

Formalizing Robotics Competitions: a Practical Case for RoboCup@Home Challenge

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Abstract—Social robots have to face several challenges in real environments where humans are very present. Thus, they have to interact and understand the world where they work. In order to address these challenges, competitions like RoboCup@Home give real-world tasks within a controlled environment. This paper presents the usage of the cognitive architecture MERLIN2 along with several perception skills to accomplish the *Carry My Luggage* form the RoboCup@Home 2023. Besides, to do it, a new perception skill is created to recognize the objects pointed to by humans, which can improve human-robot interaction.

Index Terms—Robotics Competitions, Robot Perception, Cognitive Architectures

I. INTRODUCTION

The escalating ubiquity of robotics across daily life, professional settings, and public spheres underscores the necessity of imbuing robots with sophisticated perceptual capabilities [1], [2]. This is particularly crucial in leveraging machine learning and deep learning to enhance their understanding of environmental cues and contexts [3]. As a result, it is necessary to address the constraints in perception components by enhancing these components in order to enable robots to behave more naturally and effectively with humans, which in turn will improve their cognitive abilities in dynamic environments.

Nevertheless, in the realm of social robotics, the management of multiple components becomes paramount, facilitating the effective support of individuals in their daily routines. Artificial intelligence has significantly enhanced robots' abilities to adapt and function in real-world contexts. Consequently, cognitive architectures [4] emerged as pivotal tools for controlling robots and generating autonomous behaviors, enabling them to carry out tasks autonomously. These architectures play a crucial role in organizing various components of the robot, such as the robot's skills, which include navigation, speech, and perception.

As complexity continues to increase, the necessity for developing accurate methods to model robotics systems grows. Lacking appropriate models makes it progressively challenging to characterize them and ensure their reliability and safety. This imperative aligns closely with the push to enhance standardization practices within the realm of robotics. Although strides have been made in formulating standards, the field of robotics and autonomous systems still has considerable ground to cover in this regard. Standardizing the modeling of these intricate autonomous systems to the fullest extent possible offers numerous benefits.

This paper presents the utilization of Systems Modeling Language (SysML) for modeling autonomous robots. More precisely, we delve into the application of SysML in modeling the *Carry My Luggage* test from the RoboCup@Home competition [5] solved with the cognitive architecture MERLIN2 [6] and The Robot Operating System 2 (ROS 2) [7]. Consequently, we elucidate the models of MERLIN2 and its new components through the employment of SysML.

A. Research Question and Contribution

The growing complexity of tasks that robots face in dynamic environments has motivated the need to develop more effective methods for integrating new behaviors. In this context, the research question is:

RQ How we can formalize and structure competition tasks in a practical way to facilitate the incorporation of complex autonomous behaviors in robots?

The main contribution of this work lies in the formalization of one of the RoboCup tasks using SysML. This formalization provides a solid structural basis that allows for a more effective approach to implementing new complex behaviors in robots, by offering a clear and detailed representation of the necessary requirements and interactions.

II. RELATED WORK

Systems Modeling Language (SysML) in robotics can enhance the development, design, and analysis of robotic systems. SysML, as a graphical modeling language, offers a standardized framework for expressing complex system architectures, behaviors, and interactions. In the context of robotics, where intricate interdependencies between hardware and software components abound, SysML provides a unified platform for capturing and visualizing these dynamics.

There are several cases of using SysML in robotics. For instance, the work [8] illustrates the use of SysML as a viable language for modeling autonomous systems and robotics. [9] uses SysML to model complex space robotic systems used in satellite servicing missions. They contend that SysML presents a favorable choice due to its capacity for automated requirement verification and model tracing, capabilities that can effectively minimize both cost and time in system engineering processes. Besides, [10] uses SysML in the development of a collaborative design framework.

SysML is used in more specific contexts, such as robotic manipulation. That is the case of [11] which focuses on SysML as a modeling language for mobile manipulation systems and autonomous robots. The result allows developers to observe a whole robot system, and, analyze requirements and lacking parts on target systems. Moreover, [12] presents the use of



Fig. 1. MERLIN2 subsystems available for solving the Carry My Luggage test.

SysML as a tool for representing manufacturing processes in industrial tasks to facilitate simplified robot programming and interaction.

Within the realm of ROS, MeROS [13] has emerged. It is a new metamodel, which addresses the running system and developer workspace. The ROS comes in two versions: ROS 1 and ROS 2. MeROS, built upon SysML, comprises two primary components: behavioral and structural models. Its objective is to encompass ROS concepts while preserving their original labels for as long as feasible, ensuring consistency and user-friendliness.

This way, we present the use of SysML to model the *Carry My Luggage* test from the RoboCup@Home competition taking into account the use of the cognitive architecture MERLIN2 and the creation of new components.

III. MATERIALS AND METHODS

This section aims to detail the materials used to address the *Carry My Luggage* test from the RoboCup@Home competition. Thus, the SysML diagrams created are presented. Finally, the hardware and software setup are also presented.

A. Cognitive Architecture

MERLIN2 [6], whose parts are presented in Figure 1, is a cognitive architecture that enables task planning to generate behaviors in robots. In our particular case, the Gentlebots Team provides the ability to interpret and respond coherently to tasks requested by users. The robot's goal definition, based on

established objectives, triggers corresponding actions for plan execution. This architecture stands out for its representation of memory, which is divided into long-term and short-term memory. Long-term memory reflects the environment's state and plays a key role in the planning process, managed by the KANT [14] knowledge base. MERLIN2 is structured into two fundamental systems: deliberative and behavioral. The deliberative system handles mission planning and execution, while the behavioral system encompasses the actions and skills the robot can perform. All these operations are stored in the KANT knowledge base, allowing the deliberative system to be aware of available skills and determine the successful execution of a mission. Planned actions, requiring the robot's skills, are implemented through YASMIN finite state machines [15] or through Behavior Trees [16], both of which have blackboards representing the robot's short-term memory.

B. Requirement Definition

We have established the primary objective of our proposed use case, referred to as the "Carry My Luggage" test [5], aimed at delineating the requirements for robot behavior generation. Essentially, this objective entails the robot assisting an operator in transporting luggage to a car parked outside. Additionally, we utilize a predefined set of keywords outlined by the RoboCup@Home committee, namely person following, navigation in unmapped environments, and social navigation, to further refine these requirements. In the real world, a metaphor would be a robot in the role of a hotel bellhop. With these considerations in mind, we derive the following set of requirements:

- Req1 The robot waits for the order by the operator to begin the test. Expected functionality [Perception+Talk]
- Req2 The robot picks up the bag the operator is pointing at. Expected functionality [Perception+Manipulation+Navigation]
- Req3 Once the robot has the bag, it communicates to the user that it is ready to follow him. Expected functionality [Perception+Talk+Navigation]
- Req4 The operator walks to the exit door of the arena while the robot follows him in a natural way avoiding obstacles present in the environment. Expected functionality [Perception+Talk+Perception+Navigation]
- Req5 The robot returns the bag. Expected functionality [Perception+Talk+Manipulation]
- Req6 The robot returns to the starting point. Expected functionality [Navigation]

All these requirements need two extra functionalities, reasoning and action selection parts in order to reach the goal. Manipulation is solved using human-robot interaction based on text-to-speech and speech-to-text. Thus, we have identified all the updates that we need to our architecture, and as a result, the architecture is organized and illustrated in Figure 2. It shows the two organizational layers that generate deliberative and reactive behaviors. Next, we will begin to detail all the updated components to resolve the use case.



Fig. 2. MERLIN2, the cognitive architecture employed in the *Carry My Luggage* test from the RoboCup@Home competition.

C. Perception Modules

The perception used in this work is based on a deep learning model, used to recognize objects, and a pointing system, to recognize which objects are pointed to by the person. These components are employed to recognize the person to be helped during the *Carry My Luggage* test and the bag that

the robot must carry. The SysML diagram that represents all the perception modules is illustrated in Figure 3.

1) Object Detection: The object detection used in this work is based on YOLOv8 [17]. It is a deep learning model that uses color images not only to detect and recognize objects but also to obtain the keypoints associated with the person's pose. Additionally, depth images are used to obtain 3D data related to the detected objects and keypoints of YOLOv8.

The YOLOv8 model is used to detect a person pointing at a bag, as it represents the fundamental starting point of the *Carry My Luggage* test. To achieve this, we created our dataset by building on existing public datasets and capturing our images using the robot's built-in camera. This ensured that our data closely matched real-world environmental conditions.

In the dataset generation process, various perspectives from which the robot could view the bag were considered, thereby contributing to improving the model's ability to recognize the bag from different angles. Collaborative labeling was employed using Roboflow technology. The generation of the complete dataset, encompassing the merging of public datasets with the one previously created, was carried out using the FiftyOne library. This resulted in a dataset consisting of 611 training images and 115 validation images.

The point cloud of the RGB-D camera is used to obtain the 3D point information related to the YOLOv8 detections. The point cloud is filtered using the results from YOLOv8 to generate keypoints and object detections in 3D. Subsequently, these keypoints and the 3D object detections are used to evaluate whether the person is pointing at an object with their arm. If affirmative, the recognized bag is selected during the *Carry My Luggage* test.

2) *Pointing:* The process of implementing the logic to recognize if the person is pointing at an object involves several stages. Firstly, the keypoints are obtained, knowing that the YOLOv8 human pose estimation model detects 17 keypoints: 5 for the spine, 4 for the left arm, 4 for the right arm, 2 for the left leg, and 2 for the right leg, where indices 6, 8, and 10 correspond to the right arm and indices 5, 7, 9 to the left arm.

To determine if the arm is stretched, the three points of the arm in 3D space (p_0, p_1, p_2) are taken, and the angle between the vectors $\vec{v}_1 = \vec{p_1} \vec{p_0}$ and $\vec{v}_2 = \vec{p_1} \vec{p_2}$ is calculated as presented in equation 1, where $\vec{v}_1 \cdot \vec{v}_2$ is the vector multiplication and $\|\vec{v}_1\|$ and $\|\vec{v}_2\|$ are the vector lengths. If the obtained angle is below a threshold, the arm is considered to be stretched.

$$\theta = \arccos\left(\frac{\vec{v}_1 \cdot \vec{v}_2}{\|\vec{v}_1\| \cdot \|\vec{v}_2\|}\right) \cdot \frac{180}{\pi} \tag{1}$$

Then, once it is detected that the person is pointing, the direction of the arm is calculated, indicating where the person is pointing. This involves following several steps.

• Calculation of points located in front of the arm [18]: Considering the set of points provided by the point cloud, a plane is defined by a point p1 (shoulder) and a vector normal to the plane p2 (wrist). The equation of the plane is Ax + By + Cz + D = 0, where D = -Ax - By - Cz,



Fig. 3. SysML diagram of the pointing tool.

and P = (x, y, z). Once the constant D is determined, the distance is calculated using the three-dimensional information of the point cloud locating the arm points in space. Equation 2 presents the formula for calculating the distance, where (x, y, z) are the points from the point cloud, (A, B, C) are the components of the vector normal to the plane and D is the displacement constant of the plane.

$$Distance = \frac{|Ax + By + Cz + D|}{\sqrt{A^2 + B^2 + C^2}}$$
(2)

Having the set of distances of the points of the point cloud concerning the plane formed by the arm, the threshold, which allows identifying the points that are in front of the hand, is calculated using the equation 3, where *threshold* is a predefined value that determines the minimum distance to be considered from the plane of the arm to the front and $||\mathbf{p2} - \mathbf{p1}||$ is the Euclidean distance between the shoulder (p1) y the wrist (p2). Finally, the saved points are those where the distance is greater than the calculated threshold, resulting in the points in front of the hand.

$$Thresh = threshold + \|\mathbf{p2} - \mathbf{p1}\| \tag{3}$$

• Arm direction calculation: The distance between the 3D line defined by two points $\vec{P_1}$ and $\vec{P_2}$ and each point of the set of the point cloud $\vec{Q_i} = (x_i, y_i, z_i)$. The distance of each point $\vec{Q_i}$ to the line can be expressed by the following formula presented in the equation 4, where $\vec{P_1} = (x_1, y_1, z_1)$ y $\vec{P_2} = (x_2, y_2, z_2)$ are the points of the line and $\vec{Q_i} = (x_i, y_i, z_i)$ is each point in the 3D points set.

dists
$$(\vec{Q}_i) = \frac{\left\| (\vec{Q}_i - \vec{P}_1) \times (\vec{Q}_i - \vec{P}_2) \right\|}{\left\| \vec{P}_2 - \vec{P}_1 \right\|}$$
 (4)

By defining a threshold of the distance at which each point could be separated from the three-dimensional line, the points of the point cloud that are in the direction created by the arm are calculated.

Finally, taking into account the objects recognized by the robot represented in 3D space using bounding boxes in 3D, it is calculated if any of the points obtained in the previous calculation represent the direction in which the arm points match within the bounding box of the object. If this condition is met, the person's pose and the identifier of the object they are pointing at are published, in this case, bags, but it could identify any object the person points at.

3) Follow: A person-tracking system was developed using the YOLOv8 model. It relies on point cloud and navigation map data to create a point transformation that accurately tracks the person's position on the map. Implemented in ROS 2, the system periodically recalculates the navigation point to carefully follow the person. If the person stops, the system prompts for confirmation and continues the test. The integration into the MERLIN2 architecture follows a similar approach to the pointing model, using a behavior tree associated with the 'follow_person' action.

D. Reasoning and Action Selection

To solve the *Carry My Luggage* test using MERLIN2 it is necessary to implement the actions that the robot has to use. Besides, a high-level component that generates the goals of the robot is also necessary.

1) Actions: Several actions have been created to outline the complete plan the robot must follow to complete the test (Navigation, Detect Bag, Carry Bag, Follow and Put Bag), each modeled and executed using behavior trees. For instance, the Detect Bag action, which is presented in Figure 4, instructs the person to point to a bag, detects if the person is pointing at the bag, and finally locates the pointed bag.



Fig. 4. Behaviour Tree of the Detect Bag action.

2) Mission and Goals: The execution of the entire test begins with a clear definition of the mission, which is articulated by representing goals in PDDL. In particular, the main goal of the mission is having carry the bag requested by the user. The goal generation is controlled with the YASMIN finite state machine whose states are in charge of generating the goals.

IV. EVALUATION

The objective of this evaluation is to implement the formalization of complex robot behaviors in a real environment. To achieve this, The Robot World Cup (RoboCup) has been chosen as the reference framework. RoboCup stands as an international competition and research platform dedicated to improving the fields of robotics and artificial intelligence by providing a common testbed [19].

Initially centered around football trials involving multiagent robot teams, RoboCup has progressively expanded its scope to encompass the RoboCup@Home league. The RoboCup@Home league focuses on evaluating the interaction of robots with humans in real-life social environments, where they perform specific tasks. Researchers are faced with tests that replicate everyday situations where robots must interact with people, addressing a wide range of cognitive skills necessary for natural interaction, such as perception, natural language processing, task planning, and context-based decision-making.

The evaluation of this work has been carried out at Leon@Home, which is presented in Figure 5. It is a certified testbed of the European Robotics League (ERL) [20] following the Robocup 2023 methodology. Leon@Home is a realistic domestic environment represented by a simulated home in an 8m x 7m space. It is divided by 60 cm high walls into a kitchen, living room, bathroom, and bedroom. This testbed is located on the first floor of the Cybernetics Research Module at the Vegazana Campus of the University of León (Spain). Additionally, the test was conducted using PAL Robotics' TIAGo robot, an autonomous and configurable robot designed for indoor environments with a modular ROS-based hardware and software architecture.



Fig. 5. Evaluation of the proposed solution in the Leon@Home using the TIAGo robot.

The evaluation of the entire test focuses on ensuring that the system meets the requirements set by the competition. The interaction of the robot with people during the test stands out as one of the most difficult aspects to improve. Especially the system's ability to interpret signals and commands. However, it has to be taken into account that a large part of the people interacting with the robot are individuals who have previous experience with robotics or who are receptive to its use. An evaluation with other types of users could result in negative qualitative feedback, and extensive testing such as NARS (Negative Attitude toward Robots Scale [21]) would be necessary.

The evaluation focuses on identifying areas of potential improvement, examining model adjustments, improvements in human-robot interaction, and other factors that affect overall performance. This analysis is intended to deepen the understanding of the system and pave the way for its continued refinement in future iterations.

V. CONCLUSIONS

This paper further explores the integration of software engineering into autonomous robot behavior, focusing on the modeling of a test within the RoboCup@Home competition, specifically the *Carry My Luggage* test. The approach adopted is based on the development of detailed SysML diagrams representing the architectural and perceptual components necessary for the robot to interact effectively with its environment.

One of the main contributions is the formalization of the test, which provides a clear understanding of the requirements and interactions needed to achieve effective autonomous behavior in dynamic environments. In addition, the implementation of this test has been carried out using current technologies and is documented in a demonstration video showing how the resulting system works¹.

This approach provides a solid foundation for the design and implementation of autonomous behaviors in robots, providing

¹https://youtu.be/rNqv0gxIsZ8

a resource for future competitors and research teams in the field of robotics. The combination of diagram design and practical test implementation illustrates how the integration of software engineering can significantly improve the ability of robots to perform complex tasks in real-world environments. In future works, we propose to continue developing and refining these diagrams and extend them to other tests from the RoboCup@Home.

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