LAR@MSL Team Description Paper 2026

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Abstract. The LAR@MSL team has a long history in the Middle Size League, with participations between 1999–2007, 2011, 2016, and more recently in 2023 and 2024. This Team Description Paper presents an overview of the current robot architecture, including hardware design, software structure, and system integration, while emphasizing the main developments introduced during the current season. The team has also undergone internal restructuring, with new members joining and progressively integrating into the league's technical demands. This year's primary contributions include the deployment of a new MPC navigation and obstacle avoidance, a newly developed kicking mechanism and dribbling system. Localization was enhanced through the integration of convolutional neural networks, and a dedicated vision pipeline was developed for the goalkeeper. Additionally, a new AI system and dataset were introduced to improve decision-making and overall team coordination. All software and hardware documentation are publicly available through the team's GitHub repository.

1 Introduction

The Laboratory of Automation and Robotics (LAR), integrated within the School of Engineering of the University of Minho in Guimarães, Portugal, first participated in the RoboCup Middle Size League (MSL) in 1999. Formerly competing under the name MinhoTeam, the team now adopts the designation LAR@MSL to reflect its affiliation with the Laboratory of Automation and Robotics and its broader involvement in multiple RoboCup leagues, including @Home.

Throughout its history, the team has developed its robots entirely in-house, covering mechanical design, electronic systems, and software architecture. All five robots operate under a unified codebase, with role-specific parameterization differentiating the goalkeeper from the field players. This unified structure simplifies maintenance while ensuring coordinated team behavior.

During the current season, the primary focus has been on advancing software and control systems. A Model Predictive Control (MPC) framework has been introduced to improve trajectory generation and dynamic obstacle avoidance. In parallel, a new inter-board communication architecture was implemented to enhance system reliability and data consistency across embedded components. The kicking mechanism was also redesigned to improve robustness and performance.

On the perception side, the localization approach was updated to incorporate convolutional neural networks, representing a shift toward learning-based state estimation. A dedicated vision pipeline was developed specifically for the goalkeeper, aiming to strengthen defensive responsiveness. Additionally, updates to the AI module and dataset were carried out to refine strategic decision-making and coordination during matches. Together, these developments represent an important step in the team's continuous evolution and competitiveness within the MSL.

2 Model Predictive Control for Navigation and Obstacle Avoidance

This year, we further developed our Model Predictive Control (MPC) framework for navigation and dynamic obstacle avoidance, building on the core work presented in Daniel Borges' dissertation. The proposed approach formulates robot navigation as a constrained optimization problem, where future robot states are predicted over a finite horizon while respecting kinematic constraints and actuator limits. Unlike purely reactive methods, our MPC-based solution explicitly models robot dynamics and anticipates future interactions with static and dynamic obstacles, allowing smoother and more stable trajectories under high-speed match conditions.

The controller integrates obstacle avoidance directly into the optimization cost function and constraints, enabling safe navigation in dense multi-robot scenarios typical of the MSL. The predictive formulation allows the robot to generate dynamically feasible trajectories that balance goal convergence, path smoothness, and collision avoidance. This framework forms the backbone of our motion system, providing consistent behavior across navigation tasks such as positioning, ball approach, and strategic repositioning during gameplay. The MPC module remains a central component of our architecture and continues to be refined for robustness and computational efficiency under real-time constraints.

The traditional A* algorithm can generate an optimal trajectory while avoiding obstacles[**?**][20]. Its goal is to find the path between a starting node and a destination node with the lowest cost and shortest distance. The evaluation of the function $f(N[i])$ is defined by equation (2.13), where $g(N[i])$ is the cost of the path from $N[start]$ to $N[i]$, and $h(N[i])$ is the heuristic function that estimates the lowest cost of the trajectory from $N[i]$ to $N[dest]$.

$$f(N[i]) = g(N[i]) + h(N[i]) \tag{1}$$

This algorithm has two associated matrices, one representing the map and the other of the same size indicating the position of obstacles on the map.

3 TensorRT and YOLO26

This year, the team began transitioning its perception pipeline to YOLO26, aiming to further improve detection robustness and segmentation quality in dynamic MSL game scenarios. In addition to object detection, the model incorporates instance segmentation to extract field line masks directly from the same network. These segmented line features are then used as structured input for the localization neural network, creating a tighter integration between perception and state estimation while reducing dependence on traditional color-thresholding methods.

To maximize inference performance on the NVIDIA GPU platform, the YOLO26 models were exported and deployed using TensorRT. After benchmarking different precision modes, FP16 inference was selected for competition deployment, achieving an observed performance increase of approximately 32% compared to previous configurations. Although INT8 with calibration was evaluated, it did not provide the required trade-off between accuracy and stability for our specific application. The use of TensorRT allows optimized kernel selection, memory management, and layer fusion, ensuring real-time performance suitable for the high-speed dynamics of MSL matches.

4 Localization

The current localization system relies on two neural networks [1]: one for detecting predefined field markers (e.g., corners and intersections) and another for estimating the robot's final position. This approach achieves high accuracy, with prediction errors of 3.82 cm on the x-axis and 1.61 cm on the y-axis.

However, the system depends on reliable marker visibility. Due to the MSL field dimensions (22m x 14m) and camera resolution, the effective range of markers is approximately 6 m, as verified in both simulated and real environments. In situations where markers are occluded or outside this range, localization robustness may decrease.

To overcome this limitation, a unified neural network is being developed using the PyTorch framework [3]. The goal is to directly estimate the robot's global position from multi-camera images and orientation, eliminating the dependency on a separate marker detection network.

Instead of using sparse landmarks, the new approach incorporates dense visual information from the entire field. A YOLO26-based module detects white field lines and goal posts, allowing the network to exploit broader structural cues. A cross-attention mechanism fuses features from the three camera views, enabling contextual integration before the final position regression.

This architecture is expected to improve robustness under partial occlusion and extend the effective localization range while maintaining computational efficiency for real-field deployment.

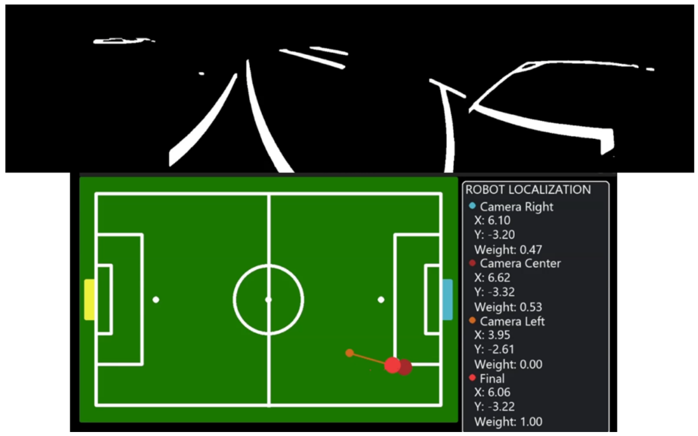

Fig. 1: Neural Network Predicted Position from YOLO Line Detections

5 AI-Driven Multi-Camera Perception for Collaborative Robotics

We are developing an innovative real-time AI-driven multi-camera perception system aimed at enhancing collaborative robotics in structured indoor environments. Our approach integrates synchronised RGB camera arrays with deep learning-based object detection and multi-view geometric reasoning, inspired by recent multi-view 3D detection frameworks such as DETR3D [5] and ImVoxelNet [6]. By combining learned feature representations with triangulation-based geometric constraints, we seek to achieve accurate 3D localisation and robust object tracking under occlusions and dynamic interaction scenarios.

Instead of relying on expensive RGB-D or LiDAR sensors, we leverage multiple low-cost RGB cameras to design a modular and scalable perception framework. Our innovation lies in the full integration of detection, depth inference, triangulation, and tracking into a unified real-time pipeline capable of supporting safer human-robot collaboration and adaptive manipulation strategies. Through this work, we aim to demonstrate that multi-camera RGB systems can provide competitive 3D performance while maintaining deployment flexibility and computational efficiency in laboratory and competitive robotics scenarios.

6 Kicking System

The current kicking system used by the team presents significant limitations in terms of force output, power, and tactical versatility, essentially allowing only direct shots or ground passes. This limitation considerably reduces the strategic options available during gameplay.

To overcome these restrictions, a new kicking system based on the same electromagnetic coil actuation methodology (solenoid-based system) is being developed, optimized both from an electromagnetic and a mechanical perspective.

In a first phase, simulations will be conducted using FEMM (Finite Element Method Magnetics) to design and optimize the electrical coil. The objective is to determine the optimal combination of ferromagnetic materials, number of turns, geometric dimensions, and magnetic configuration, maximizing the force generated on the plunger. At this initial stage, integration constraints related to the robot platform will not yet be considered, as the focus is exclusively on electromagnetic performance. Subsequently, an experimental prototype will be built to validate the simulation results, considering the inherent limitations of the numerical model. At the mechanical level, three distinct solutions were designed:

- **Direct impact system:** the plunger accelerates freely and directly impacts the ball, transferring most of its linear kinetic energy at the moment of collision.

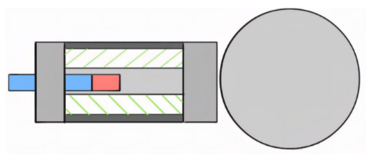

Fig. 2: Mechanical architecture representation of the direct actuation system.

- **Lever-based system**: incorporates a mechanical lever mechanism that converts linear motion into an angular trajectory, enabling elevated shots and aerial passes, significantly expanding tactical possibilities.

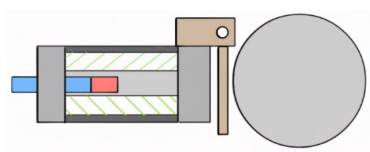

Fig. 3: Mechanical architecture representation of the lever-based actuation system.

- **Continuous initial-contact system:** the solution currently used by the team, in which the plunger extension remains in contact with the ball from the initial instant, eliminating distinct acceleration and impact phases between independent bodies.

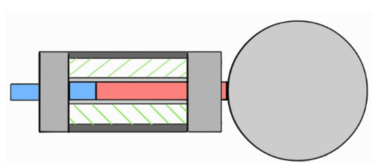

Fig. 4: Mechanical architecture representation of the initial-contact actuation system.

The main objective is to determine which mechanism provides the best balance between final ball velocity, energy transfer efficiency, and system repeatability. To achieve this, physical prototypes will be developed to validate the analytical and numerical models used, ensuring consistency between simulation results and real-world behaviour before final integration into the competition robot.

7 Dribbling System

Regarding the dribbling system, the team aims to implement incremental improvements to enhance efficiency and ball control performance in different gameplay situations, including normal locomotion, ball acquisition, rapid directional changes, and sudden braking.

The current system relies on conventional elastic elements, which exhibit predictable behaviour and significant mechanical wear over time, compromising long-term consistency. As an alternative, a mass–spring–damper dynamic system is proposed, integrating both an energy absorption component and a dissipative element. This approach is expected to provide improved impact absorption, reduced unwanted oscillations, increased ball control stability, and enhanced mechanical robustness [22].

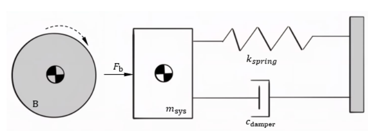

Fig. 5: Equivalent mass–spring–damper model used to represent the contact dynamics between the ball and the dribbling system.

Additionally, a geometric reconfiguration of the motor+wheel assembly is proposed through a 90° angular offset in the orientation of the system. This modification maintains direct engagement with the ball while improving the efficiency of the tangential force component applied to it, resulting in more effective and consistent control. These improvements aim to enhance the team's technical execution capability while expanding the tactical possibilities associated with ball control.

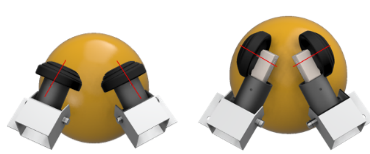

Fig. 6: Comparison between the original LAR@MSL dribbling system configuration and the proposed configuration, highlighting the 90° angular offset of the motor–wheel assembly: (a) original solution; (b) implemented solution.

8 GoalKeeper

We present a new Shot Prediction and Optimal Goalkeeper Positioning module designed to upgrade our goalkeeper's defensive responsiveness by leveraging the same real-time perception and tracking principles used across the team's architecture. At the perception layer, the system detects the ball using a YOLO-based detector and supports multiple visual sources (e.g., RealSense and the three-camera rig), producing per-frame ball candidates with confidence and source metadata. These candidates are converted into metric observations and fused by a MOT-style tracker that combines Hungarian assignment (global association between measurements and tracks) with a 6-state Kalman Filter (position + velocity), ensuring stable tracking through noise, intermittent detections, and source switching [**?**]. Crucially, the tracker performs robot-motion compensation between cycles and maintains a "trustiness" score per track to automatically down-weight and remove unreliable hypotheses, while also estimating ball relative velocity with respect to the robot, information that is needed for prediction and control.

On top of the tracked state, the system implements a dedicated ball-to-goal reasoning layer that predicts the shot outcome on a goal-aligned basis. Each cycle, the goal geometry is projected into the robot frame, and the ball is classified using the velocity component along the goal normal (e.g., COMING / GOING / KICK) with explicit thresholds for strong shots, while simultaneously computing time-to-goal, distance-to-goal, and the estimated crossing point at the goal line. These predictions directly drive the goalkeeper controller: classification is mapped into high-level actions (IDLE -> PRE_DEFENCE -> DEFENCE), with latency compensation and target smoothing, and the controller generates a defensive target that prioritizes early alignment with the predicted crossing region while respecting safety-limited motion. In practice, this means the goalkeeper no longer reacts only to the current ball position, it anticipates the shot line, select the appropriate defensive mode, and moves to the ideal blocking pose before the ball reaches the critical zone, matching the intended behavior showcased by the camera/field visualization workflow in the system demonstration.

Fig. 7: Ball movement prediction and goalkeeper position visualization

9 Conclusions

In summary, this paper presented the main developments carried out by the LAR@MSL team in the continuous evolution of its robotic platform. Throughout this season, substantial improvements were introduced across multiple subsystems, reflecting a consistent effort toward performance optimization and system robustness. Among the most relevant advancements is the implementation of a Model Predictive Control (MPC) framework, enhancing trajectory planning and real-time decision-making capabilities. Communication between electronic boards was restructured to increase reliability and efficiency, while the kicking system underwent a comprehensive redesign to improve power delivery, energy transfer efficiency, and overall in-game effectiveness.

The localization module was significantly enhanced through the integration of convolutional neural networks, resulting in higher positioning accuracy. A dedicated goalkeeper vision system was also developed to strengthen defensive performance. Furthermore, updates to the AI architecture and dataset contributed to more effective strategic planning and match adaptability. In addition to these electronic and control-level improvements, mechanical refinements were introduced in the dribbling system. Through a purely mechanical reconfiguration—without altering the existing electronic architecture—the efficiency and consistency of ball control were improved, contributing to greater stability and tactical flexibility during gameplay. Overall, these developments demonstrate the team's sustained commitment to innovation, systematic validation, and continuous performance enhancement in robotic soccer systems.

All LAR@MSL files are available on GitHub (https://github.com/LARobotics) or on the team website (http://lar.dei.uminho.pt/msl).

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