Mountain Extended Abstract for Humanoid Kid-size League of RoboCup 2026

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Abstract: This paper presents the overall preparation scheme and technical route of our team for the first participation in the RoboCup Humanoid League (kid-size) competition. We focus on the development and optimization of the robot's walking algorithms, vision systems, and decision-making processes. By building a complete simulation test system and formulating systematic training protocols, we aim to achieve basic stability, positioning accuracy, and multi-robot cooperative capabilities for the upcoming competition.

1. Lessons Learned and Problems

As a team participating in the RoboCup Humanoid League for the first time, we face challenges such as insufficient practical experience, untested hardware performance, and immature algorithm stability. We have identified that carrying out a large number of simulated matches in the early stage is the core link of preparation. These simulated matches can help detect potential hardware problems including motor overload and structural vibration. They can also support the preliminary debugging and optimization of the robot's basic gait. To address these challenges, we have established a standardized simulation test process and a component replacement and maintenance manual. These measures are designed to ensure the reliability of the robot during the formal competition.

2. Plans of the major changes

2.1 Walking

To ensure the robot's basic movement ability on the competition field, we have carried out a comparative study of three advanced gait algorithms: Central Pattern Generators (CPG), Model Predictive Control (MPC) and Reinforcement Learning (RL).

- CPG algorithm is used to construct the basic rhythmic gait of the robot. We have adjusted the parameters of joint oscillation frequency and amplitude through simulation tests to ensure the smoothness of the robot's walking and turning at low speed.
- MPC algorithm is oriented to dynamic movement scenarios such as fast walking and obstacle crossing. By predicting the robot's motion state in the next few steps, we realize the real-time adjustment of the center of gravity and avoid falling caused by sudden changes in motion state.

- RL algorithm is used for autonomous gait optimization. We have built a reward function based on motion stability and energy consumption, and let the robot learn the optimal gait strategy in the simulation environment with different ground friction and slope conditions.

We will carry out a two-stage test for the above algorithms: first, verify the algorithm performance in the Gazebo simulation environment, and screen out the two algorithms with the best stability; then carry out physical machine tests, and further optimize the algorithm parameters according to the actual motion data of the robot. Finally, we will determine the final gait scheme according to the test results, and reserve the switching interface of multiple algorithms to deal with different competition scenarios.

2.2 Vision and Simulation

A high-precision vision system is the premise of the robot's field positioning and ball recognition, so we have built a complete vision processing pipeline combining hardware selection and algorithm development.

1. Hardware and algorithm development

We have completed the development of a Line Segment Detector (LSD) with real-time performance. The detector can quickly extract the boundary lines and penalty area lines of the competition field, and effectively filter the interference of light reflection and robot shadow through the adaptive threshold segmentation algorithm.

We have integrated the LSD with the Particle Filtering Algorithm. On the basis of the line feature information, the algorithm fuses the robot's odometer data to realize high-precision positioning of the robot on the field, with the positioning error expected to be controlled within 5cm.

In terms of hardware, we have selected a monocular camera with a resolution of 1280×720 and a frame rate of 60fps as the visual sensor, which balances the calculation amount and recognition effect.

2．Simulation environment construction and test plan

We have built a simulation environment consistent with the actual competition field by using Webots software, and set up multiple test scenarios such as different lighting intensities, field line wear and robot mutual occlusion.

The vision system will enter the comprehensive testing and refinement stage in the upcoming spring semester. We will collect the data of the simulation test and physical machine test, and optimize the algorithm's recognition speed and positioning accuracy through iterative training. At the same time, we will also develop a fault-tolerant mechanism. When the vision system fails to recognize the field features, the robot will switch to the odometer positioning mode to ensure the continuity of the movement.

2.3 Decision making

To realize reliable multi-robot cooperation for our first competition, we adopt a **lightweight peer-to-peer decision framework** based on improved UDP communication, and design a behavior-tree-driven modular decision model to simplify tactical execution.

1. **Peer-to-peer communication architecture**

We optimized the UDP communication protocol with a packet loss retransmission mechanism, setting the data transmission frequency at 25Hz to balance real-time performance and stability. Unlike the single-host mode, each robot serves as an equal communication node. Each node independently uploads its own perception data including position and ball detection results, and synchronously receives data from other nodes to avoid system paralysis caused by single-node failure.

2. **Behavior-tree-based decision model**

We built a two-level decision model driven by behavior trees instead of the traditional layered structure.

The **basic behavior module** includes pre-written action primitives such as ball chasing, obstacle avoidance and shooting. The behavior tree triggers corresponding actions according to sensor input, which reduces the difficulty of logical debugging.

The **tactical trigger module** is designed for simple scenarios suitable for new teams. We preset two tactical modes: single-robot offense and multi-robot zone defense. The system switches modes automatically according to the number of robots near the ball.

3. **Fault tolerance optimization**

We added a **10-second state caching mechanism**. When communication is interrupted, the robot will rely on the latest cached field data to execute basic obstacle avoidance and ball searching actions. This prevents the robot from entering a stagnant state in short-term communication failure.

Conclusion

As a new team in the RoboCup Humanoid League, we are committed to building a stable and reliable humanoid robot system through systematic technical research and standardized preparation. By focusing on the development of gait, vision, and decision-making systems, and with the support of a complete simulation test and training system, we aim to overcome the challenges faced by first-time participants. We strive to achieve good results in RoboCup 2026, accumulate valuable practical experience, and lay a solid foundation for the team's long-term development in the field of humanoid robotics.