RO:BIT Team Description Paper for Humanoid Large League of RoboCup 2026

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Abstract. This paper details the technical evolution of RO:BIT as it transitions to the 2026 Humanoid AdultSize League. Our research focuses on mitigating the inertial instability of large-scale bipedal systems by integrating empirical motion data with deep reinforcement learning. We propose a hybrid control framework designed to enhance mechanical durability and real-time environmental perception..

Keywords: Walking Control, Sim-to-Real Transfer, Imitation Learning, Probabilistic Localization

1 Introduction

Entering the AdultSize League requires a new approach to handle increased inertial loads. Our previous KidSize control logic cannot stabilize the higher center of mass and increased weight of the new platform. RO:BIT is currently deploying a decentralized control system to solve this. This framework maintains structural safety while providing the agility needed for 2026 match conditions.

2 System Components

2.1 Walking Control and Motion Control

In the 2024 RoboCup Humanoid competition, our kid-sized robot employed pattern- and Capture Point (CP) walking [2]. Subsequently, since 2025, we have been exploring a PPO-based reinforcement learning controller. Pattern gaits were simple but required offset tuning, while CP methods improved stability yet were sensitive to sensor error. Our RL-based gait showed the greatest promise: it adjusted to changes in link lengths and masses and delivered more natural trajectories with less manual tuning. However, we observed a significant sim-to-real gap arising primarily from inaccurate actuator modelling and insufficient domain randomization during training.

For the adult-size platform, which is still under development, we are training locomotion policies using the RSL-RL library [3] in Isaac Lab, then evaluating them in MuJoCo. To address the identified sim-to-real issues, we employ aggressive domain randomization and are developing an actuator network to model motor dynamics, inspired by recent UAN approaches [4]. We plan to collect long-horizon, whole-body loco-manipulation data using the TWIST2 framework [5] for scalable whole-body demonstration collection, which will enable agile full-body actions when hardware arrives. The combined architecture aims to translate the adaptive benefits of RL into stable and practical real-world performance for competition deployment.

2.2 Vision and Localization

In the past Kid League, we labeled all field landmarks inside the stadium as a single class and detected them using YOLO, and then performed MCL-based localization based on the detection results. However, because the landmark types were not distinguished, the observations lacked specificity, which made the MCL measurement update unstable and prevented us from achieving sufficiently accurate pose estimation. To address this issue, we plan to refine the labeling by subdividing landmarks into corner points, cross points, and T points, train YOLO to detect each type separately, and incorporate these type-aware detections into the MCL-based localization [1] pipeline to improve localization accuracy.

3 Development Strategy and Implementation

RO:BIT follows a rigid integration schedule to ensure hardware-software reliability.

3.1 Infrastructure and Hardware Synchronization

Early development focuses on modular vision code. We are currently building the housing for ZED stereo sensors and testing the IMU-to-motor communication bus. This phase ensures the "nervous system" of the robot delivers stable data for balance control.

3.2 Empirical Stress-Testing and Integration

Intermediate events like the RoboCup Open act as a testing ground. We focus on verifying that the power systems can handle the high current spikes required for AdultSize walking. These tests find hardware weak points before we freeze the design.

3.3 Final Design Lock and Performance Tuning

The last phase removes hardware artifacts like joint backlash and ground friction noise. After locking the mechanical setup in February, we focus solely on soccer-specific tactics and optimizing high-speed positioning.

4 Conclusions

RO:BIT's 2026 strategy replaces simple heuristics with a sensor-integrated, data-driven architecture. By wrapping RL policies in safety-critical code, we have built a robot that is both fast and mechanically durable. This platform serves as our technical baseline for the 2026 competition season.

References

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