UT Austin Villa 2025 AdultSize Extended Abstract

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Abstract. UT Austin Villa is a new entrant in the RoboCup Humanoid League AdultSize competition. We introduce our team, outline our hardware and software infrastructures, and present our short-term development plans to enhance our robots' agility and perception. We also discuss several research directions—whole-body control, learning from human soccer videos, and multi-agent coordination—that we aim to pursue using RoboCup as a testbed.

1 Introduction

UT Austin Villa, a newly formed team competing in the RoboCup Humanoid League AdultSize category, seeks to advance humanoid robotics through agile motion control, robust perception, and multi-agent strategy. While new to this competition, we build on established robotics and AI research traditions [1–5] at The University of Texas at Austin.

We briefly describe our initial hardware platform, current software capabilities, and immediate plans for the next four months. These efforts target improved locomotion, perception, and team coordination. Beyond the competition, we aim to leverage RoboCup as a platform for research on whole-body control, visual imitation learning, and multi-agent strategies.

2 Hardware and Software

Our primary hardware platform, *Booster T1*, is a 1.18-meter-tall humanoid robot with 23 degrees of freedom and omnidirectional walking capability. It is equipped with a RealSense D455 RGB-D camera for ball and markers detection, as well as a 9-axis IMU for whole-body control[1]. We currently possess two of these robots, enabling us to explore multi-robot strategies.

Our current software framework is a combination of C++ and Python, with data streaming handled through ROS2. We rely on a Booster Robotics SDK that provides the interface for low-level motor control, odometer, and a default walking gait with push recovery trained by Reinforcement Learning (RL). We adapt soccer skills based on the RoboCup Demo, which provides a perceptron system

[1] Although the onboard IMU includes a magnetometer, it is currently disabled and not used for odometry.

for ball and markers detection using a fine-tuned YOLO-v8 model. In addition, the RoboCup Demo offers two soccer skills, strike and defense, implemented by behavior trees chaining multiple walking behaviors (navigating to the ball and kicking) and head movements (locating the ball and the goal).

3 Short-Term Plans

End-to-End Strike Skill: The current strike skill follows sequential steps: locating the ball, navigating to it, aligning with the goal, and striking. This step-by-step process is slow and prone to instability from step transitions. We plan to develop an end-to-end RL policy that performs strike directly from a distance, reducing strike time and eliminating instability from behavior switching.
Integrate Depth Images for Object Pose Estimation: the current system uses kinematics-based transformations from the camera to base frame for marker and ball detection, which become inaccurate during motion. To address this, we plan to leverage depth images to estimate and align the field plane, correcting camera-to-base transformations. This will enable more robust object ball and markers pose estimation and improve localization during dynamic movements.

4 Research Interests

Learning Whole-Body Control: We aim to develop controllers that move beyond standard gaits. Through reinforcement learning, we seek agile, whole-body behaviors suited for dynamic soccer scenarios.
Learning from Human Soccer Videos: We will explore using abundant soccer footage to facilitate policy learning. By extracting movement primitives and tactics, we hope to achieve more natural and adaptable robot behaviors.
Multi-Agent Coordination: RoboCup's team-based competitive game setting provides a rich environment for studying multi-agent collaboration, competition, and role allocation. Our goal is to develop teams that adapt to diverse opponents and non-stationary conditions.

References

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