Neural-Augmented Inertia-Adaptive MPC with Whole-Body Control for 10-DoF Bipedal Robots

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***Abstract*— Model Predictive Control (MPC) using single rigid body dynamics (SRBD) performs well in legged locomotion, but is less accurate for bipeds due to their relatively large leg mass. To address this, we adopt an Inertia-Adaptive MPC (IA-MPC) that incorporates centroidal inertia predicted in real time by a Centroidal Composite Inertia Neural Network (CCINN). This inertia enables MPC to achieve posture-dependent control accuracy. Additionally, a Whole-Body Controller (WBC) maps the MPC-computed contact forces and moments into joint torques consistent with full-body dynamics. Simulation results show improved long-horizon walking stability, with reduced lateral deviation and more than 50% reduction in roll error.**

I. INTRODUCTION

Various control strategies for legged robot locomotion have been actively studied in recent years. Among them, Model Predictive Control (MPC) approaches that treat the robot as a single rigid body have demonstrated excellent walking performance, particularly in quadrupedal robots [1]. These methods have also been extended to bipedal robots to achieve stable walking [2]. However, modeling the robot as a single rigid body introduces limitations, especially for bipedal systems. Unlike quadrupeds, bipedal robots have legs that contribute a larger portion of the total mass, making the rigid body approximation less accurate. This paper proposes a control framework to enhance walking stability in a 10-DoF bipedal robot by combining an Inertia-Adaptive MPC (IA-MPC) that incorporates predicted centroidal inertia varying with future posture and a Whole-Body Controller (WBC).

II. CONTROL APPROACH

A. Inertia-Adaptive MPC

To formulate the proposed controller, the robot shown in Fig. 1(a) is modeled as a single rigid body to derive a simplified bipedal dynamics model [2]. The dynamics are expressed in (1), where f_i is the 3-D contact forces from foot i, m_i is the 2-D moments excluding roll, and r_i is the vector from the center of mass (CoM) to each contact point.

$$\begin{bmatrix} m(\ddot{p}_{\text{com}} + g) \\ \frac{d}{dt}(I_G \omega) \end{bmatrix} = \sum_{i=1}^{2} \begin{bmatrix} f_i \\ r_i \times f_i + m_i \end{bmatrix} \tag{1}$$

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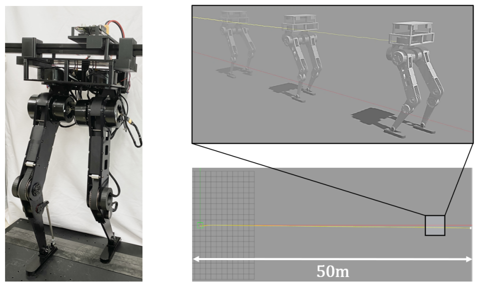

(a) Bipedal Robot (b) Trajectory during forward walking

Fig. 1. (a) The 10-DoF bipedal robot. (b) Top-view trajectory during a 50 m forward walk (yellow line: torso trajectory, red line: x-axis).

By linearizing the dynamics in (1), the system is expressed in continuous-time state-space form as follows:

$$\frac{d}{dt}\begin{bmatrix} p_{\text{com}} \\ \dot{p}_{\text{com}} \\ \Theta \\ \omega \end{bmatrix} = A \begin{bmatrix} p_{\text{com}} \\ \dot{p}_{\text{com}} \\ \Theta \\ \omega \end{bmatrix} + B \begin{bmatrix} f_1 \\ f_2 \\ m_1 \\ m_2 \end{bmatrix} + \begin{bmatrix} 0 \\ g \\ 0 \\ 0 \end{bmatrix} \tag{2}$$

In (2), the matrix B includes the inverse centroidal inertia tensor I_G^{-1}, which significantly affects the rotational dynamics of the robot. In bipedal systems, where the legs are relatively heavy, I_G varies considerably with posture. This variation is evident in floating-base humanoids, where assuming constant inertia becomes unreliable.

To adaptively account for this variation, we employ a Centroidal Composite Inertia Neural Network (CCINN) [3] that predicts the centroidal inertia tensor I_G at each time step. The CCINN takes interpolated foot positions and orientations over the prediction horizon as input and outputs corresponding inertia tensors. This allows the MPC to recognize accurate posture-dependent dynamics for each configuration. The dataset for training was generated using the `Pinocchio` library by computing the centroidal inertia tensor under various postures. The CCINN is a 3-layer neural network with two 128-neuron hidden layers using `ReLU` activation.

The convex MPC problem is formulated as follows:

$$\min_{x,u} \sum_{i=0}^{N-1} \|x[i+1] - x_{\text{ref}}[i+1]\|_{Q[i]} + \|u[i]\|_{R[i]} \tag{3}$$

Here, $x[i]$ is the robot state, $u[i]$ is the control input (contact forces and moments), and $Q[i]$, $R[i]$ are weighting matrices. Equation (3) defines the MPC cost over the N-step horizon with posture-dependent inertia predicted by CCINN.

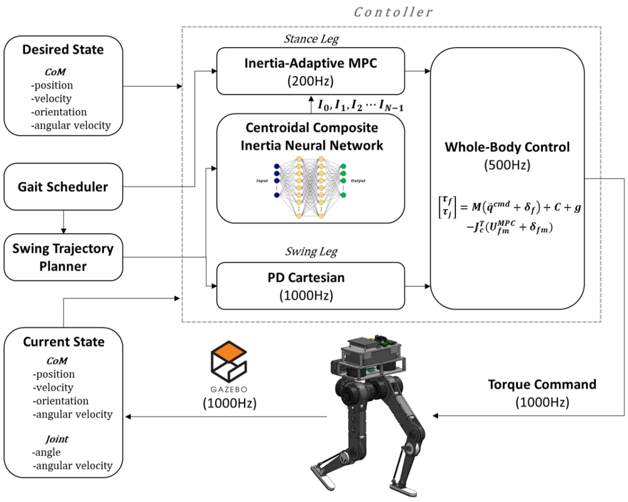

Fig. 2. Overview of the proposed control framework. The whole-body controller (WBC) is designed after the Model Predictive Control (MPC) block to compute joint torques based on the computed ground reaction forces and moments.

B. Whole-Body Control

The overall control framework, illustrated in Fig. 2, incorporates a whole-body controller (WBC) [4] operating downstream of the model predictive controller (MPC). While simplified dynamics suffice for predictive optimization in MPC, incorporating a full-body dynamics model allows the optimized contact forces and moments to be translated into joint torques more accurately through WBC, enabling precise and physically consistent actuation.

The full-body dynamics, including the floating base and actuated joints, are expressed as follows:

$$M \begin{bmatrix} \ddot{q}_f \\ \ddot{q}_j \end{bmatrix} + C + g = \begin{bmatrix} \mathbf{0} \\ \tau_j \end{bmatrix} + J_c^\top U_{\text{fm}} \tag{4}$$

To construct (4), a prioritized task execution is adopted to compute the commanded joint accelerations $\ddot{q}^{\text{cmd}}$. This approach uses the null-space projection technique, assigning orientation as the primary task and position as the secondary. Accordingly, $\ddot{q}^{\text{cmd}}$ is computed progressively based on task priority as follows:

$$\ddot{q}_i^{\text{cmd}} = \ddot{q}_{i-1}^{\text{cmd}} + \bar{J}_{(i|\text{pre})}^{\text{dyn}} \left(\ddot{x}_i^{\text{cmd}} - \dot{J}_i \dot{q} - J_i \ddot{q}_{i-1}^{\text{cmd}} \right) \tag{5}$$

where,

$$\begin{aligned} J_{(i|\text{pre})} &= J_i N_{i-1}, \\ N_0 &= I - J_c^\dagger J_c, \\ N_{(i|i-1)} &= I - J_{(i|i-1)}^\dagger J_{(i|i-1)}, \\ N_{i-1} &= N_0 N_{(1|0)} \cdots N_{(i-1|i-2)} \end{aligned}$$

The task-space accelerations $\ddot{x}_i^{\text{cmd}}$, computed by a PD control law (6), are used in (5) to compute joint accelerations.

$$\ddot{x}_i^{\text{cmd}} = \ddot{x}_i^{\text{des}} + K_p^{\text{wbc}}(x_i^{\text{des}} - x_i) + K_d^{\text{wbc}}(\dot{x}_i^{\text{des}} - \dot{x}_i) \tag{6}$$

To maintain consistency with the floating-base dynamics while ensuring that task-space accelerations remain feasible, a Quadratic Programming (QP) problem is formulated to compute correction terms for the contact forces and moments δ_{fm} and the base acceleration δ_f:

$$\min_{\delta_{\text{fm}}, \delta_f} \|\delta_{\text{fm}}\|_{K_1} + \|\delta_f\|_{K_2} \tag{7}$$

$$\begin{aligned} \text{s.t.} \quad & S_f \left\{ M(\ddot{q}^{\text{cmd}} + \delta_f) + C + g \right\} = S_f J_c^\top \left(U_{\text{fm}}^{\text{MPC}} + \delta_{\text{fm}} \right) \\ & \text{lb} \leq W \left(U_{\text{fm}}^{\text{MPC}} + \delta_{\text{fm}} \right) \leq \text{ub} \end{aligned}$$

Finally, the optimal solutions from the QP in (7) (solved using the `qpOASES` solver) are incorporated into the full-body torque command in (8) to compute the joint torques.

$$\begin{bmatrix} \mathbf{0} \\ \tau_j \end{bmatrix} = M(\ddot{q}^{\text{cmd}} + \delta_f) + C + g - J_c^\top (U_{\text{fm}}^{\text{MPC}} + \delta_{\text{fm}}) \tag{8}$$

TABLE I

RMSE COMPARISON AND REDUCTION IN ORIENTATION TRACKING

Axis	**SRBD-MPC + WBC** (rad)	**IA-MPC + WBC** (rad)	**Reduction** (%)
Roll	0.033975	0.016758	50.68 ↓
Pitch	0.019174	0.017555	8.44 ↓
Yaw	0.063965	0.058662	8.29 ↓

III. RESULTS

To validate the proposed controller, simulation experiments were conducted in Gazebo using a custom 10-DoF bipedal robot developed in our lab. As shown in Fig. 1(b), the robot walked 50 m forward at 0.7 m/s. With SRBD-MPC only, the robot showed large yaw drift and fell after 10 m. Adding WBC enabled stable walking over 50 m, but resulted in a 10.9 m lateral deviation. In contrast, the proposed IA-MPC combined with WBC reduced the lateral deviation to 0.51 m, keeping the robot aligned with the desired path. Furthermore, Table I shows improved orientation tracking across all axes, including over 50% reduction in roll error.

IV. CONCLUSIONS

This paper proposed a control framework that enhances MPC by incorporating centroidal inertia varying with future posture and whole-body control. The method was demonstrated on a 10-DoF bipedal robot, showing improved torso orientation and position tracking during forward walking. Future work will involve validation on real humanoid hardware.

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