u_{base}}(t+k|t)$ and the effect of the predicted disturbance $n(t+k|t)$.
- $\mathbf{y_{opt}}(t+k|t)$ is the effect of the optimizing control actions $\delta\mathbf{u}(t|t), \ldots, \delta\mathbf{u}(t+N_u-1|t)$, with $\delta\mathbf{u}(t+k|t) = \mathbf{u}^* = \mathbf{u}(t+k|t) - \mathbf{u_{base}}(t+k|t)$, in a control horizon N_u.

The optimized output $\mathbf{y_{opt}}(k)\,, \forall k \in [1, 2, \ldots, N_2]$ can be expressed as the discrete time convolution of the unit impulse response coefficients $h_1, \ldots, h_{N_2}$ and unit step response coefficients $g_1, \ldots, g_{N_2}$ of the system as

$$\begin{aligned}\mathbf{y_{opt}}(t+k|t) = h_k\delta\mathbf{u}(t|t) + h_{k-1}\delta\mathbf{u}(t+1|t) + \ldots \\ +g_{k-N_u+1}\delta\mathbf{u}(t+N_u-1|t)\,.\end{aligned} \tag{4}$$

Combining (3) and (4) and writing them in vector form, the key EPSAC formulation becomes

$$\mathbf{y} = \overline{\mathbf{y}} + \mathbf{G}\mathbf{u}^*\,. \tag{5}$$

Then, the control effort, $\mathbf{u}$, is optimized by minimizing the cost function:

$$\sum_{k=N_1}^{N_2} \left[\mathbf{r}(t+k|t) - \mathbf{y}(t+k|t)\right]^2\,. \tag{6}$$

The horizons N_1, N_2 and N_u are the design parameters and $\mathbf{r}(t)$ represents the desired trajectory to the set point [16]. It is possible to represent the *reference trajectory* using a first-order function with initialization $\mathbf{r}(t|t) = y(t)$ as:

$$\begin{aligned}\mathbf{r}(t+k|t) &= \alpha\mathbf{r}(t+k-1|t) + (1-\alpha)\mathbf{w}(t+k|t), \\ &\quad \forall k \in [1, \ldots, N_2]\end{aligned} \tag{7}$$

The signal $\mathbf{w}(t)$ represents the desired set-point and α is a design parameter to tune the MPC performance [16] modulating the rate to converge towards the given reference.

The cost function (6) can be represented as:

$$(\mathbf{r}-\mathbf{y})^{\mathbf{T}}(\mathbf{r}-\mathbf{y}) = [(\mathbf{r}-\overline{\mathbf{y}}) - \mathbf{G}\mathbf{u}^*]^{\mathbf{T}}[(\mathbf{r}-\overline{\mathbf{y}}) - \mathbf{G}\mathbf{u}^*]\,,$$

where $\mathbf{r} = [r(t+N_1|t)\ldots r(t+N_2|t)]^T \in \Re^{N_2}$. That can be transformed into the standard quadratic cost index

$$J(\mathbf{u}^*) = \mathbf{u}^{*T}\mathbf{H}\mathbf{u}^* + 2\mathbf{f}\mathbf{u}^* + c\,, \tag{8}$$

with,

$$\begin{aligned}\mathbf{H} = \mathbf{G}^T\mathbf{G} \quad \mathbf{f} = -\mathbf{G}^{\mathbf{T}}(\mathbf{r}-\overline{\mathbf{y}}) \\ c = (\mathbf{r}-\overline{\mathbf{y}})^{\mathbf{T}}(\mathbf{r}-\overline{\mathbf{y}})\,,\end{aligned} \tag{9}$$

where $\mathbf{G}^T\mathbf{G} \in \Re^{N_u \times N_u}$.

Finally, the feedback characteristic of MPC is given by the fact that only the first optimal control input $u(t) = \mathbf{u_{base}}(t|t) + \delta\mathbf{u}(t|t) = \mathbf{u_{base}}(t|t) + \mathbf{u}^*(1)$ is applied to the plant and then the whole procedure is repeated again at the next sampling instant $(t+1)$, where $\mathbf{u}^*$ can be analytically found for the unconstrained case as:

$$\mathbf{u}^* = [\mathbf{G^T G}]^{-1}[\mathbf{G^T}(\mathbf{r}-\overline{\mathbf{y}})]\,. \tag{10}$$

However, for a better performance, constraints can be considered when minimizing $\mathbf{u}^*$.

III. Control Strategy

The control strategy developed in the present work, aims to stabilize a pre-planned walking gait where the ZMP trajectories, feet trajectories and CoM trajectory are pre-computed. As previously exposed in the work [8], the errors during locomotion that arise due to complaint actuators as those of the Walk-Man robot, impacts, model errors and so on, make impossible to directly execute a pre-planned pattern and require the implementation of additional strategies that allow the proper performance during the gait.

In order to execute the pattern, at each sample time the corresponding reference is loaded and the stabilizing controller is used to compensate the given tracking errors in the robot. The modified trajectories are computed and then converted to the joint space of the robot using inverse kinematics.

Given that the gait is pre-planned, the provided CoM trajectory is designed such that the desired ZMP trajectory is tracked and the robot preserves the balance during the gait execution. The proposed balancing strategy in this work minimizes the CoM tracking error. Additionally, it offers better tracking in an indirect way of the ZMP trajectory, and provides the desired stability performance of the robot.

This control has two layers, the first layer uses the measured CoM error with a desired settling point of zero, indicating a perfect tracking. The control effort of the first layer is the modification of the ZMP reference. In other words, how much should the ZMP be modified to minimize the CoM tracking error. The second layer compensates the error between the modified ZMP reference, provided by the first controller, and the desired ZMP reference. This compensation is done applying a shift in the pelvis reference since a direct change of the CoM is not trivial. By executing the pelvis modification, the controller permits the system to track the modified ZMP reference that reduces the CoM tracking error and this way recover the gait. Given that the CoM trajectory was pre-computed to track properly the desired ZMP reference, by reducing the CoM tracking error, the ZMP trajectory is tracked as well.

Given that the walking gait in this work is pre-computed using a multibody model, the use of MPC strategy is of particular interest since this controllers consider the future behavior, based on a model response, and future trajectories of the system with in a time window of length N_2, which differs from the instantaneous control strategies as PIDs. Therefore, the calculated control effort will provide a ZMP modification to compensate the CoM error within a time window. In this way, the error is corrected ahead considering the future trajectory and the present robot states. Therefore, the control action is smoother and the tracking error minimized.

The control proposed in this work implements in the first control layer the EPSAC, where the used predictive model for the biped's CoM error is a double integrator, which is a representation of a free body in the space. Given that the control objective is to correct the CoM tracking error through a local modification of the ZMP. The used system for the EPSAC controller has as measured stated the CoM error with respect to the actual reference ($CoM_{err}(1:N_2) = CoM_{measure} - CoM_{ref}(0)$). The desired tracking reference is the error evolution from the present desired reference $CoM_{err}(0) = 0$. Therefor, the control reference is $0 - CoM_{ref}(1:N_2)$. It is assume that the evolution of the error trajectory given the measured CoM error, is the trajectory itself.

The used model (1) is:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}, \qquad \mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D} \tag{11}$$

$$\mathbf{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \mathbf{C} = \begin{bmatrix} 1 & 0 \end{bmatrix}, \mathbf{D} = [0],$$

the output of this system is the position state and the control effort, $\mathbf{u}^*(1)$, that minimizes (8) is the CoM error acceleration. In particular how much the body should be accelerated to make the position to converge towards the desired trajectory. Notice that the selected system representation does not depend on any physical parameter and can be extended to other robotic platforms. However, the use of more complex models such as the spring-loaded inverted pendulum might increase the controller performance. Within the implementation of this controller, the proper tuning of noise observer (2) will increase the system response and the reference trajectory (7) will permit to have a softer response by properly tuning the parameter α (7).

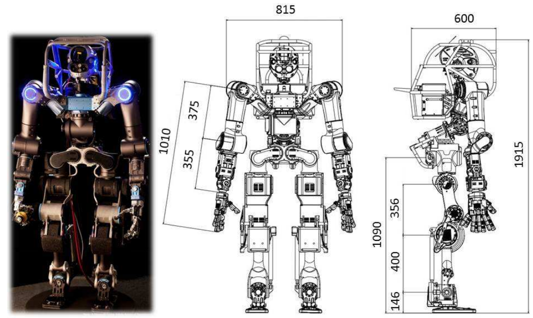


Fig. 1: Walk-Man body size specifications (mm)

Once the desired CoM error acceleration $\mathbf{u}^*(1)$ is found, it is necessary to calculate the ZMP location, within the support polygon, that minimizes the CoM tracking error. As long as the ZMP remains inside the support polygon the walking biped robot will not tip around the stance foot [17]. A common representation of a walking gait based on ZMP trajectories, is the car-table model which equation is:

$$p_x = x - \frac{\ddot{x}}{g} z_c \ . \tag{12}$$

To find the modified ZMP that reduces the CoM error toward the future trajectory, we have

$$\Delta p_x = (CoM_{err}) - \frac{U^*}{g} z_c \ , \tag{13}$$

Having Δp_x, the modified ZMP reference is $ZMP_{mod} = \mathbf{ZMP_{ref}}(0) + \Delta p_x$. Which is the input to the second layer of our stabilizer.

The aim of the second control layer is to provide a modified position reference at the pelvis level that allows the new reference ZMP_{mod} to converge towards the desired trajectory $\mathbf{ZMP_{ref}}(0)$. We used a PID controller that takes the modified ZMP reference ZMP_{mod} as measure output, $\mathbf{ZMP_{ref}}(0)$ as reference and $\Delta Pelvis$ position is output. In the second layer we used the PID controller given that the future modified ZMP trajectory is constantly changing and the future trajectory is not know ahead. Additionally, an estimation of the ZMP behavior implies the used of a delay system with unstable nature [13].

IV. Simulation results

To evaluate the performance of the presented work, we implement the walking and balance methods developed by [8], and we compared the CoM and ZMP tracking errors with respect to the ones obtained when using the proposed balance method during the locomotion of the Walk-Man biped.

The Walk-Man dimensions are depicted in Fig. 1. This humanoid's dimensions are similar to those of an adult human, it is 191 cm height from the sole to the head, 81.5 cm between shoulders, and the depth at the torso level is 60 cm. Walk-Man's total weight is 132Kg. The upper body of the robot has 17 degree of freedom excluding hands and neck and the lower body has 12 DOF. Walk-Man is a compliant robot due to the SEA actuators which flexible element is a torsion bar. As mentioned in [18], when a pattern is executed in a feed forward manner, modelling and environment reconstruction errors can induce to unstable locomotion. These errors are more evident when compliant actuators are used, making necessary the use of a feedback controller to stabilize the robot while executing different gaits.

The first layer control parameters are:

- z_c (assumed CoM constant height): 1 m, this height is assumed to be constant through the walking gait.
- N_2 (Prediction Horizon): 200, given that the used sampling time is 5 ms, the prediction horizon is equivalent to 1 s. The CoM error is predicted within a step.
- N_u (control horizon): 1, the optimization selects the best control effort considering only a single control action.
- α (reference modulation (7)): 0.5, provides a softer approximation during the error minimization. Therefore, softer control effort is obtained.
- Noise observer Filter (2): In this controller, we used a low pass first order Butterworth filter with cut-off frequency at 0.9 Hz given the nominal oscillation frequency $\sqrt{g/z_c} \approx 0.45$ Hz given z_c. We select to filter at the double of this frequency to reject frequencies close to the operation point reducing the phase error.

The second layer controller which is a PID controller has the following parameters $[0, 0.0035, 0.001]$ which were obtained experimentally.

To compare the behaviour of the presented strategy, we performed a 1 m walk with 20 cm step length and step time of 1.2 s. We compare the performance of the motion when using the original control strategy present in [8] and the controller presented in this paper. As shown in Fig.2(a) and Fig. 2(b) (left side), both controllers offer a good tracking of the CoM reference in both planes. However, when our controller is used, there are smaller tracking errors as depicted in Table. I, where mean errors and maximum absolute errors are depicted.

On the other hand, analyzing the ZMP tracking performance, the proposed controller actually offers a better tracking of the desired reference as seen in the zoomed area of each figure. The better ZMP tracking increases the stability of the overall walking. It is seen as well that the obtained trajectories present less spikes, present less tracking error and are more consistent (stairs like shape) with respect to the original ZMP reference. In addition, the original control strategy present higher frequency response in the modified ZMP reference given that it tries to correct the instantaneous CoM error. Instead, the MPC controller provides a smoother yet more effective ZMP reference modification reducing spikes in the measure ZMP. Having a lower frequency component further increases the overall stability reducing vibration and stress to the structure. In addition, better ZMP tracking provides bigger interaction margin for additional feedback controllers given that the

TABLE I: CoM and ZMP error when using the proposed (new) and the original (old) stabilizers

Data	sagittal data error		Lateral data error	
	mean [m]	max[m]	mean [m]	max [m]
CoM_{new}	0.0074	0.0243	0.0104	0.0284
CoM_{old}	0.013	0.039	0.0174	0.065
ZMP_{new}	0.0074	0.0243	0.0157	0.156
ZMP_{old}	0.0132	0.03	0.02	0.2839

ZMP is further from the support polygon edges. This will provide more capabilities to the robot while walking.

The lateral ZMP response shows a "cleaner" tracking performance in the case of the new stabilizer, as it is seen the frequency component is lower and the measured ZMP presents fewer spikes with respect to the previous methodology. As depicted in Table. I, both controllers present spikes. However, the ones in the given method have less magnitude compared with the ones obtained with the initial control strategy. Therefore, the impacts have less effect when using the proposed controller.

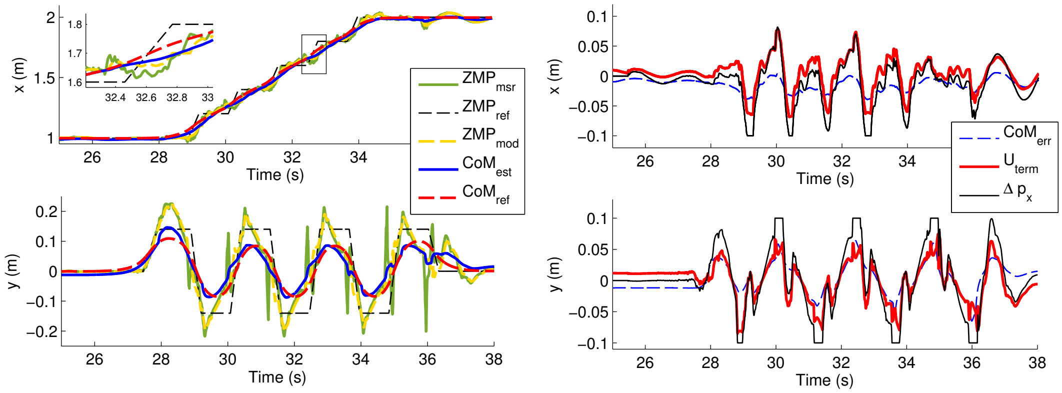
The control effort contribution to the modified ZMP reference (13), is shown in Fig. 2(a) and Fig. 2(b) right side, where Δp_x, CoM_{err} and $U_{term} = -\frac{\mathbf{u}^*}{g} z_c$ are plotted. In this figures we analyzed the contribution of the control effort $\mathbf{u}^*$ that the MPC control provides and compare the behavior with the results from the simulation when using the original control strategy. To this aim we used (13) and extract the corresponding U_{term} signal from data while we directly used the $\mathbf{u}^*$ obtained during the simulation in the case of the MPC controller.

As it is seen, the frequency components of the control effort have lower frequency in both lateral and sagittal planes with respect to the response when using the control proposed in [8]. In both cases U_{term} presents a significant contribution to the system response. However, it can be seen from data that the terms Δp_x and Δp_y, which are the maximum ZMP modification allowed, are reaching the saturation levels when the original control strategy is applied. Notice the magnitude of the CoM_{err} in both planes, that reflects the necessary correction that needs to take place.

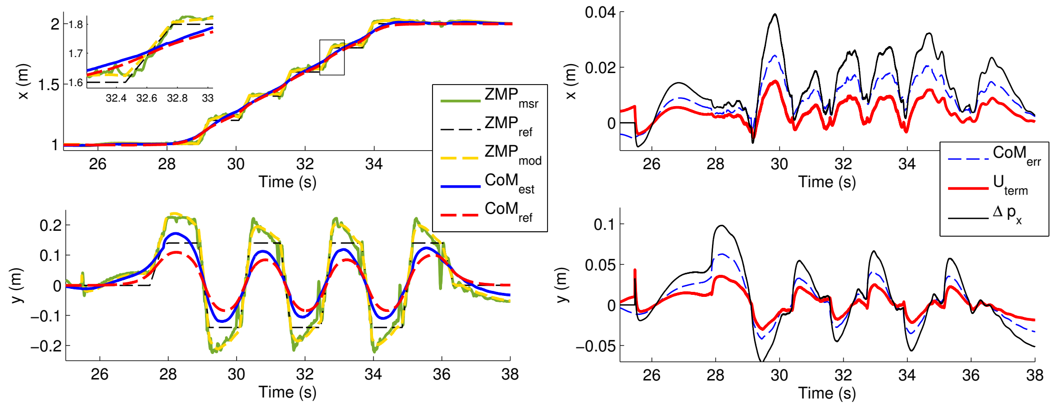
V. Experimental results

For implementing the controller on the real robot, the same MPC parameters were used while the PID controller gains were tuned experimentally. The final tuned parameters were $[0.02, 0.001, 0.0004]$ for the sagittal plane and $[0.01, 0.0001, 0.0003]$ for the lateral one. To compared the data we have a three step walk of 20 cm with a stepping time of 1.2 s when using our method and we are comparing it with a two steps walk of 20 cm with a stepping time of 1.2 s when using the double PID control strategy method. Experiments where ran in different moments so, we are comparing different scenarios. However the evaluated methods are using the same trajectory generator and hardware.

As seen in Fig. 3(b) and Fig. 3(a), the robot is able to perform the required gait in both cases with not significant differences. The CoM tracking permits the robot to have a stable walk. In the sagittal plane, both controllers have simi-



(a) Old Control results.



(b) New control results.

Fig. 2: Simulation Results. (Left) CoM and ZMP behavior, (Right) Control effort contribution.

lar control errors, the tracking is good during the cruise state but during the landing, the impact generates some oscillations as expected given the robot's compliant actuators.

The similar performance between the two controllers can be explained due to the natural oscillatory frequency of the robot $T_c = sqrt(g/z_c)$ which is closed to 0.45 Hz as mention before. This is clearly seen in Fig. 4 where it is clear that the principal component of the frequency response is located at this frequency for both ZMP responses. As it is seen, by applying the proposed controller the system is compensating the natural frequency response. Given the compliant actuation of the system, this behavior becomes more difficult to handle and affects the performance of the proposed controller. In order to increase the reliability and have a better system response, from the control point of view, one can used a different model for the CoM estimation in the MPC controller. A more accurate model will increase the performance of the controller providing a more accurate control effort to compensate the system dynamics. Another consideration is the tuning process. As mention before, the MPC controller we used for the experiments was exactly the same we used for the simulations. however, we consider that the used of a different noise observer and different control horizons might affect positively the overall control performance.

VI. Conclusions

In this paper we proposed the used of MPC control techniques to increase the performance of a balancing strategy for bipedal walking. By applying the proposed method, it was shown that a better tracking of the CoM and ZMP references is obtained. The better tracking increases the reliability of the walking and providing a more stable response. In addition, the controller reduces the effect of natural oscillation during the performed walking during the experiments while providing a stable walk. As it was shown, the method reduces the glitches and presents a softer response in comparison with the used of other controller which reduces the hardware stress. The simulation and experimental results show that the method permits to stabilize the walking gait and was able to permit a compliant humanoid to successfully execute the proposed walking gait.

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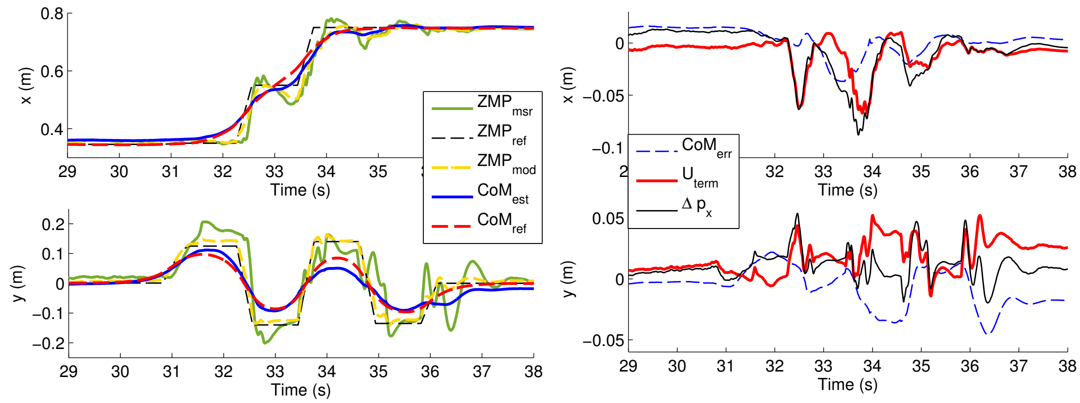
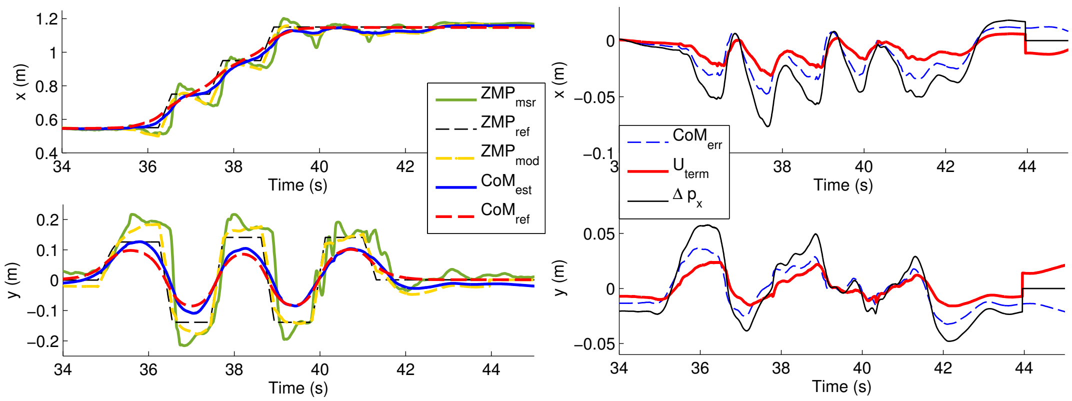


(a) Old Control results. Two steps walk with 20cm step length and 1.2 s step time.



(b) New control results. steps walk with 20cm step length and 1.2 s step time.

Fig. 3: Experimental Results. (Left) CoM and ZMP behavior, (Right) Control effort contribution.

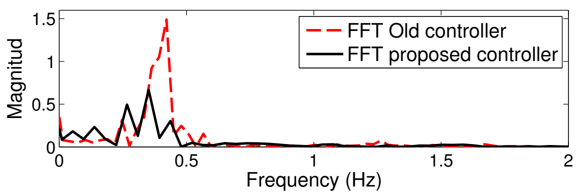


Fig. 4: FFT for the ZMP response comparison

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