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A Framework based on Real-Time OS and Multi-Agents for intelligent autonomous robot competitions

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Abstract—**Robots interacting with human beings are widespread in modern environments, and those performing intelligent tasks without human supervision need to take into account potential criticalities. Making robots compete enable their evaluation with respect to navigation, mapping, object recognition, tracking and manipulation capabilities. Robot competitions date back to the early '80s proving to be useful for educational and research purposes. Several competitions are focused on human-robot interaction, even though they rarely produce as outcome robots capable to seamlessly interact with human beings. The main reason for this is the lack of understanding of human intentions and the failure to rapidly react to human actions. In other words, an ideal robot must be able to communicate and coordinate with humans or with other robots, to act autonomously, and to react under real-time constraints. This paper proposes a new framework to simplify the development of intelligent robots, testing them in a real robot competition. The framework combines (i) a multi-agent system to interact with humans, other robots and perform object identification and pathfinding, and (ii) a real-time motion control deployed on the Erika RTOS, to move the robot and react in a timely fashion to changes in the environment. In the considered competition scenario, the robot is required to identify and collect common objects in a bounded arena with dynamic obstacles in a limited amount of time, receiving commands from humans and competing with other robots. This approach confirms the powerful combination of multi-agent systems, computer vision, and real-time systems.**

Keywords: Multi-Agent Systems, Path-planning, Robot Competition, Real-time control.

I. Introduction

The first mobile robot competitions were proposed in the early 80s and inspired generations of students and researchers in the development of AI and intelligent robotics. Competitions provide a goal, objective performance measures and media coverage to present research prototypes to a wide audience [1]; moreover, they are a well-known practice to test collaborative and competitive behaviours [2]. Faster and smarter robots started to be employed in competitions over the years, and thus, as a result, competitions changed and pushed the limits to explore new research challenges. For example, with the introduction of better sensors, the competitions started to take place in open environments rather than strictly defined ones. The same pattern can be observed in autonomous and industrial robotics. Currently, robots perform preprogrammed sequences of operations in highly controlled and constrained environments. However, some robots are able to perform basic intelligent actions, in terms of motion or reasoning, with no need for human supervision. The need for autonomous robots that can interoperate with other robots and human beings comes from different application fields, ranging from manufacturing to ambient assisted living [3]. Making robots able to operate in unknown environments and facing unexpected situations, involving variables not known a priori, is a challenge that will last for years. Commonly known as drones, self-driving cars and smart terminals, autonomous robots are starting to pervade our increasingly "smart" society. In the future, they will be able to produce, share and consume services autonomously as part of a fully connected network [4]. To achieve such a goal, concepts and techniques from both Artificial Intelligence (AI) [5] and embedded and distributed systems [6] have to be integrated.

This paper describes a framework for autonomous mobile robots which makes use of AI techniques, (mainly obstacle avoidance and path planning), under real-time constraints. To show the advantages of the proposed solution, robot capabilities are tested in a real environment presented as an open arena competition with other autonomous robots, with the goal of finding, collecting and returning objects back to their home base in a given amount of time, while avoiding obstacles and opponents. Typically, AI algorithms tend to optimize paths without taking time into account . However, in robotic systems, time is a correctness metric. Indeed, it may be counterproductive to perform an optimal action if it takes too much time to do it. In robotic scenarios, having a delayed optimal result is useless and even dangerous. For example, it is worthless to determine the optimal path after the robot has crashed into an obstacle and could put human security at risk.

The solution described in this paper employes two distinct computational models: *(i)* event-driven model and *(ii)* imprecise computation. The event-driven model is typical for agent-oriented programming in which agents must be reactive to external stimuli, and are proactive based on their internal status. The event-driven computational model is also useful for communication and reasoning. The imprecise computational model is instead useful to produce an approximate sub-optimal result in time even when the system is in an overload condition. Time-critical tasks such as path planning and obstacle avoidance are particularly suited for this computational model.

The main contribution of the proposed approach is the integration of the two computational models into a single software system and a single autonomous robot. Software agents are compliant with the IEEE standard for agent communication and interactions established by the Foundation for Intelligent Physical Agents (FIPA) [7]. The developed software agents take communications and high-level reasoning into account, reacting to external commands coming from humans or other software entities, while - at a lower abstraction level - real-time tasks take care of sensing and motion control. The proposed solution combines different agents into a single robotics platform: each agent is specialized in executing precise tasks. Modeling the required computing processes as a multi-agent system allows implementation of the demand, and delegation [8] of the tasks needed by the robot. Thanks to the communication mechanism between agents, based on asynchronous standard messages, agents can be substituted and task updated without affecting normal system operation. In addition, using a multi-agent platform, agents (and their services) can migrate from an embedded system to another, migrating the code towards the system that needs the elaboration, rather than moving the data.

The paper is structured as follows: Section II proposes a brief analysis of the state of the art of autonomous robots in terms of software analysis and applications. Section III briefly presents the scenario and experimental setup. Section IV presents the AI and real-time techniques used on the robot. Section V discusses the experimental results. Finally, Section VI concludes the paper with a critical analysis.

II. Related Work

The term “autonomous” describes a class of robots that is supposed to perform high-level tasks without external intervention. Autonomous robots are used in various fields and require a timely reaction when operating with both humans or other robots. The set of techniques and technologies involved in robotics is quite heterogeneous [9]. A wide range of components must be integrated to satisfy several kinds of requirements relative to temporal constraints, physical and control level, commands elaboration, and decision-making. Complex architectures can even provide interoperability tools and libraries.

For example, the CARMEN [10] project provides a three layers architecture based on software agents for mobile robots. Similarly to the proposed approach, motion and strategic tasks are conceptually separated. In CARMEN, the lower layer is a hardware interface that provides low-level control and sensor integration, while in the presented framework, the motion relies on a Real-Time Operating System (RTOS). The CARMEN’s middle layer implements strategies per tasks such as intermediate navigation and localization, followed by the upper layer, which realizes user-defined applications connected to the middle layer. On the other hand, in the presented approach, strategies and human interactions are ruled by interactions in the agents ecosystem.

ORCA2 [11] is another interesting robotics software integration framework. It makes use of concepts of the component-oriented software engineering paradigm and is based on ZeroC’s internet communication engine (ICE) middleware system. ORCA2 composes a robotic software application as a network of communicating independent modules, which are architecture and transport mechanism independent, as in the proposed solution. The differences between ORCA2 and the proposed framework rely on the structure design and communication method, which exploits the standard FIPA in the case of the presented solution.

Robotic frameworks can also be supported by the well-known Robot Operating System (ROS) [12] which is a collection of open-source software applications including a communication middleware. Unlike the Jade [13], the Multi-Agent System used in the proposed framework, ROS provides hardware abstraction, device drivers, libraries, visualizers, message-passing and package management. The ROS system is composed of independent processes called nodes, that are organized in a graph. In such a platform, nodes talk to each other (exchanging messages) through a *publish-subribe* mechanism.

In the context of robot competitions, the main deliberation functions typically taken into consideration for robots are six: planning, acting, observing, monitoring, goal reasoning, and learning. Normally, a mobile robot or a service domestic robot, such as IDEA [14] or T-REX [15], performs just a small subset of the aforementioned deliberation functions (i.e., planning and acting). More complex systems need more deliberation functions; for example, the proposed framework and DS1/RAX [16] (an autonomous spacecraft) need planning, acting, monitoring, goal reasoning and observing functions.

A common approach to evaluate strengths and weaknesses of different designs is to organize robot competitions. Such competitions provide a standardized testbed for different robotic systems [17]. Competitions can be classified in two main categories [18]: software-based and software/hardware-based. The first set of competitions is mainly about planning problems, vision, and speech processing. The performance metrics are the computational time, the number of problems solved, and the quality of the solutions. The second set of competitions involves robotic competitors running in real environments. The performance metrics takes into account capabilities of navigation, mapping, object recognition tracking and manipulation, etc. Different techniques and algorithms are proposed for each of these parameters with motion and obstacle avoidance as key activities. The competitions can take place in both known and unknown environments. Either way, a common approach is to implement a navigation system in two steps [19]: the first is to compute a collision free path from the start to the target position, whilst the second is to define and perform the motion commands. A common sensor for navigation systems is a Laser Range Finder (LRF) [20] that helps to define the surrounding environment. In the literature, several works assume the robot as a point [21], [22]. However, modeling it as a finite area offers several advantages [23]. In the case of unknown fields, an approach can be to develop a full coverage path [24]. It can be based on a field decomposition, performing a complete exploration with the robot, detecting and memorizing all the environmental features. This method provides full knowledge of the field but it is extremely resource and time-consuming and not suitable for changing environments. Another approach is to perform a fuzzy navigation [25] with onboard proximity sensors [26] or cameras. In the case of fields known a priori, the main challenge is to shift to object recognition [27] (i.e., color, shape, etc.). Identifying an object according to its color involves solving light variations problems [28] and applying a Fuzzy Color Contrast Fusion (FCCF) algorithm [29] to perform color segmentation enhancing the contrast or degrading it resolves them. A useful color segmentation method was used to identify the orange ball in the Robocup soccer humanoid league in 2010 [30]. An object can be also identified performing a shape detection [31]. Such a technique involves solving misalignment problems [32] and shape matching [33].

Summarizing, in line with the most effective existing frameworks, motion control and intelligence functions are separated. Furthermore, recruiting a standardized communication protocol simplifies interaction, extensibility, and modularity. The intelligence realized through an agent ecosystem exploits the efficiency and robustness typical of Multi-Agent Systems (MAS). Finally, thanks to the RTOS, the motion control system timely interacts with the strategic layer respecting the specified timing constraints.

III. Scenario and experimental setup

The robot described in this paper took part in a robot competition held at the “Università Politecnica delle Marche”, Ancona, Italy. Each team was required to program identical robot platform consisting of an STM Discovery board, a PandaBoard ES, and a Logitech high-definition (1080p) webcam. The STM Discovery board was equipped with an STM32F4 Cortex M4 micro-controller running the Erika RTOS [34] to control two DC motors, while the PandaBoard ES used a dual-core ARM Cortex-A9, 1 GByte DDR2 RAM for high-level computation. A laptop equipped with an Intel Core 2 Duo P8700 2.53 GHz and 4 GB DDR3 RAM was used to run software that provides competition-management services and another Logitech HD webcam was shared among robots to acquire aerial pictures of the race field. The onboard webcam and the shared webcam were identical. The robot 3D model is shown in Figure 1(a), and the real robot (internal components, cover prototype, and final version in the competition field) is shown in Figure 1(b). According to the competition rules, the teams had to develop a software agent container based on the JADE agent framework [13]. This container had to run on the PandaBoard and join a common JADE-based agent platform so that all the agents could communicate. In this scenario, an agent is an autonomous software entity operating in a network of peer agents. According to Wooldridge and Jennings [35] a software agent is autonomous, meaning that it owns the control over its internal state; it has social abilities, in the sense that it is able to communicate with other agents with asynchronous messages; it is reactive, meaning that it is able to react to external stimulus such as messages from other agents. Finally, an agent can be proactive, in the sense that it can exhibit goal-oriented behavior. The teams were required to adhere to such an agent definition. Indeed, each agent had to have its own tasks, communicating with other agents by means of FIPA-ACL messages. Each agent had to pursue its own goal, such as object recognition, path planning, etc. The entire decision-making process took place at the agent level. During the match, the team could communicate with the robot using Android Application Programming Interfaces (APIs) for automatic speech recognition. Finally, the STM Discovery board was in charge of robot motion, subject to real-time constraints.

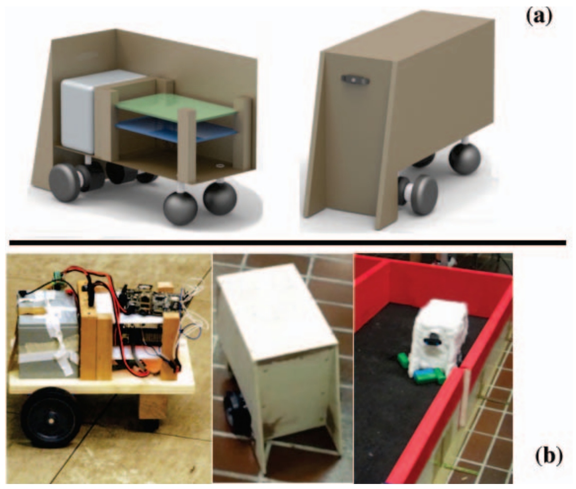


Fig. 1. (a) Robot 3D model; (b) Robot real model.

A. Goals

Focusing on research challenges, the competition aimed at integrating artificial intelligence and real-time systems techniques: the robot combined computer vision and obstacle avoidance, with the need *(i)* to perform movements on time to avoid hitting other competitors, field borders, and obstacles, and *(ii)* to gather objects before the opponent in a minimum amount of time.

B. Rules

The minimal set of rules follows:

- Robots must start at the given home base;
- Robots must collect as many targets as they can;
- Robots cannot hit the obstacles or with each other;
- Robots cannot steal targets from opponents home base;
- Robots must operate autonomously;
- Robots must obey penalties and commands from the *referee* agent.

The competition started when a *Referee* agent registered one agent for each team. The *Referee* agent sent them a FIPA-ACL message with content “Start”. During the competition, an agent from each teams JADE container could demand the “AirCamera” agent, at most every 200 ms, to take a picture from a camera placed above the race field. Illegal requests were refused. The robot not following the rules received a penalty from the *Referee* agent, in the form of a FIPA-ACL message with content "penalty". After receiving such a message, the agent in the robots agent container had to stop for a specified amount of time. The *Referee* ended the round sending an FIPA-ACL message with content "Stop".

C. Race field

The competition took place in a real race field. A 3D and 2D view of the race field model is shown in Figure 2. The field's ground was black with the borders of the field and the obstacles in red. The yellow and purple squares at opposite corners were the robots' home bases where they had to bring the blue and green cardboard parallelepipeds, the objects, collected in the field. The competition organizers set different objects and obstacle maps for each round.

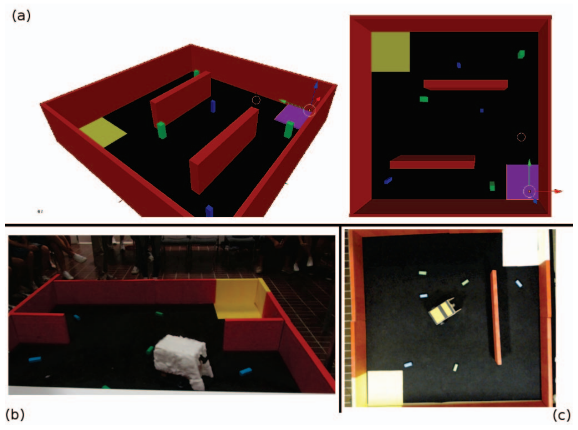


Fig. 2. Competition scenario: (a) Field 3D model; (b) Real Fild side view; (c) Real Field *airCamera* view.

IV. The proposed solution

This section presents the proposed solution and its components, motivating the strategic choices. The strategy is to delegate and distribute duties among agents in order to maximize parallelism and agents' specialization on specific functions. Each agent has specific functionalities that can be triggered by time, specific agents' goals, reception of specific requests, or specific events. Such functionalities are coded as combinations of JADE's behaviors (waker, cyclic ticker, and oneShot) [13]. The first step is to require the field image Figure 2(c) to the *AirCamera* agent, which provides an aerial image of the field. There is a time limit of 200 *ms* on consecutive requests placed on *AirCamera* and those that come in a shorter time period are rejected. Once processed, the image provides the robot's position and orientation and the obstacles positions. The second step is to find the target and determine the path needed to reach it. Recalling that software agents interact by exchanging messages, Figure 3 shows the proposed agent system and interactions between them. Agents are distributed among an Android smartphone, a robot, and a laptop is in charge of the competition control.

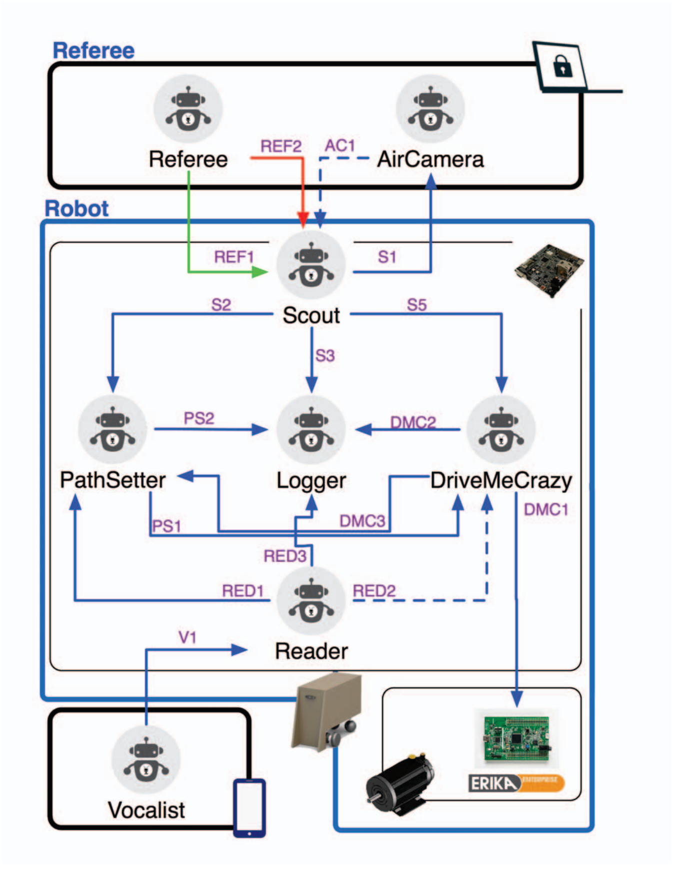


Fig. 3. Agents Framework: organization and interactions.

Referring to Figure 3, the *Vocalist* is the agent working on the mobile phone. It makes the communication between the team and the autonomous robot possible, translating the human (vocal) indications into actual messages, thus activating the interaction V1:

- **V1:** target values and the *"ready state"* (from the team) have to be communicated to the *Reader* agent in order to start the robot.

When the *Reader* receives messages from the *Vocalist*, it reacts performing interactions RED1, RED2 and RED3:

- **RED1:** information about target values, which impacts on target selection, is sent to the *PathSetter* agent, along with both the "ready state" and the actual "start race". This means that the race is started.
- **RED2:** if the *Reader* receives motion commands from a human, it sends them to the *DriveMeCrazy* agent in charge of communicating with the motion system.
- **RED3:** all the information received is sent to the *Logger* agent in charge of publishing them in the web page depicted in Figure 4.

As described in Section III, the match actually starts when the *Referee* agent communicates to the robots (in the ready status) the actual "start race". The *Scout* agent is in charge of exchanging information with *Referee* and *AirCamera*. The start of the match generates the message REF1.

- **REF1:** is a single message that communicates to the robot that the match has started.

This event triggers the following interactions:

- **S1:** *Scout* is allowed to ask an image from *AirCamera* at most every 200 *ms*. If the request is accepted, *AirCamera* sends *Scout* a message with an image. Otherwise, it will notify an error.
- **S2:** saves the image and notifies *PathSetter*.
- **S3:** sends match status, info and behaviours to *Logger*.

PathSetter is in charge of visual processing and path-finding. This agent is characterized by a ticker behavior which activates a set of tasks every 200 *ms*. The image processing algorithm is composed of multi-step activities: cell decomposition, robot detection, target identification, target selection and obstacle detection. This algorithm is presented in Section IV-B. When path calculation is finished, *PathSetter* sends the messages PS1 and PS2:

- **PS1:** communicates to *DriveMeCrazy* the set of movements needed to reach the target.
- **PS2:** communicates to *Logger* the robot's position, target position and path.

When *DriveMeCrazy* receives PS1, it performs the interactions DMC1 and DMC2:

- **DMC1:** transfers motion commands to the STM Discovery board which is in charge of the DC motors.
- **DMC2:** receives information from the STM Discovery board about the motors' status, and then sends them to *Logger*.

If an error is detected with respect to the path to follow, the interaction DMC3 is activated.

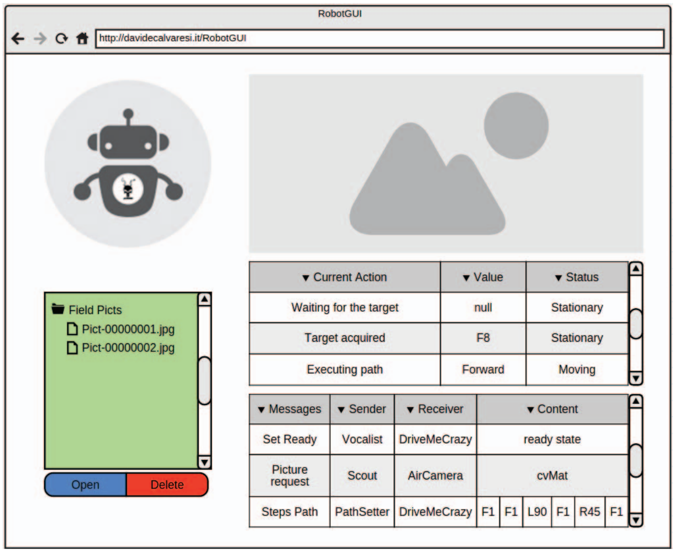
- **DMC3:** *DriveMeCrazy* communicates variations with respect to the expected path (e.g. the robot has been hit by the opponent, an error happened during the motion control, etc.), requiring a new input from *PathSetter*.

If *Referee* sends "penalty" or "end game" commands, interactions S4 and S5 are activated.

- **S4:** *PathSetter* does not need to compute until a new order is received or time penalty is expired.
- **S5:** Motor "stop" is immediately required.

A. Vocal Interaction

The system makes use of the Google APIs to perform speech recognition. The *Vocalist* agent, Figure 3, runs on an Android smartphone by means of the JADE-LEAP add-on for JADE [13]. JADE-LEAP allows to create a lightweight container (the "front-end") on smartphones and embedded devices, providing a basic JADE run-time environment; advanced JADE functions are delegated to a "back-end" container running on a remote server. When all the needed functionalities are activated, the *Vocalist* agent is created. As a regular agent, *Vocalist* is registered into the JADE Agent Management System, which is automatically provided by the JADE main



▾ Current Action	▾ Value	▾ Status
Waiting for the target	null	Stationary
Target acquired	F8	Stationary
Executing path	Forward	Moving

▾ Messages	▾ Sender	▾ Receiver	▾ Content
Set Ready	Vocalist	DriveMeCrazy	ready state
Picture request	Scout	AirCamera	cvMat
Steps Path	PathSetter	DriveMeCrazy	F1 | F1 | L90 | F1 | R45 | F1

Fig. 4. Robot Log Web Interface.

container running on the robot. *Vocalist* acts as a listener in an app to control the robot, and sends instructions to the *Reader* agent. Thus, the vocalist agent is an interface between the human operators (the members of the team) and the robot control. Figure 5 shows the app interfaces. Commands are divided into two categories. The mandatory commands, Figure 5(a) are: "stop", "Command List", "Send a command". In each competition round, before the actual "start race", each team was requested to vocally communicate the color of the targets to be gathered by the robot. Hence, during the competition, the mobile app did not interfere with the autonomous systems, even if optional commands ("start", "stop", "go home", "left", "right", "step forward", "step back"), usable only in case of emergency, were implemented.

B. Computer Vision

As said before, during the match, the *Scout* agent sends every aerial image of the field received from the *airCamera* to the *PathSetter*, which is in charge of managing the computer graphic. The image processing makes use of the OpenCV library (a set of tools used for the computer vision [36]). cvBlob is a subset of libraries that allows a real-time image processing of moving objects [37]. In the computer vision domain, a blob is a group of connected pixels with the same logical state.

The first step of the analysis requires to identify robot position and orientation, through a special marker on the top of the robot. To find the marker, parameters such as minimum and maximum dimensions of the blob area, and the HSV color code need to be set. Since the field illumination is not homogeneous, to identify the marker in all the fields, a range of HSV values, rather than a single color code, need to be set. The HSV range tuning is shown in Figure 6(a). In order to facilitate the understanding of the tuning effectiveness, a

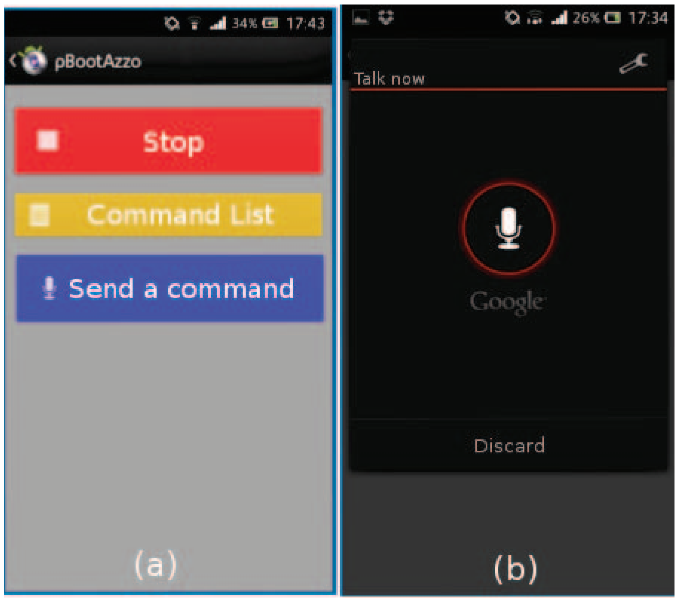


Fig. 5. Smartphone App for Human-Robot Interaction.

merge made out the of several real pictures has been realized and processed. Figure 6(b) shows the results of such a process.

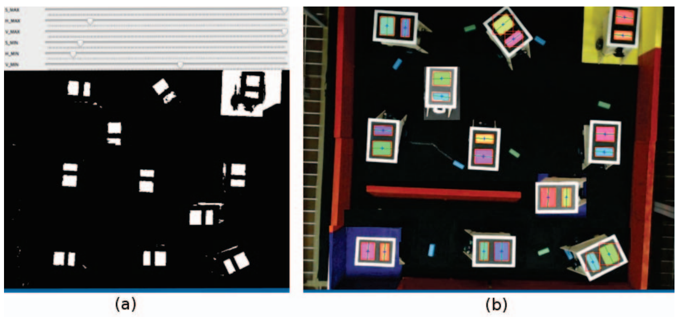


Fig. 6. Robot marker image processing: (a) HSV range tuning, (b) processing results.

The second step consists in finding targets and identifying the most "convenient" one using a proper cost function. First of all, the image is cropped to the field dimension to exclude objects out of the field, thus avoiding incorrect target identification. As stated in Section III, targets are a combination of blue and green objects. In the processed image, their area and color can vary due to their position in the field. Thus, the same blob technique described above for marker identification is used. Proper settings for area and HSV color range are used. To comply with the rule "robots cannot steal targets from the opponent home base", hence, an additional filter is introduced to exclude targets already collected from the opponent. This is done reducing the area to be processed, introducing constraints to exclude the robots' home bases.

Figure 7 shows that the algorithm is able to discriminate from the same picture the blue targets, Figure 7(a), the robot, Figure 7(b), and the green targets, Figure 7(c).

The above mentioned algorithm is also used to perform fixed obstacle identification. Figure 8 shows a picture taken by the *AirCamera* agent *(a)* and the result of fixed obstacle identification process *(b)*.

To detect mobile obstacles (e.g., opponents) an imprecise computation approach is used. The goal is to identify the mobile robot competitors as soon as possible to avoid collisions. To this end, the robot exploits the frontal webcam, reducing the processed area to a narrow horizontal stripe near the center of the image. The cropped image is divided horizontally into several sectors. The analysis starts performing the elaboration of the central and the most external sectors at the same time. If the algorithm identifies a possible obstacle in one of the sections, it immediately stops communicating to the *DriveMeCrazy* agent the instructions to avoid the impact. If the strip can be processed while meeting the real-time constraints, further iterations analyze the sectors converging to the center.

C. Path Planning

At this stage, the *PathSetter* agent is aware of the robot position and orientation, the most convenient target, and obstacles position. The path required to reach the target and to bring the target to the home base is determined using a revised and discretized version of the potential field algorithm that will be fully presented in a future work. According to the imprecise computing approach, such an algorithm produces a sub-optimal path as a first solution, which is optimized by further iterations, if allowed by the specified timing constraints. The use of this algorithm shows good results in terms of CPU load, converging time and number of iterations. Figure 9 shows the 3D representation of the values mapping the field. The matrix of such values represents the field discretization explored by the path planning algorithm.

D. Moving the robot

PathSetter sends the path to *DriveMeCrazy* which converts it into a series of low-level commands. It is then sent through a UART connection to the STM Discovery board, which is in charge of actuating the motors.

Control: The robot position is represented by its coordinates in space $\bar{x} = (x, y)$ and its angle θ.

When the robot needs to change its position, the two motors are activated. The resulting trajectory is a function that depends on the movement of both wheels. For this reason, the rotational speed of each wheel must be continuously monitored by the motor encoders and controlled by the wheel speed controller, represented in Figure 10.

The G element represents the open-loop transfer function of the DC Motor:

$$G(s) = \frac{K}{(Js+b)(Ls+R)+K^2} \qquad (1)$$

where all the parameters depend on the wheel and motor characteristics, obtained by experimental measurements:

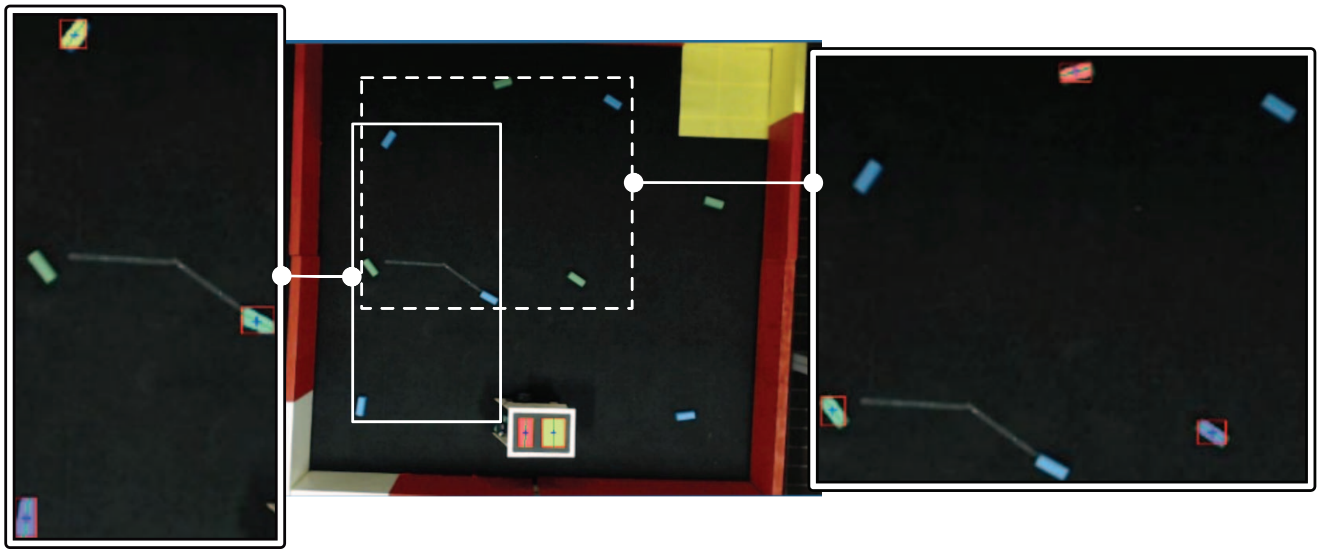


Fig. 7. Output of the graphical elaboration: (a) Blue target identification, (b) Marker identification and (3) Green target identification.

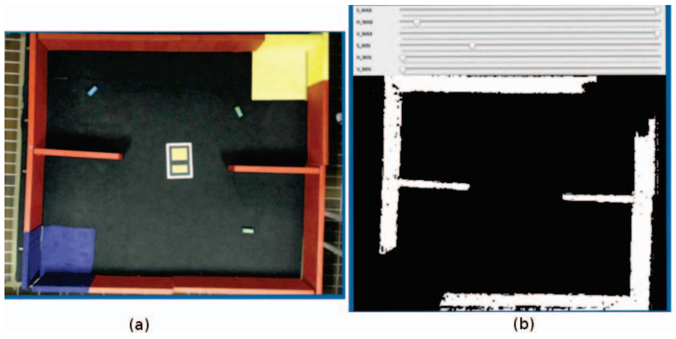


Fig. 8. Obstacles identification: (a) aereal field image, (b) HSV range tuning.

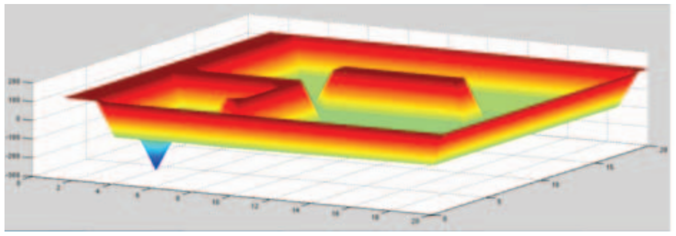


Fig. 9. Battle field discretization: a 3D model.

- $J = 0.188(kg \cdot m^2)$: moment of inertia of the rotor.
- $b = 0.05(N \cdot m \cdot s)$: motor viscous friction constant.
- $K = 0.7639(V/rad/sec)$or$(N \cdot m/Amp)$: electromotive force constant, equal to the motor torque constant.
- $R = 4.5(Ohm)$: electric resistance.
- $L = 0.587(H)$: electric inductance.

The speed controller Q is implemented by a proportional-integral-derivative (PID) regulator. A preliminary controller tuning has been performed by using the Ziegler-Nichols rules, and then the obtained parameters were finely tuned by experimental tests.

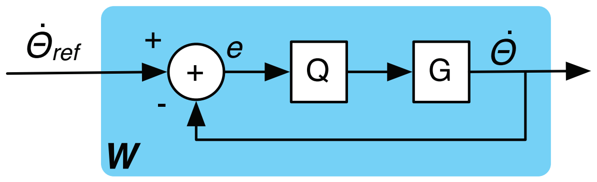


Fig. 10. Wheel Speed Controller.

An error on the actual position can arise despite the wheel speed controllers. This happens because the robot position depends on the speed of both wheels, but the two speed controllers are independent of each other. Another control loop is added to solve this problem, as shown in Figure 11. This loop uses the module S to calculate the robot position based on the two wheels speeds and sends it back to the controller module C, which adapts the speeds of the wheels according to the desired trajectory.

Depending on the scenario, the agent *DriveMeCrazy* exploits different behaviors to interact with C:

- Ref_{cmd}: handles the requests performed by the referee.
- U_{cmd}: manages the users' requests interacting with C and P_{cmd}.
- P_{cmd}: sends the path to be followed to the autopilot.

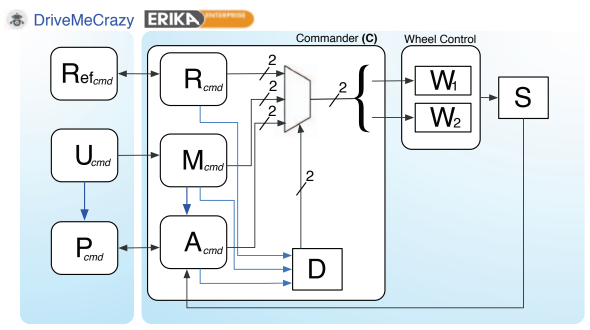


Fig. 11. Motion Controller.

E. Tasks

The software has been organized in the following tasks:

- $W1$, $W2$: perform proportional controls on the speed of the associated wheel.
- S: detects the wheels movements and calculates the robot position.
- The controller C decides the speed of each wheel. This module includes the following tasks:
  - A_{cmd}: is the autopilot that depending on the current sensed position and the path received by P_{cmd} actuates the motors. Furthermore, such autopilot sends messages back to the *DriveMeCrazy* agent to notify eventual errors or new request.
  - M_{cmd}: handles user manual commands.
  - R_{cmd}: manages requests from the *referee*, in particular the stop command.

The C module internally chooses - with a multiport switch, whose control input is decided by the D module - the correct reference speeds among the speeds proposed by the tasks A_{cmd}, M_{cmd} and R_{cmd}, based on their availability and relevance. The decisions taken by R_{cmd} are the most important because the *referee* must be able to stop the robot regardless of other commands or the internal robot status. M_{cmd} is more important than A_{cmd} because the user commands have higher value than the robot's own decisions. If none of the mentioned tasks proposes a command, then the robot stops.

M_{cmd} and R_{cmd} are sporadic tasks, while A_{cmd}, S, $W1$ and $W2$ are periodic tasks.

Tasks are assigned fixed priorities and scheduled according to the Rate Monotonic (RM) algorithm [38].

The total number of tasks, identified with n, is equal to 6. By defining the computational time of the generic task i as C_i, the activation period as T_i and the utilization factor as $U_i = C_i/T_i$, the schedulability test can be performed by using the Liu and Layland sufficient condition [38]:

$$\sum_{i=1}^{n} U_i \leq n\left(2^{1/n} - 1\right). \tag{2}$$

The most time-critical task is S because its correct timing behavior is required in order to preserve a good approximation of the robot position. Supposing that each encoder has a precision of $n_e(ppr)$ and the maximum rotational speed of each wheel is $w_{max}(rpm)$, in order to preserve the accuracy of the encoders, the task S must have a maximum period defined by the following relation

$$T_S < \frac{1}{w_{max} \cdot n_e} \cdot 60(s). \tag{3}$$

Even though M_{cmd} and R_{cmd} are sporadic, it is possible to assume a minimum inter-arrival time to verify the system's schedulability. Those tasks manage interactions with humans, so a period of 50 ms is enough to guarantee a responsive user-perceived system.

The minimum periods of $W1$, $W2$ and A_{cmd} are calculated by finding their maximum utilization factors that preserve the task set schedulability.

V. Experimental Results

This section presents the results obtained from the real experimental setup outlined above. Experiments are conceived to test compliance with time constraints at each level of the software architecture, from the high-level decision making to the low-level motion control algorithms. Communications with services that can be used by more than one robot are also tested, taking into account their mutual-exclusive usage.

The interaction between the *Scout* and the *AirCamera* agents is depicted in Figure 12. This interaction, is not cooperative but competitive, in the sense that the *AirCamera* agent arbitrates the access to a shared resource. This means that when more than one agent tries to communicate with *AirCamera* the response can be delayed, as highlighted in the experimental results reported in Table I.

When a single *Scout* agent interacts with *AirCamera*, the message exchange (consisting of a request message, the image acquisition, and a response message) lasts on the average 673.6 ms, ranging from 634 ms in the best case and 1514 ms in the worst case. Such values are obtained on 1000 iterations. Execution times for each step are listed in Table I. When more than one *Scout* agent tries to communicate with the *AirCamera*, the time to serve the request arise due to the waiting time needed to serve the queued previous requests. For example, in such a scenario, the second agent being served experiences a total waiting time which is the sum of the time needed to serve the other request and the time needed to serve its request. This means that the interaction timing nearly doubles. Indeed, experimental measurements for this second scenario outlined above confirmed this. The message exchange in this scenario lasts on average 1330.7 ms while the best case is 1260 ms and the worst case is 3004 ms. Since the image from the *AirCamera* is used to plan a strategy (identifying the target and planning the path), such a worst-case scenario means that three seconds might pass before the autonomous robots can change its strategic plans. However, it does not affect the reacting and moving capabilities of the robot, which are based on the last deliberated plan. Moreover, moving obstacles can be detected by the onboard frontal webcam for which there are no competing agents.

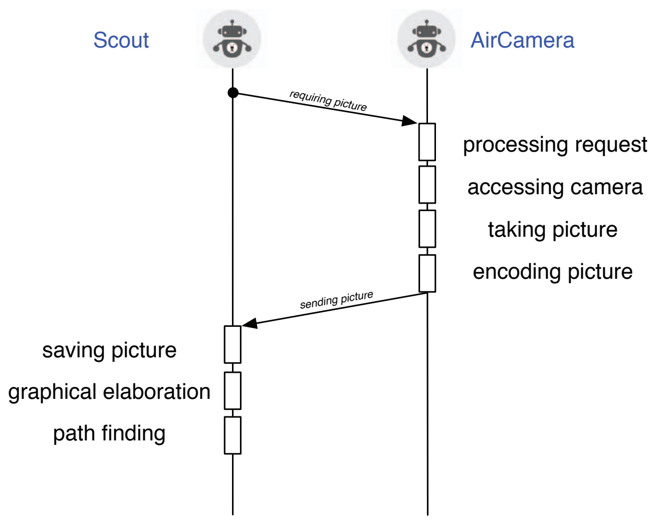


Fig. 12. Scout-AirCamera interaction.

Once the image is received, agents have to decode, save and process it in order to deliberate the target and identify the set of commands to reach it. This process makes use of computer vision and pathfinding algorithms, as outlined above. Table II reports the processing time derived on 1000 executions of such tasks. The amount of time required to determine the path to follow is on average 51.6 ms, which reduces to 32 ms in the best case and peaks at 378 ms in the worst case.

Regarding the low-level motion control systems, worst-case execution times (WCET) for motion control tasks were experimentally measured and are reported in Table III.

In the experimental setup, each wheel is able to rotate at a maximum speed of $150(rpm)$, while the encoder has a precision of $4480(ppr)$. Using Equation (3), the resulting period is $T_S \leq 89.28\ \mu s$.

TABLE I
SCOUT-AIRCAMERA MESSAGE EXCHANGE TIMING

	best case time (ms)	worst case time (ms)	average time (ms)
send picture request	8	22	16.5
take and encode picture	580	1228	602.4
send picture	46	263	54.7

TABLE II
DELIBERATION PROCESSES TIMING

	best case time (ms)	worst case time (ms)	average time (ms)
saving	27	359	39.2
compute vision elaboration	3	11	8.3
pathfinding	2	8	4.1

TABLE III
TASK'S EXPERIMENTAL WCET

Task	WCET (μs)
W_1, W_2	24.4
S	16.3
A_{cmd}	40.9
M_{cmd}, R_{cmd}	19.9

Applying equation (2) to the system's taskset, we have:

$$\frac{C_{W1}}{T_{W1}} + \frac{C_{W2}}{T_{W2}} + \frac{C_S}{T_S} + \frac{C_{A_{cmd}}}{T_{A_{cmd}}} + \frac{C_{M_{cmd}}}{T_{M_{cmd}}} + \frac{C_{R_{cmd}}}{T_{R_{cmd}}} \leq n\left(2^{1/6} - 1\right) \tag{4}$$

The dynamic of the outer control loop must be slower than the dynamic of the internal control loop to allow the internal loop to reach stability. For this reason and due to the equality of T_{W1} and T_{W2} the period is taken as $T_{Wi} = T_{W1} = T_{W2} = 20 \cdot T_{A_{cmd}}$. Performing this substitution and bringing the known terms to the right, the previous equation becomes:

$$T_{Wi} \geq \frac{C_{A_{cmd}}/20 + C_{W1} + C_{W2}}{n\left(2^{1/n} - 1\right) - \frac{C_S}{T_S} - \frac{C_{M_{cmd}}}{T_{M_{cmd}}} - \frac{C_{R_{cmd}}}{T_{R_{cmd}}}}. \tag{5}$$

The previous equation can be solved for periods substituting numerical values. Making some pessimistic approximations, the resulting periods are: $T_{W1} = T_{W2} = 100\ \mu s$ and $T_{A_{cmd}} = 2\ ms$.

From a functional point of view, the system resulted to be effective and efficient. In all the experimental runs, the robot was able to identify itself, the targets and all the obstacles. Furthermore, the pathfinding heuristic obtained the 100% of success, meaning that the path connecting the robot and its target was always identified, if existing. Considering the executed experiments, 70% of the identified paths were identical to the optimal ones. With respect to the most known A* [5], D* [39] and Dijkstra algorithms [5], the proposed algorithm achieved a substantial gain in terms of computational load, converging time and sub-optimal solution quality.

VI. CONCLUSIONS

This paper presented an autonomous mobile robot designed to collect objects in a competition arena, interact with humans, software agents and other robots, in a given amount of time. AI and real-time methods and techniques were combined together to obtain a robot able to autonomously perform intelligent actions under real-time constraints. A two-level software architecture was used, in which the high-level agent-based software was in charge for decision-making and communication while a low-level real-time software controlled motion and reacted to environmental changes.

The solution described in the paper highlights the strength of a modular approach solving complex and very different problems, like image processing, path planning, and robot control in a competitive scenario. cvBlob seems to be a good choice with respect to real-time constraints, performing image recognition tasks fairly well even in the worst-case scenario when used on the embedded board on the robot. On the other hand, delays due to concurrent access to shared resources and the amount of messages exchanged between software agents in response to a change in the environment seems to affect the performance of the system. From a functional point of view, software agents are able to achieve their goals on a regular basis, thus placing the real-time motion control system in better operational condition. However, software agents lack a mechanism to take into account real-time constraints, thus making it difficult to coordinate them during transient overload conditions.

Making software agents aware of real-time requirements seems to be a good research challenge on its own that can open the way to real-time agent-oriented programming. As a first step, Real-Time Publish-Subscriber (RTPS) protocol could be integrated into agent-based systems, thus providing them with a real-time communication protocol integrated into the distributed nature of the multi-agents paradigm.

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