Inha-United 2026 Team Description Paper

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Abstract. Team Inha-United is a research-driven group formed by four robotics laboratories at Inha University. Each laboratory focuses on core robotic technologies including perception, sensing, intelligence, decision-making, and control, and the team integrates these elements to develop multi-robot control systems for humanoid soccer. Through this platform, we address the challenge of achieving stable and cooperative autonomy under dynamic, adversarial, and partially observable environments.
Our approach emphasizes accessible system design, practical deployability, and robust integration of robotic subsystems. By validating these design choices in RoboCup competitions, we demonstrate how advanced core robotic technologies can be translated into reproducible, system-level solutions that support cumulative progress within the RoboCup and broader robotics communities.

1 Introduction

Our team, **Inha-United** at Inha University, is primarily composed of undergraduate students and is guided by principal investigators from multiple robotics laboratories. The laboratories collectively contribute expertise across core robotic technologies, including vision, sensing, intelligence, and control, forming the foundation of a unified, system-level humanoid robotic platform. The participating principal investigators bring a strong track record of success in international robotics competitions (e.g., DARPA Robotics Challenge 2015, Virtual RobotX Challenge 2019, and ICRA 2024 Workshop on Construction Robots), which drives the team's technical direction, system design choices, and research objectives.

To support full-scale operation in the RoboCup Humanoid League, we have constructed dedicated experimental environments that closely reflect real competition conditions. These efforts include the availability and operation of three humanoid robots, the installation of both half-court and full-court soccer fields, and the integration of a motion capture system for ground-truth localization. In addition, high-performance computing servers equipped with NVIDIA A6000 and RTX 5090 GPUs are utilized for large-scale training, simulation, and model optimization. Figure 1 provides an overview of the experimental environments.

This Team Description Paper summarizes the outcomes of development efforts by presenting the overall system architecture and operational framework

(a) Laboratory (b) GPU Server (c) Booster K1

Fig. 1. Experimental infrastructure established for RoboCup League preparation.

of the Inha-United humanoid system. Detailed technical implementations, extended experimental results, and supplementary materials are publicly available through the team's website and GitHub repository[1] to support transparency and reproducibility.

2 Our Contributions to RoboCup

The primary scientific contribution of our team lies in the design of a high-level, strategy-centered decision-making framework for humanoid robot teams. While individual capabilities such as perception, localization, and motion control are continuously improved, we focus on how team-level strategies are systematically designed and executed under the physical and computational constraints of humanoid platforms. In line with the league's vision, humanoid robot soccer is used as a representative setting for studying adaptive behavior in incomplete and highly dynamic environments.

To enable effective team performance under such conditions, our framework is built on modular skill representations and their composition into higher-level tactical behaviors. This structure allows strategies to be reconfigured and switched at runtime as situations evolve, while maintaining a consistent decision-making interface. As a result, role assignments, coordination policies, and tactical decision rules can be systematically instantiated and evaluated, with humanoid robot soccer serving as a testbed for rapid strategy iteration.

Beyond a single competition entry, our work establishes an extensible and practical decision-making architecture for multi-robot teams. By sharing this framework with the RoboCup community, we aim to lower the barrier to developing team-level intelligence and to promote reproducible research across diverse robotic applications.

In summary, our contributions to RoboCup are as follows:

1. A modular skill integration framework that supports independent development and evaluation of perception, localization, and motion algorithms.
2. A unified strategy construction and management framework enabling flexible composition, selection, and adaptation of team-level behaviors.
3. An accessible team-level architecture that simplifies the implementation of complex multi-robot strategies beyond humanoid soccer.

[1] `https://inha-united-soccer.github.io/Soccer2026`, `https://github.com/Inha-united-soccer`

3 Results

We built our algorithms on top of the Booster K1 platform [2] by reorganizing the data flow across perception, planning, control, and communication, and by incrementally updating individual algorithms. Sensor data from onboard IMU and RGB-D camera are processed in the perception module and refined through particle-filter-based localization to estimate robots and ball states. Based on these estimates, each robot executes a predefined role —striker, defender, or goalkeeper— in a 3 vs 3 configuration, and the planning module selects goal-directed behaviors using role-specific Behavior Trees [3]. The selected behaviors are executed through motion primitives and low-level control. All estimated states, intentions, and actions are shared via communication to enable coordinated team behavior. The same decision-making and execution pipeline can be consistently deployed in both simulation and real-world experiments. The data flow and overall architecture are shown in Fig. 2.

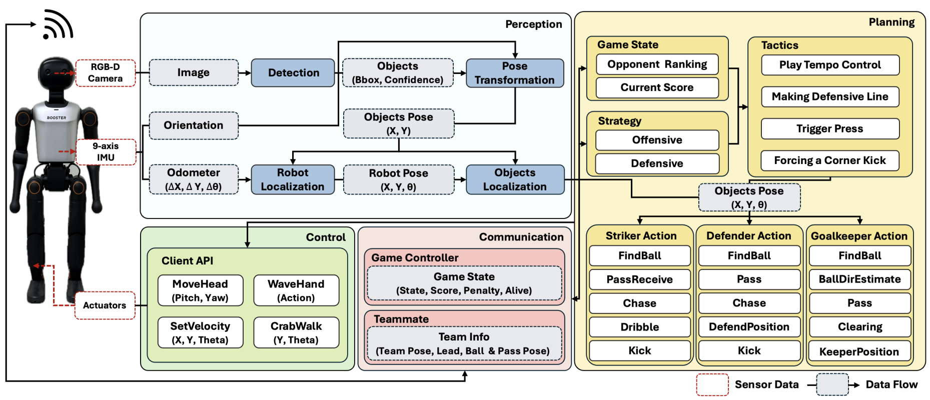
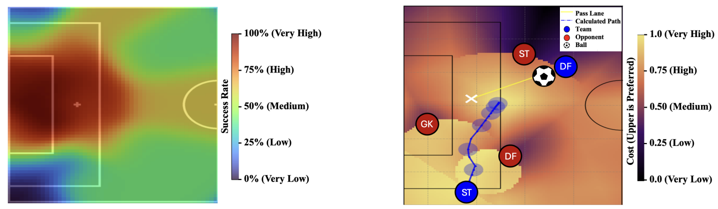


Fig. 2. Overview of the modularized system architecture for humanoid soccer.

Given the limited space, the implemented methods and key results are briefly summarized as follows:

- **Detection:** A YOLOv8-based detector [4] trained on the Torso21 dataset [1] and additional in-house data is combined to detect field markers, goalposts, balls, and robots. Additional data collection improves detection accuracy in terms of $mAP_{0.5:0.95}$ for all classes (+0.015) and ball detection (+0.03), while IMU heading compensation reduces the mean position error by 31.9 % compared to the K1 baseline. The average inference time is 33 ms.
- **Estimation:** An adaptive particle filter fusing vision-based field marker observations and odometry is employed, where data association is used to avoid multiple observations being assigned to the same landmark and clustering-based pose selection is applied to handle symmetric ambiguities with temporal consistency. Over a continuous 7 min. evaluation, the localization system maintained a mean position error about 0.17 m without divergence.
- **Planning:** A decentralized Behavior Tree–based planner is adopted, where each robot executes a role-specific strategy (ST, DF, GK) and selects actions



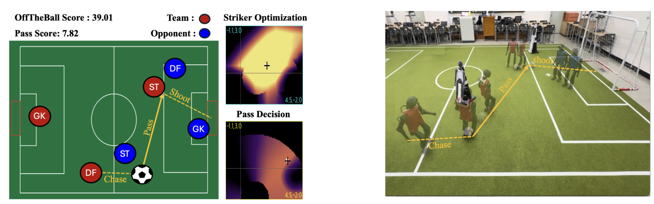
(a) Position-dependent shooting success rate

(b) Cost-Based optimal movement trajectory

Fig. 3. Trajectory from multi-term cost function, including shooting success rates.

using grid-based utility cost maps. The cost function integrates position-dependent shooting success rates (Fig. 3(a)), pass-receivability, opponent occlusion, defensive free-space availability, and safety penalties. Fig. 3(b) visualizes the resulting optimal movement trajectory obtained by cost-based position optimization under dynamic multi-robot interactions.

– **Control:** Motion execution is implemented on top of the provided low-level APIs (e.g., `SetVelocity`, `MoveHead`, `GetUp`), enabling robust target tracking and the composition of motion skills such as walking, dribbling, and kicking. Ball chasing and shooting behaviors are realized through perception-driven position alignment and velocity control based on detected ball states.



(a) Simulation results of a defender-to-striker passing scenario

(b) Reproduction of simulation results on the real robot

Fig. 4. Pass-and-shoot example with cost-driven pass targeting and receiving.

Figure 4 illustrates a pass-and-shoot scenario realized by the developed modular framework, where both the pass target and the free-space receiving position are selected based on role-specific cost functions. Beyond that, multiple team-play scenarios such as 2-on-1 passing, through passes, pass-and-shoot plays, and one-on-one situations with the goalkeeper were implemented and are demonstrated on our YouTube channel[2].

4 Conclusion

This work presented a modular humanoid robot soccer system developed together with a large-scale competition environment, providing a practical testbed for evaluating high-level intelligence through the integration of research-level perception, estimation, planning, and control modules. The proposed modularization and open-source design facilitate extensibility and reuse, enabling both researchers and educators to readily experiment with multi-robot decision-making and coordination. Future work will focus on advanced sensor fusion, decentralized and centralized coordination with effective communication, and reinforcement learning–based motion skill acquisition.

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[2] `https://www.youtube.com/@Inha-United_Soccer`

References

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