Tech United Eindhoven Team Description 2026

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Abstract. Tech United Eindhoven, an eight-time World Champion in the Middle-Size League (MSL), is actively transitioning to the Humanoid League (HL) with a team of Booster T1 robots. Building on this legacy, the team recently competed at the 2025 RCAP Beijing Masters and the Rome Maker Faire. This paper outlines the transfer of the soccer strategy and implementation from MSL to HL, highlighting the intended development of a passing skill for humanoid robots, a lightweight simulator for humanoid soccer, and automatic dataset generation for training vision-based perception networks, as well as our work towards a quadrupedal goalkeeper. These developments are designed to improve existing capabilities of Tech United towards establishing the team as a competitive force in the Humanoid League.

Keywords: RoboCup Soccer · Humanoid League · Strategy · AI Vision · Synthetic Data · Quadruped · Goalkeeper

1 Introduction

Tech United Eindhoven represents Eindhoven University of Technology (TU/e) in the RoboCup competition. The team joined the Middle Size League (MSL) in 2006 and played in 14 finals of the world championship, winning it eight times. In 2025, the team expanded its ambitions into the Humanoid League, competing in the RCAP Beijing Masters. The experience strengthened the team's enthusiasm and motivated them to pursue participation in the next RoboCup.

The team consists of 5 PhD, 7 MSc, 11 BSc, 3 TU/e staff members and a number of alumni. This paper describes the developments made by the Tech United team to apply knowledge of MSL[5] to the Booster T1 humanoid robot.

2 Passing Skill

One of the main strengths of our MSL robots is their ability to pass. Whereas other teams excel with their quick dribbling or defensive skills, our robots pass the ball around relatively often to try to outplay the opponent. We are porting our strategy framework to humanoid robots, so that they can start using similar strategical patterns[3]. To execute these plans, the passing skill is essential, both on the giving and receiving side. The skill of giving a pass is similar to kicking a ball towards the goal, as the robot has to hit the ball in a specific direction, often with a desired velocity. For the skill of receiving a pass, the robot should be able to react quickly enough to a ball approaching it, estimating the position and time of arrival, and making sure it positions itself there. Once the ball arrives at the robot, it has to control it in such a way that it does not bounce off towards an opponent or outside of the field lines. This skill of receiving a pass is challenging, but implementing it will contribute not only to the game-play of our robots, but also to the attractiveness humanoid soccer leagues in general.

3 Simulation

Our team is refining the simulation environment for the humanoid robots. While the current IsaacSim simulator provides robust capabilities for simulating robot dynamics, its high GPU requirements limit accessibility for development in larger teams and during tournaments. Moreover, to develop strategy and teamplay rather than training robot physics, a more lightweight simulation would be adequate. Additionally, to enhance teamplay developments and enabling live debugging, it is crucial to have multiple robots within one single simulation environment. The existing simulation environment for our MSL robots already

Fig. 1: Visualization of the Tech United robots and opponents, which can be used during both simulations and real matches.

incorporated many of these essential aspects, making it a valuable tool when transitioning to the humanoid league. Figure 1 illustrates real-time interactions between our robots and opponents. For instance, robot 4's intended target location is marked by a red circle, and the location of the ball is visualized in yellow alongside its estimated velocity and direction. Additional strategic gameplay details for the selected robot are presented on the left side of the interface.

4 Synthetic Data Generation

As AI vision advances, many RoboCup teams now use CNNs for object detection, as they outperform classical feature-based methods and provide robust performance [7]. These models require thousands of annotated images that teams currently capture and label manually, which is a slow and error-prone process. Existing datasets and pre-trained models cannot be reliably used in MSL due to the lack of robust public models for MSL robots. To address this, we explore synthetic dataset generation to automatically produce large annotated datasets [4].

Figure 2 illustrates the proposed method. By capturing images of the target objects, we create 3D photorealistic models using LUMA AI [6]. The models are integrated into a virtual environment to generate synthetic datasets across diverse lighting conditions, object poses, lens settings, and camera orientations. These automatic annotated datasets are used as input for the supervised CNN object detection models enables the rapid development of a robust detection solution.

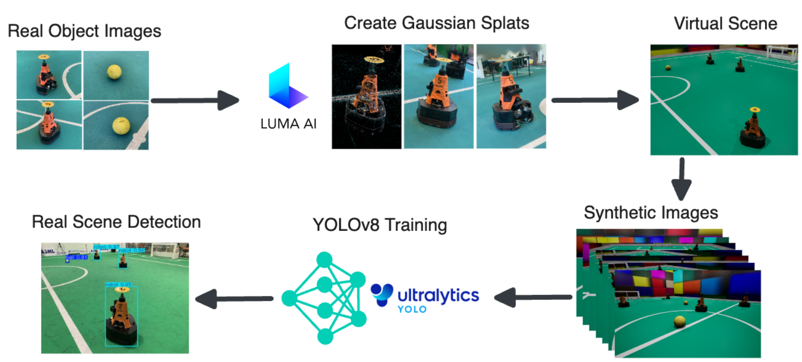

Fig. 2: The proposed pipeline for generating synthetic datasets for object detection using 3D Gaussian splats.

The evaluation uses a synthetic dataset of 5000 images built from four 3DGS model classes: the ball, the Tech United robot, and the two Falcons MSL platforms[1]. An mAP50 of 93% indicates a solid baseline for synthetic data generation in MSL. The recall of 84% shows a limited dataset size, and increasing the number of images is likely to improve it. Moreover, the high precision (94%) relative to the low recall indicates that reducing undesirable false positives will benefit both estimation and tracking.

Given these results, our aim is to use this method to detect robots and balls at RoboCup 2026 in both MSL and Humanoids.

5 Mini Cheetah Goalkeeper

Transitioning from wheeled robots to the humanoid league, quadruped robots offer an intermediate platform capable of both manoeuvring and ball handling through loco-manipulation. Current research aims to develop a quadrupedal goalkeeper that leverages jumping and agile motion, with the potential to transfer these capabilities to humanoid systems.

Model-free methods have proven to be robust to modeling errors and dynamic environments, motivating the use of hierarchical reinforcement learning (RL). This approach decomposes locomotion into low-level skills coordinated by a high-level policy that processes inputs such as ball position and the goalkeeper's pose for strategic positioning and ball interception [2]. The architecture in Figure 3 provides the overall framework from sensor input to joint-level control.

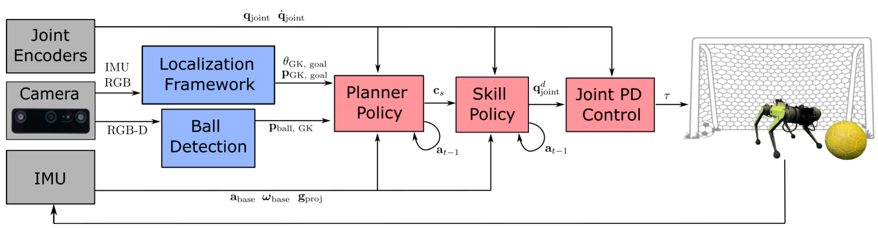

Fig. 3: The localization framework (blue) processes raw RGB-D data into a compact state representation for the high-level planner in the locomotion framework (red). The planner uses this representation to select a skill policy, which outputs the motor setpoints for the quadruped's movements.

Despite successful deployment, camera-retrieval delays and the sim-to-real gap limited performance to 23% goal coverage using a side-step skill. Future improvements include hardware-based retraining and expanding the skill set with actions such as diving and jumping.

6 Conclusion

This paper summarizes the main scientific and technological advances of the Tech United soccer robots over the past year. We transferred the MSL strategy framework to the humanoid platform via pass-giving and receiving skills, and a lightweight simulator accelerates strategy and team-play development.

We also introduced synthetic datasets for training CNN-based object detection, improving perception while reducing annotation time and simplifying the integration of new robots and objects.

The quadrupedal goalkeeper trained with hierarchical reinforcement learning shows how low-level goalkeeping skills can be coordinated within a structured decision-making framework, aligning with the 2050 objective of advancing legged robotic systems.

Together, these advances enable more dynamic and competitive future RoboCup matches.

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