LAR@MSL Team Description Paper 2025

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Abstract. The LAR@MSL team has participated in MSL for years, from 1999-2007, 2011, 2016, and again in 2023 and 2024. This Team Description Paper aims to briefly explain the robots' structure, hardware, and software and highlight the most significant changes introduced this year. It is important to note that new students have joined the team and are adapting to the league. This year's updates include implementing a new Model Predictive Control (MPC) system, a new communication method between boards, and a redesigned kicking system. Additionally, we have improved localization by incorporating convolutional neural networks and developed a dedicated vision system for the goalkeeper. A new AI and dataset were also introduced to enhance decision-making and team performance. This paper provides a bottom-up perspective of the robots, covering hardware, vision systems, low-level software, and strategy, and concludes with key findings. The entire codebase and hardware documentation are publicly available in a GitHub repository.

1 Introduction

The Laboratory of Automation and Robotics (LAR) is part of the School of Engineering at the University of Minho, Guimarães, Portugal, and first participated in the RoboCup MSL in 1999. Previously known as MinhoTeam, the name LAR@MSL reflects the research identity of the Laboratory of Automation and Robotics (LAR) and its participation in the MSL league, as LAR is also involved in other RoboCup leagues, such as @Home.

Over the years, the robots have been entirely developed in-house at LAR, including mechanics, electronics, and software. All five robots share the same codebase, with specific parameters distinguishing the goalkeeper. This year, the team has focused on significant software and control systems improvements, introducing a Model Predictive Control (MPC) system for enhanced decision-making and trajectory optimization. Additionally, a new communication method between boards has been implemented to increase reliability and efficiency. The kicking system has also been redesigned for improved performance.

On the perception side, the localization system has been changed to use convolutional neural networks, providing a different approach for the localisation method. A dedicated vision system has been developed to enhance the defensive capabilities of the goalkeeper. Furthermore, the AI and dataset have been updated to optimize strategic planning and in-game decision-making. These advancements mark a significant step forward in the team's evolution, ensuring better adaptability and competitiveness in the MSL league.

2 Localisation

To develop a more reliable self-localisation system, last year's research [1] concentrated on creating a Neural Network capable of associating features present in the camera images with the robot's position and orientation. The Neural Network was trained using images and coordinates captured with the Webots simulator [2] and visual markers corresponding to standard football field markings (as defined by FIFA and MSL regulations).

This method, although efficient and accurate, has some limitations; given the conditions of the MSL football field size (22m x 14m) and the resolution of the installed cameras (640X480 pixels), the maximum distance at which a marker can be detected is 6m. This value was obtained after testing in both simulated and real environments. With this 6-metre range, in certain situations, the number of markers detected in specific locations might pose a challenge for the system, as the robot may lose necessary visual references for precise localisation.

A customised Convolutional Neural Network (CNN) is currently being developed using the PyTorch framework [3] to enhance the reliability and efficiency of robot self-localisation. As depicted in Figure X, the architecture combines convolutional and recurrent layers to extract spatial features from input images while also utilising separate dense layers to capture sequential dependencies from sensor data. This year, the primary aim is to create a unified neural network that can extract and analyse all relevant features independently, eliminating the need for a field marker detection network to support the training of the localisation network.

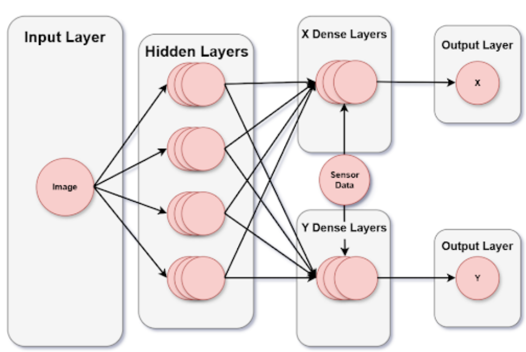


Fig. 1: Localisation Neural Network Architecture using Convolutional Layers

3 Model Predictive Control

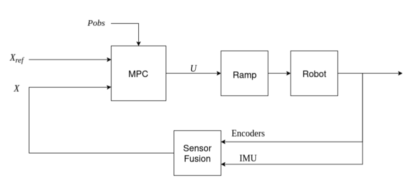
The diagram in the image 2a shows the architecture implemented for the new control system, which uses MPC (Model Predictive Control). This controller predicts the robot's future behaviour over a prediction horizon, allowing it to anticipate movements to minimise trajectory errors and control input variations. One of the main advantages of MPC is the ability to deal with system and input control constraints, such as the presence of moving obstacles and the maximum speed, certifying that they are not violated.

The MPC receives as parameters the current state of the robot represented by X, the reference state X_{ref} and the positions of the obstacles represented by P_{obs}.

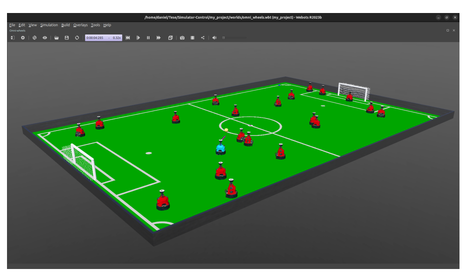
The current state X of the robot is estimated from an EKF (Extended Kalman Filter), where it performs a fusion of the encoders and the IMU (Inertial Measurement Unit). This system does not depend on the absolute localisation of the robot to prevent the control system from continuing to work if some localisation failure occurs.

However, drift can occur if the robot is pushed or collides with another object or the control inputs are too aggressive [4]. To address this issue, the implemented EKF can asynchronously receive the position from the localisation, helping to reduce the drift accumulated over time and the control signal U generated by the MPC is processed by a ramp system to limit the acceleration and jerk (rate of change of acceleration). This ramp system aims to reduce abrupt control actions that could lead to slippage and maintain the robot's safety so it doesn't get damaged. MPC does not impose these restrictions to reduce computational complexity and decrease processing time.

To develop and test the new control system, a simulation world in Webots was made, as shown in the image 2b. This world has a field similar to the one used in RoboCup MSL games with the exact dimensions and a robot with 3 omnidirectional encoders and an IMU to simulate our robots.



(a) Control System Architecture



(b) WeBots Simulation for MPC

Fig. 2: Model Predictive Control

4 Kicking System

The kicking system is one of the key components for the overall performance of Middle Size League (MSL) robots. The main goal is to ensure an effective kick, capable of reaching high speed without compromising precision and accuracy, thus maximizing the chances of success during competitions.

In this section, we detail the approach adopted for the development of a new kicking system, divided into three main phases:

1. Initial simulations in SimWise for analyzing impact points and kicker geometries.
2. Studies on different force generation systems, exploring electrical and pneumatic alternatives.
3. Advanced simulations in ANSYS to optimize the energy transfer between the kicker and the ball.

(1) Initial Simulations in SimWise

In the initial phase, SimWise 4D software was used to simulate and optimize the interaction between the kicker and the ball based on a desired trajectory. These simulations aimed to determine the ideal impact points on the ball, ensuring a controlled direction and minimizing energy losses. Also, the kicker geometry will be analyzed, various configurations will be tested, and the influence of each on the kicking efficiency will be evaluated.

The results obtained will be compared with practical tests conducted on a physical prototype of the kicking system, allowing the validation of data and the adjustment of model parameters to ensure greater accuracy.

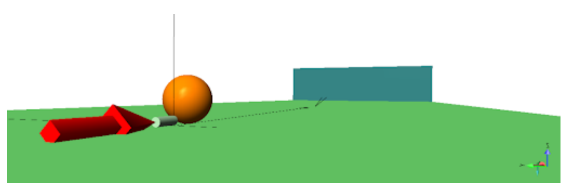


Fig. 3: Testing the ideal position for kicking

(2) Analysis of Force Generation Systems

Force generation in the kicking system is a critical factor, as it directly determines the final speed of the ball. Different approaches to actuating the system were studied to explore new solutions, namely, the electrical models, based on using coils to generate linear motion through electromagnetic forces. The FEMM (Finite Element Method Magnetics) software will conduct detailed coil simulations, analyzing various factors such as materials and coil geometries.

Also, we are considering the pneumatic systems, which present high potential due to their fast response and ability to generate high forces.

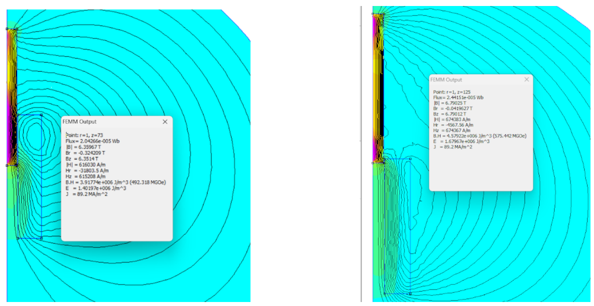


Fig. 4: FEMM Kicking Simulation

(3) Advanced Simulations in ANSYS

To further optimize the performance of the kicking system, simulations will be conducted focusing on the energy transfer between the kicker and the ball. Preliminary results indicate that the kicker's material and geometry directly impact the kick's speed, precision, and accuracy. These factors are crucial for achieving the best possible performance and will be thoroughly analysed to optimize the system.

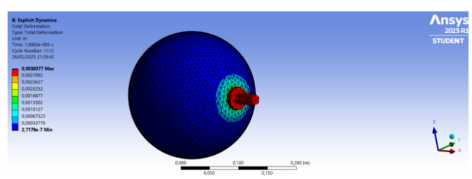


Fig. 5: Ansys Kicking Simulation

5 GoalKeeper

The old goalkeeper [9] vision system relies on a Kinect camera for greater reliability in detecting the ball's position relative to the goal. Despite its generally good performance, the Kinect has some inconveniences due to its design, such as the need for two connections, one USB for data and another external connection for power, as well as the space it occupies in the robot's assembly, especially in the goalkeeper, where the defence system is also mounted. In addition to the mechanical aspect, the Kinect limits our system, which operates at a base frame rate of 60fps on the other three cameras due to its acquisition rate of only 30fps. This discrepancy causes the defence system to lag behind its potential performance.

We are currently investigating a replacement for the goalkeeper's RGBD camera by testing the Realsense D415 against the Kinec. The RealSense camera has a volume of 30,435.9 mm^3, occupying significantly less space than the Kinect, which has a volume of 587,860 mm^3, a reduction of 19.3 times, and the RealSense uses a single USB connection, eliminating the need for external power. In terms of performance, the Realsense achieves rates of up to 90 fps for depth images and 60 fps for the RGB channel, which can speed up the detection of both the ball and opponents and has demonstrated better connection stability in the tests performed. On the other hand, the Kinect maintains advantages in accuracy for measurements at longer distances and has a lower cost.

Fig. 6: Goalkeeper New Vision System

6 Dataset

The 2025 version of the dataset will come with the addition of the field lines because our robots currently rely on color to find the field lines, which results in tuning a threshold each time there is a change in the environment, through traditional methods. [10] To prevent this, our YOLO model will incorporate an instance segmentation of the lines, a semantic segmentation could also be used, but that would require having two YOLO models running at the same time since an instance segmentation model is already being used, the lines detection will be added to the instance segmentation model the following image illustrates a beta version of the field lines mask generated by the model using the three cameras of the robot.

Fig. 7: New Line Detection System

Because our team also relies on computer vision to distinguish between allies and robots, there is a need to create a model that can effectively make this distinction, meaning our model should know if blue or red shirts are allies and the rest are just robots.

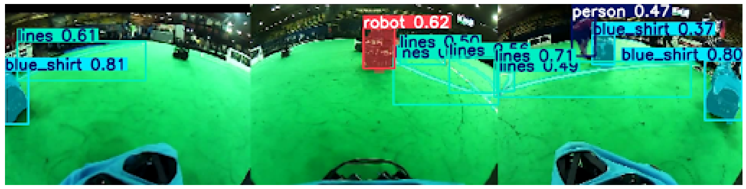


Fig. 8: New Dataset in Game Situations

With the YOLO model trained, we aim to track the ball with partial or total occlusion, meaning that if the ball rolls behind a robot, our model can predict where the ball will be in the future. There is also a need to build an algorithm that can predict the trajectory that the ball will take when moving in a straight line, with the stopping point, which will be helpful to make more strategic ball passes and to defend penalties.

7 Ethernet

The robot initially employed USB connections to interface with other boards for actuator control and sensor data acquisition. However, this approach led to several issues. The simultaneous use of cameras via USB resulted in port congestion, which, compounded by the data traffic from peripheral boards, caused frequent USB connection failures, necessitating reconnections. A specific insertion order was also required to ensure proper connectivity, introducing further operational inconvenience.

To address these challenges, USB connections were replaced with Ethernet communication. This modification effectively eliminated the USB connection failures and reduced data traffic on USB ports, benefiting camera performance. The WIZ850io module enabled microcontrollers to interface via Ethernet, ensuring more stable communication. All devices are interconnected through the SG108 v4.0 switch, which was selected for its compact size and 5V power requirement. The following diagram illustrates the implemented connection topology.

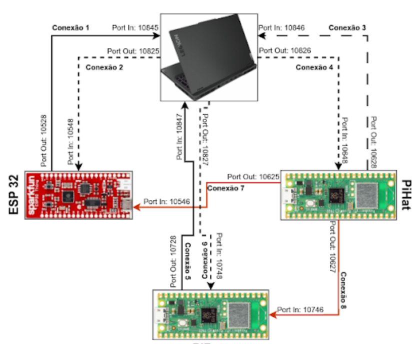


Fig. 9: Connection between the robot devices

8 Conclusions

In conclusion, this paper has provided an overview of the LAR@MSL team's efforts in developing and improving their robotic system. This year, the team introduced significant advancements, including a new Model Predictive Control (MPC) system, which enhances decision-making and trajectory optimization. A new communication method between boards was implemented to improve reliability and efficiency, while a redesigned kicking system provides better performance during gameplay.

The localization system has been significantly improved using convolutional neural networks, increasing the accuracy of the robot's positioning. Additionally, a dedicated vision system for the goalkeeper has been developed to enhance defensive capabilities. The AI and dataset have also been updated to optimize strategic planning and in-game decision-making. These advancements collectively demonstrate the team's commitment to innovation and continuous improvement in robotic technology.

The strategy being used is the Probability-Based Strategy presented in [5]. 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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