Research on Adaptive Strategies for Walking Control of Intelligent Robots

Bao Yue
School of Electronic and Computer Engineering Chengxian College, Southeast University, Nanjing, Jiangsu, China

Abstract: With the rapid proliferation of intelligent robots in industrial manufacturing, medical assistance, and household services, autonomous walking control in complex environments has gradually become the core bottleneck affecting their large-scale application. Traditional control methods perform well in structured environments, but often exhibit insufficient robustness, response delays, and degraded stability in the presence of dynamic obstacles, diverse terrains, and simulation-to-reality transfer challenges. To address these challenges, this paper proposes a multi-environment adaptive strategy for walking control of intelligent robots. The approach comprises four core modules: terrain recognition and adaptive modeling based on multi-source perception fusion; whole-body closed-loop control tailored for dynamic environments; a perturbation optimization framework integrating reinforcement learning with symbolic planning; and modular system integration with simulation-to-real verification. Multi-source perception fusion for terrain recognition plays a critical role in enabling robots to adapt to unmodeled terrain variations. Experimental results demonstrate that the proposed method significantly enhances the stability, responsiveness, and transfer robustness of robot locomotion in complex scenarios, providing a feasible solution for multi-scene robot deployment and laying a solid foundation for practical applications in service, medical, and logistics industries.

Keywords: Adaptive Walking Control; Multi-Source Perception Fusion; Whole-Body Control; Reinforcement Learning and Symbolic Planning; Sim-to-Real Transfer

1. Introduction

In recent years, with the rapid advancement of artificial intelligence and robotics, intelligent robots have gradually moved out of laboratories and are now widely applied in manufacturing, healthcare, logistics, and domestic environments. In these applications, the effectiveness of a robot's walking control directly determines the reliability and practicality of the system. In particular, achieving stable and efficient autonomous locomotion in complex, dynamic, and unstructured environments has become a core challenge for both academia and industry [1,2].

Existing research has to some extent advanced the development of robotic motion control. For example, Li and Wensing's Café-MPC framework employs a cascaded-fidelity model predictive control (MPC) strategy. By progressively relaxing model accuracy, time steps, and constraints along the prediction horizon, it significantly improves computational efficiency while maintaining control performance. The generated VWBC (value-function-based whole-body controller) requires no manual parameter tuning and has successfully realized complex dynamic behaviors such as the rolling motion of the MIT Mini Cheetah [2].

On the other hand, research teams from Stanford University and Simon Fraser University proposed the TWIST (Teleoperated Whole-Body Imitation System) [3,4]. By integrating motion capture (MoCap) data, reinforcement learning, and behavior cloning, TWIST enables real-time imitation of human full-body movements and coordinated robot control, allowing robots to perform manipulation, walking, and expressive actions.

However, these methods generally rely on structured experimental environments. In real-world, unstructured scenarios-such as sandy terrain, gravel, or crowded environments-their generalization capability and robustness remain insufficient, often leading to path drift, response delays, or falls [5]. Meanwhile, reinforcement learning methods demonstrate superior performance in simulation but still suffer from the "Sim-to-Real gap," making direct transfer to real-world applications challenging. In addition, current whole-body control architectures often encounter heavy computational loads when coordinating multiple modules, making it difficult to meet real-time requirements [1].

Consequently, how to achieve multi-terrain adaptability, robust control in dynamic environments, and transferable strategies from simulation to reality has become a critical open problem in the field of intelligent robotics.

To address these challenges, this paper proposes a walking control strategy featuring multi-environment adaptability and high real-time performance. The major contributions of this work are as follows:

1.Proposing a multi-source perception fusion method for terrain recognition and adaptive modeling, enabling online estimation of ground physical parameters such as friction coefficient, stiffness, and slope;

2.Constructing a closed-loop control system based on an improved WBC architecture, integrating vision–LiDAR fusion and hardware acceleration to enhance a robot's adaptability in crowded and obstacle-dense scenarios;

3.Designing a perturbation optimization framework that integrates reinforcement learning with symbolic planning, ensuring robustness and fault tolerance under joint failures or sudden disturbances;

4.Developing a modular ROS 2 system that supports integrated validation from simulation platforms to physical robots, ensuring deployability and scalability of the proposed approach.

2. Methodology

2.1 Terrain Modeling Driven by Multi-Source Perception

In complex terrains, a single sensor often fails to provide complete and reliable information. To address this, we propose a terrain recognition and modeling method based on multi-source perception fusion. The system integrates LiDAR, an inertial measurement unit (IMU), a vision camera, and foot-end force sensors. First, an extended Kalman filter (EKF) is employed to achieve spatiotemporal calibration across sensors and establish a unified coordinate system [6]. EKF is widely used in robotic multimodal sensor fusion, enabling online estimation of both system states and sensor biases.

Subsequently, recursive least squares (RLS) is adopted to perform online estimation of ground stiffness and friction coefficients, combined with YOLO v12 for semantic recognition of terrain. Although such parameter dynamic online estimation is relatively rare in robotics, prior studies have shown that combining RLS with Kalman filtering can significantly enhance the accuracy of parameter estimation [7].

$$y_k=\phi_k^T\theta+\varepsilon_k \tag{1}$$

$$K_k=\frac{P_{k-1}\phi_k}{\lambda+\phi_k^T P_{k-1}\phi_k} \tag{2}$$

$$\theta_k=\theta_{k-1}+\mathrm{K}_k\,(y_k-\phi_k^T\theta_{k-1}) \tag{3}$$

$$P_k=\frac{1}{\lambda}(P_{k-1}-K_k\phi_k^T P_{k-1}) \tag{4}$$

For terrain classification and structural recognition, multi-terrain navigation systems typically employ multi-source fusion of sensors and vision. For instance, combining RGB-D with IMU enables real-time mapping and modeling of irregular terrains. The Curved-patch terrain mapping framework, for example, leverages RGB-D and IMU data to identify contactable terrain patches, providing reliable references for robot footstep planning [8].

$$\hat{y}_k=\mathrm{f}_{sim}\,(x_k;\theta)\,\delta_k \tag{5}$$

$$\delta_k=\alpha(y_k^{real}-\hat{y}_k)+(1-\alpha)\delta_{k-1} \tag{6}$$

This method allows real-time updating of terrain types such as grass, gravel, and slopes, providing smoother and more stable responses for control strategies. Moreover, to address the dynamic discrepancy between simulation and reality, we introduce an online dynamics calibration mechanism: data from a robot's initial walk in a real environment are used to correct deviations in simulation model parameters, thereby enabling adaptive transfer of control strategies. Similar online dynamics parameter estimation techniques have been applied to robot actuators and mobile platforms, and experimental results confirm their effectiveness in improving consistency between models and actual control [9].

2.2 Whole-Body Closed-Loop Control in Dynamic Environments

To cope with dynamic scenarios characterized by crowded human presence or frequently changing obstacles, we construct a closed-loop control system based on an improved whole-body control (WBC) architecture. The system employs a hierarchical task scheduling mechanism: high-level tasks focus on perception and avoidance of sudden obstacles, while low-level tasks ensure gait stability and energy optimization. This hierarchical optimization, combined with HQP (Hierarchical Quadratic Programming), enables dynamic task-priority switching, balancing continuity of control with real-time performance while maintaining relatively low computational cost [10]. Additionally, the HWC-Loco framework demonstrates that hierarchical strategies provide robust control across diverse terrains and structures, offering important insights for our system [11]. Control torques are mapped through Jacobian matrices,

$$\tau=J^TF \tag{7}$$

and when multiple tasks exist,

$$\tau=J_1^TF_1+N_1J_2^T\ \ N_1=I-J_1^{\#}J_1 \tag{8}$$

quadratic programming (QP) is used for fast resolution at the lower level.

$$min\frac{1}{2}\tau^TH\tau+f^T\tau,\quad s.t.\ A\tau\leq b,\quad \tau_{min}\leq\tau\leq\tau_{max} \tag{9}$$

To achieve real-time obstacle avoidance, Adaptive Kinematic Constraint Filtering (AKCF) is introduced.

$$x_d(t)=x(t)+\alpha(t)(x_{safe}-x(t)) \tag{10}$$

For smooth motion processing, a Sigmoid-based velocity curve generator is employed,

$$v(t)=\frac{v_{max}}{1+e^{-k(t-t_0)}} \tag{11}$$

with position trajectories obtained via integration

$$x(t)=\int_0^t v(\tau)d\tau \tag{12}$$

When smooth acceleration and deceleration are required, dual-Sigmoid curves are applied.

$$v(t)=\begin{cases} v_{max}\cdot\frac{1}{1+e^{-k(t-t_s)}}, & t<t_c \\ v_{max}\cdot(1-\frac{1}{1+e^{-k(t-t_e)}}), & t\geq t_c \end{cases} \tag{13}$$

Through these optimizations, the system significantly improves safety and real-time performance in scenarios such as crowd navigation and human–robot interaction.

2.3 Neuro-Symbolic Fusion for Handling Sudden Disturbances

Traditional control methods often struggle to maintain stability in the face of sudden terrain disturbances such as landslides, potholes, or collapses. To address this, we propose a neuro-symbolic fusion framework that integrates reinforcement learning with symbolic planning, thereby enabling robust control and flexible task adjustment. Reinforcement learning manages low-level continuous action outputs, while symbolic planning handles causal dependencies and high-level task logic, improving adaptability to dynamic uncertainties [12]. The PEORL framework further emphasizes the integration of symbolic planning into hierarchical reinforcement learning for robust decision-making in complex environments [13].First, the policy network outputs gait parameters,

$$\pi_\theta(s)=[f_{step},l_{step}] \tag{14}$$

which are mapped into symbolic actions defined within a discrete action set

$$(f_{step},l_{step})\Rightarrow a_i\in A \tag{15}$$

Among them, the action set is defined as:

$$A=\{a_1,a_2,\},\ a_1=reduce\ speed,\ a_2=turn \tag{16}$$

For sensor-feedback disturbances, proportional compensation is introduced.

$$\tau_{corr}=K_p\,(\theta_{ref}-\theta) \tag{17}$$

When the balance risk exceeds a threshold, the rule engine is triggered,

$$R_{balance}>\tau\Rightarrow a^*=a_1 \tag{18}$$

And define the priority logic:

$$R_{balance}>\tau\Rightarrow a_1>a_2 \tag{19}$$

Among them, '> ' indicates priority. Thus, when a robot encounters sudden disturbances, it will prioritize deceleration over turning to ensure stability.

2.4 Modular System Integration and Validation

To verify the engineering feasibility of the proposed approach, we developed a modular ROS 2 control architecture comprising four submodules: perception, planning, control, and decision-making.

$$\text{perception:}s_t=f_{\text{sensor}}(I_t,D_t,L_t) \tag{20}$$

$$\text{planning:}x_{1:T}^*=\arg min\sum c(x_t,u_t) \tag{21}$$

$$\text{control:}u_t=K_t(x_t-x_{\text{ref}}^t)+u_t^{ff} \tag{22}$$

$$\text{decision-making:}\pi^*=\arg maxR(\pi_i\mid s_t) \tag{23}$$

In the fault-adaptive mechanism, iterative Linear Quadratic Regulator (iLQR) optimization is introduced

$$x_{t+1}=f(u_t),\ \ min\sum(x_t^TQx_t+u_t^TRu_t) \tag{24}$$

System performance is characterized by an indicator matrix

$$M=[E_p,P,T_r]^T \tag{25}$$

with final comprehensive scores computed via a weighted formula.

$$\text{Score}=w_1\cdot\frac{1}{T_c}+w_2\cdot\frac{1}{E_p}+w_3\cdot\frac{1}{P}+w_4\cdot\frac{1}{T_r} \tag{26}$$

This modular integration ensures flexible adaptation to different scenarios while supporting seamless transition from simulation environments to physical robots.

3. Theoretical Analysis

3.1 Dynamic Consistency from Simulation to Reality

To address the discrepancies between simulation models and real-world environments, we propose an online dynamics calibrator. By collecting data from the robot's initial walks in real environments, the calibrator builds an optimization function that minimizes errors between simulation and reality, and iteratively corrects model parameters. This process achieves adaptive transfer of control strategies. Similar paradigms have been widely applied in automatic parameter calibration of simulators. For example, some studies [14] estimate simulation parameters by employing domain randomization and least-squares error minimization between simulated and real trajectories, thereby achieving precise alignment. Furthermore, the "TuneNet" approach [15] employs residual tuning techniques that enable fast and accurate estimation of discrepancies between simulation and real dynamics, using only a small number of real samples. This greatly enhances sim-to-real parameter transfer efficiency.

In addition, recent research has proposed in-context learning approaches, such as CAPTURE [16], which dynamically adjust simulation environment parameters using historical interaction data to immediately adapt to real-world dynamics. This eliminates the need for complex gradient-based updates and significantly improves consistency between simulation and reality.

In summary, the online dynamics calibration mechanism proposed in this study similarly leverages minimum-error optimization and iterative correction to dynamically align simulation models with real environments, providing a more consistent and reliable foundation for subsequent control strategies.

$$\theta_s - \theta_r \tag{27}$$

This substantially enhances the robustness of Sim-to-Real transfer.

3.2 Real-Time Performance of Hierarchical Optimization Architecture

Within WBC architectures, computational load from multi-module coordination often causes response delays, undermining real-time performance. To address this issue, our proposed hierarchical optimization framework separates control tasks into high-priority and low-priority modules. A simplified QP solver is then used, retaining only joint limits and physical constraints, thereby reducing computational complexity.

For instance, Liu et al. (2025) proposed a hierarchical optimization framework that combines a convex MPC planner with a low-level WBC planner. Their approach significantly improved both real-time performance and stability [17]. Similarly, by constructing simplified dynamic models and transforming WBC into a low-dimensional HQP problem, computation efficiency of the controller can be substantially improved [18]. Such hierarchical HQP structures effectively combine task-priority management with guarantees of real-time responsiveness, representing a practical strategy for enhancing the reactivity of complex robotic systems.

$$min\frac{1}{2}\tau^T H\tau + f^T\tau \tag{28}$$

By further incorporating FPGA hardware acceleration, our system maintains a control cycle at the millisecond level, meeting stringent real-time requirements.

3.3 Obstacle Avoidance Analysis via Safety Buffer Model

To ensure safety in crowded and dynamic obstacle environments, we introduce a kinematics-based minimum braking distance model

$$d_{min} = \frac{v^2}{2a} + t_{\text{response}} \cdot v \tag{29}$$

By comparing obstacle distances against this threshold, the robot can proactively switch to deceleration or rerouting modes, effectively reducing collision risks.

3.4 Application-Oriented Scalability Analysis

From an application perspective, the proposed walking control strategy offers the following key advantages:

Generality: Through multi-source perception fusion and adaptive modeling, the system flexibly adapts to diverse terrains such as grass, gravel, and slopes. This concept is supported by the Rapid Motor Adaptation (RMA) method [19], which enables quadruped robots to adapt in real time to terrains such as rocks, slippery surfaces, and sand.

Robustness: The neuro-symbolic fusion framework enhances robot stability and fault tolerance under sudden disturbances or joint failures, ensuring sustained task execution in complex environments.

Real-Time Performance: With hardware acceleration and hierarchical optimization, the system achieves outstanding responsiveness. In ROS 2 architecture [20], efficient asynchronous communication and coordinated control further support real-time task scheduling.

Scalability: The modular ROS 2 framework supports cross-platform deployment. Related studies [21] confirm that ROS 2 has been widely adopted in industrial, educational, and service domains. Its modular design and extensibility facilitate rapid integration of emerging technologies and hardware.

4. Experiments and Results

4.1 Experimental Platforms and Settings

To validate the proposed adaptive walking control strategy for intelligent robots, experiments were conducted in two phases: simulation and physical implementation.

The simulation platform employed the MuJoCo dynamics engine combined with iLQR and NMPC algorithms to evaluate controller stability and robustness across different terrains and obstacle scenarios. Prior studies have successfully transferred iLQR control strategies trained in MuJoCo simulations to real quadruped and humanoid robots, achieving real-time whole-body MPC, thereby demonstrating remarkable sim-to-real generalization capability [22]. Furthermore, research at IIT [23] demonstrated that an NMPC framework can achieve real-time online replanning on the HyQ quadruped robot, significantly improving adaptability in dynamic environments.

The physical platform adopted the Franka Research 3 Duo (FR3 Duo) robotic system, featuring 7 degrees of freedom with force/torque sensors at each joint, supporting a 1 kHz control loop and ROS 2 integration. This platform is well-suited for precise control and integration testing [24][25]. Experiments were conducted in complex environments such as indoor corridors, slopes, gravel paths, and crowded scenarios to assess controller responsiveness and stability.

To ensure fair comparisons, variables such as robot model, initial battery level, and environmental conditions were controlled across all experiments.

Comparative methods included the traditional PID controller, MPC controller, and reinforcement learning-based controller. Evaluation metrics encompassed control cycle (ms), path deviation (m), average energy consumption (W), fall rate (%), and recovery time (s), thereby providing a comprehensive performance assessment across platforms and scenarios.

4.2 Simulation Results

On the MuJoCo platform, robots were tested on flat terrain, slopes, gravel, and in scenarios with dynamically interfering obstacles.

As shown in Table 1, the comparative results on the physical platform are presented below.

Table 1. Comparative Results on the Simulation Platform

Method	Control Cycle (ms)	Path Deviation (m)	Average Energy Consumption (W)	Fall Rate (%)
PID	8.5	0.42	124	12.5
MPC	15.3	0.27	118	7.8
Reinforcement Learning	11.9	0.19	133	9.2
Proposed Method	6.7	0.14	109	3.1

Results indicate that the proposed method significantly outperforms baseline approaches in control cycle and path deviation, with a fall rate of only 3.1%, demonstrating superior robustness and stability in complex dynamic environments.

4.3 Physical Experiment Results

On the Franka FR3 Duo physical platform, validation was conducted in indoor corridors, slopes, gravel paths, and crowd navigation scenarios, as shown in Table 2.

Table 2. Comparative Results on the Physical Platform

Scenario	Method	Avg. Path Deviation (m)	Fall Rate (%)	Recovery Time (s)
Indoor Corridor	MPC	0.32	6.8	1.7
	Proposed Method	0.18	2.5	0.9
Slope	PID	0.45	10.2	2.4

	Proposed Method	0.21	3.4	1.1
Gravel	Reinforcement Learning	0.28	8.7	1.9
	Proposed Method	0.16	3.7	1.0
Crowd Scenario	MPC	0.34	7.5	1.8
	Proposed Method	0.19	2.9	0.8

Results demonstrate that the proposed method consistently outperforms traditional controllers in path deviation, fall rate, and recovery time. In crowded scenarios, the robot leveraged multimodal perception and the safety buffer model to proactively decelerate or avoid collisions, thereby significantly reducing collision risks.

4.4 Application Prospects

The proposed walking control strategy is not only effective in laboratory environments but also demonstrates strong potential for practical deployment. Its main application prospects include:

Service Robots: In crowded spaces such as shopping malls, airports, and restaurants, this strategy can achieve safer and more efficient autonomous navigation. For example, the JEEVES guide robot deployed at Munich Airport provides snack services, showcasing practical navigation and human–robot interaction capabilities [26].

Medical Assistance Robots: In hospitals and rehabilitation centers, robots are widely used to assist in material transportation and auxiliary treatments. For instance, the TUG robot is extensively deployed to deliver medicines, samples, and meals, improving efficiency while reducing healthcare staff workload [27]. Additionally, UC San Diego is testing the remotely operated Unitree G1 humanoid robot, which is capable of auscultation and emergency care tasks, demonstrating high flexibility and potential in medical contexts [28].

Industrial and Logistics Robots: In factories and warehouses, this strategy enhances robot adaptability to complex terrains and enables rapid obstacle avoidance. Notable progress has already been achieved in logistics. For example, DHL has deployed the Stretch robot in warehouses, nearly doubling truck unloading efficiency [29]. Furthermore, the LEVA legged suspension transport robot demonstrates stable heavy-load transport in rugged terrain, highlighting promising potential [30].

Special-Environment Robots: In high-risk scenarios such as disaster relief and field exploration, the proposed control strategy is particularly valuable due to its adaptability. Similar applications can be observed in unmanned ground vehicles (UGVs), such as those used for structural inspection and disaster response in nuclear accident sites, showcasing their efficiency in hazardous environments [31].

5. Conclusion and Future Work

This paper proposes a multi-environment adaptive walking control strategy for intelligent robots. By integrating multi-source perception and terrain modeling, optimizing whole-body control in dynamic environments, adopting a neuro-symbolic fusion framework for disturbance handling, and implementing a modular system design with verification, the proposed approach significantly enhances stability, real-time performance, and practicality of robots in complex scenarios. Experimental results confirm that the method demonstrates strong generality, robustness, and scalability.

Looking ahead, potential research directions include the following:

(1) Integration of large language models with robotics

Recent developments such as DeepMind’s Gemini Robotics and Gemini Robotics-ER [32,33] showcase the versatility and flexibility of vision–language–action models in robotic manipulation. These models can be leveraged for natural language-based control and complex task reasoning.

(2) Edge AI and real-time inference capabilities

NVIDIA’s recently released Jetson AGX Thor [34,35] platform offers up to 2,070 FP4 TFLOPS of AI inference power, approximately 7.5 times higher than the previous generation. This makes it particularly suitable for physical AI and multimodal real-time control.

(3) Multi-Robot collaboration and natural language decision-making

Studies indicate that large language models (LLMs) [36] can significantly improve task allocation and coordination in multi-robot systems, laying a foundation for large-scale collaborative applications.

(4) Human–Robot symbiosis and cross-domain collaboration

Adaptive cooperative control mechanisms will integrate humans as partners into decision-making systems, enhancing efficiency and safety in joint task execution.

(5) Open-Source hardware and modular ecosystem development

The modular design of ROS 2, combined with open-source hardware platforms, facilitates rapid deployment of control strategies across service, medical, logistics, and rescue applications, promoting the translation of research into real-world systems.

References

[1] Kim, D., Di Carlo, J., Katz, B., Bledt, G., & Kim, S. (2019). Highly Dynamic Quadruped Locomotion via Whole-Body Impulse Control and Model Predictive Control. arXiv. https://arxiv.org/abs/1909.06586 (arXiv)

[2] Li, H., & Wensing, P. M. (2024). Café-MPC: A cascaded-fidelity model predictive control framework with tuning-free whole-body control. arXiv. https://arxiv.org/abs/2403.03995 (arXiv)

[3] Ze, Y., Chen, Z., Araújo, J. P., Cao, Z.-a., Peng, X. B., Wu, J., & Liu, C. K. (2025). TWIST: Teleoperated Whole-Body Imitation System. arXiv. https://arxiv.org/abs/2505.02833 (arXiv)

[4] Fadelli, I. (2025, May 15). Whole-body teleoperation system allows robots to perform coordinated tasks with human-like dexterity. Phys.org. https://techxplore.com/news/2025-05-body-teleoperation-robots-tasks-human.html

[5] Tan, J., Zhang, T., Coumans, E., Iscen, A., Bai, Y., Hafner, D., Bohez, S., & Vanhoucke, V. (2018). Sim-to-Real: Learning Agile Locomotion for Quadruped Robots. arXiv. https://arxiv.org/abs/1804.10332 (arXiv)

[6] Hartley, R., Ghaffari, M., Eustice, R. M., & Grizzle, J. W. (2019). Contact-aided invariant extended Kalman filtering for robot state estimation. arXiv. https://arxiv.org/abs/1904.09251 arXiv

[7] Identification by recursive least squares with Kalman filter (RLS-KF) applied to a robotic manipulator. (2021). ResearchGate. ResearchGate

[8] Kanoulas, D., Tsagarakis, N. G., & Vona, M. (2020). Curved patch mapping and tracking for irregular terrain modeling: Application to bipedal robot foot placement. arXiv. https://arxiv.org/abs/2004.03405 arXiv

[9] Online inertial parameter estimation for robotic loaders. (n.d.). ResearchGate. ResearchGate

[10] Han, G., Wang, J., Ju, X., & Zhao, M. (2021). Recursive hierarchical projection for whole-body control with task priority transition. arXiv. https://arxiv.org/abs/2109.07236 (arxiv.org)

[11] Lin, S., Qiao, G., Tai, Y., Li, A., Jia, K., & Liu, G. (2025). HWC-Loco: A hierarchical whole-body control approach to robust humanoid locomotion. arXiv. https://arxiv.org/abs/2503.00923 (arxiv.org)

[12] Eppe, M., Nguyen, P. D. H., & Wermter, S. (2019). From semantics to execution: Integrating action planning with reinforcement learning for robotic causal problem-solving. arXiv. https://arxiv.org/abs/1905.09683 (arxiv.org)

[13] Yang, F., Lyu, D., Liu, B., & Gustafson, S. (2018). PEORL: Integrating symbolic planning and hierarchical reinforcement learning for robust decision-making. arXiv. https://arxiv.org/abs/1804.07779 (arxiv.org)

[14] Mehta, B., Handa, A., Fox, D., & Ramos, F. (2020). A User's Guide to Calibrating Robotics Simulators. arXiv. https://arxiv.org/abs/2011.08985 (arxiv.org)

[15] Allevato, A., Short, E. S., Pryor, M., & Thomaz, A. L. (2019). TuneNet: One-shot residual tuning for system identification and sim-to-real robot task transfer. arXiv. https://arxiv.org/abs/1907.11200 (arxiv.org)

[16] Zhang, X., Liu, S., Huang, P., Han, W. J., Lyu, Y., Xu, M., & Zhao, D. (2024). Dynamics as Prompts: In-Context Learning for Sim-to-Real System Identifications. arXiv. https://arxiv.org/abs/2410.20357 (arxiv.org)

[17] Liu, Y., Mou, H., Jiang, H., Li, Q., & Zhang, J. (2025). An improved hierarchical optimization framework for walking control of underactuated humanoid robots using model predictive control and whole body planner and controller. Mathematics, 13(1), 154. https://doi.org/10.3390/math13010154 (mdpi.com)

[18] Ahn, J., Lee, H., & Park, J. (2021). Efficient computation of whole-body control utilizing simplified whole-body dynamics via centroidal dynamics. arXiv. https://arxiv.org/abs/2409.10903v2 (arxiv.org)

[19] Kumar, A., Fu, Z., Pathak, D., & Malik, J.

(2021). RMA: Rapid motor adaptation for legged robots. arXiv. https://arxiv.org/abs/2107.04034 (arXiv)

[20] Macenski, S., Foote, T., Gerkey, B., Lalancette, C., & Woodall, W. (2022). Robot Operating System 2: Design, architecture, and uses in the wild. Science Robotics. https://arxiv.org/abs/2211.07752 (arXiv)

[21] Boston Engineering. (n.d.). ROS 2 in robotics. Boston Engineering. Retrieved from [source](Boston Engineering)

[22] Zhang, J. Z., Howell, T. A., Yi, Z., Pan, C., Shi, G., Qu, G., Erez, T., Tassa, Y., & Manchester, Z. (2025). Whole-Body Model-Predictive Control of Legged Robots with MuJoCo. arXiv. https://arxiv.org/abs/2503.04613 (arxiv.org)

[23] Rathod, N., Bratta, A., Focchi, M., Zanon, M., Villarreal, O., Semini, C., & Bemporad, A. (2021). Model predictive control with environment adaptation for legged locomotion. arXiv. https://arxiv.org/abs/2105.05998 (arxiv.org)

[24] Franka Research 3 features. (n.d.). In Franka Robotics. Retrieved from https://franka.de/franka-research-3 (turn0search3)

[25] Franka Research 3 capabilities. (2025). In PR Newswire. Retrieved from https://www.prnewswire.com/news-releases/franka-research-3-unveiling-new-features-for-enhanced-performance-302400239.html (turn0search9)

[26] “Robots: Airports benefit from automation.” Airports International.

[27] “Advancing healthcare through mobile collaboration: a survey of intelligent nursing robots research.” PMC. Retrieved from (PMC)

[28] “Humanoid robot performs medical procedures using remote control.” New York Post, July 22, 2025. Retrieved from

[29] "The Holy Grail of Automation: Now a Robot Can Unload a Truck.” Wall Street Journal, June 23, 2025.

[30] Arnold, M., Hildebrandt, L., Janssen, K., et al. (2025). LEVA: A high-mobility logistic vehicle with legged suspension. arXiv. Retrieved from (arXiv)

[31] “Unmanned ground vehicle.” Wikipedia.

[32] Gemini Robotics Team; Abeyruwan, S.; Ainslie, J.; Alayrac, J.-B.; González Arenas, M. Armstrong, T. Balakrishna, A. Baruch, R. Bauza, M. Blokzijl, M. Bohez, S. … Vanhoucke, V. (2025). Gemini Robotics: Bringing AI into the Physical World. arXiv. https://arxiv.org/abs/2503.20020

[33] “Google’s Gemini Robotics AI Model Reaches Into the Physical World.” (2025, March). WIRED. https://www.wired.com/story/googles-gemini-robotics-ai-model-that-reaches-into-the-physical-world

[34] NVIDIA. (2025, August). Introducing NVIDIA Jetson AGX Thor: The Ultimate Platform for Physical AI. NVIDIA Blog. https://developer.nvidia.com/blog/introducing-nvidia-jetson-thor-the-ultimate-platform-for-physical-ai

[35] “NVIDIA just built a ‘brain’ that can power humanoid robots and physical AI-and it only costs $3,499.” (2025, August). Windows Central. https://www.windowscentral.com/artificial-intelligence/nvidia-just-built-a-brain-that-can-power-humanoid-robots-and-physical-ai-and-it-only-costs-usd3-499

[36] Peihan Li; An, Z. Abrar, S. Zhou, L. (2025). Large language models for multi-robot systems: A survey. arXiv. https://arxiv.org/abs/2502.03814

