4. Working programme

4.1. Título do programa de trabalhos **4.1. Title of the working programme**	
Adaptive Coordination of Robotic Teams using Machine Learning Methodologies	
Domínio Científico **Scientific Domain**	
Inteligência Artificial	
Data de início do programa de trabalhos **Work programme starting date**	**Duração (meses)** **Duration (month)**
	48

Data de início pretendida para a bolsa **Fellowship starting date**	**Duração (meses)** **Duration (month)**
\	48

4.2. Sumário
4.2. Abstract

This research project aims at developing generic coordination and cooperation methodologies to enable teams of heterogeneous, autonomous robots, with different skills, and made by different manufacturers, to accomplish complex collective tasks, with emphasis on playing robosoccer games and urban search and rescue in disaster space. The main result of the thesis will be a new approach to cooperative robotics in general with emphasis on applying learning approaches, especially reinforcement learning, to improve the coordination methodologies developed.
The project will be developed with two main objectives: (i) design and implementation of a common software framework suitable for the implementation of agents that may control different robots to be used for several cooperative robotic tasks including the development of coordination based on machine learning methods that enable teams of heterogeneous robots, built and programmed by different entities, to accomplish complex collective tasks; (ii) application and adaptation of the framework and its methodologies to different scenarios including robotic soccer leagues (simulation 2D, simulation 3D, SPL and middle size) and rescue simulation leagues(agent and virtual robots).

4.3. Estado da Arte
4.3. State of the art

Several authors have proposed general models for flexible coordination. However, most of the approaches either are not sufficiently reactive to perform efficiently in real time and dynamic domains or do not provide agents with sufficiently developed social behavior to perform intelligently as members of a team in continuous, multi-objective and complex multi-agent environments [1]. One notable research may be recognized, like Stone's and Veloso's work [2] that has been applied with success to RoboCup soccer and network routing.
In order to achieve complex behavior acquisition using machine learning methods, Stone and Veloso[3] proposed to introduce a layered learning system with basic skills such as "shootGoal", "shootAway", "dribbleBall", and so on. Kleiner et al [4] also proposed multi-layered learning system for behavior acquisition of a soccer robot.

Most implementations of multi-agent coordination frameworks rely on domain specific coordination. However, some relevant exceptions may be identified. An example is Jennings' joint responsibility framework [5], which is based on a joint commitment to the team's joint goal which was implemented in the GRATE* system. One other approach to automated planning is discussed in hierarchical task network (HTN) where the dependency among actions can be given in the form of networks [6]. Regarding one possible and commonly used testbed for the framework, the Robotic Soccer competition [7, 8, 9], the UVA Trilearn team's coordination graphs provides a way to parameterize a coordination structure over a continuous domain [10]. To manage coordination between agents three options are proposed in [11]: environment partitioning, centralized direct supervision and decentralized mutual adjustment. Among these three approaches, the decentralized approach is more flexible but it does not mean it is always better. Regarding rescue simulation as another possible tesbed for the framework, in [12] a hybrid approach is proposed to use advantages of both centralized and decentralized approach. In order to make a decision about the number of ambulances which should cooperate to rescue civilian, evolutionary reinforcement learning is utilized by [13]. In [14] fire brigade learns to do task allocation and learn how to choose the best building for extinguishing to maximize the final score. In [15] fire brigades learn how to distribute in the city using neural reinforcement learning. Another method is to prioritize fire sites from a fire brigade's perspective [18].
Recently the candidate developed a generic reinforcement learning based model for coordination of fire brigades agents [16]. This model uses reinforcement learning method that uses the Temporal Difference (TD) methodology, based on the consideration that TD methods update the estimated data without waiting the final outcomes, allowing in such a way to react promptly in complex environments like disaster spaces. In other previous research work, a market-based model for cooperation between rescue agents was proposed in which the parameters of the model were optimized using genetic algorithms [18]. We plan to extend this approach applying reinforcement learning for improving generic team coordination models at several levels and with application to distinct cooperative tasks.

In summary there are several coordination and communication solutions based on machine learning but only a few, flexible, strategy solutions proposed for cooperative robotics. However most of them are domain specific and there isn't a framework that can encompass a generic solution from sensor and actuator data, intelligent communication exchange and cooperative approach problem solving with strategically planning in multi-agent systems. Also the use of learning for improving high-level robot programming is mostly limited to simulated systems, where the difficulties about sensor noises, non-deterministic effects of actions, time and resource constraints and real-time requirements are limited. This research work will aim developing a generic framework to solve the decision making and cooperation problems in complex stochastic multi agent environments including real and simulated systems using machine learning algorithms such as Genetic algorithms, Neural Networks and Reinforcement Learning.

4.4. Objectivos
4.4. Objectives

The main purpose of this work is to develop a framework using machine learning methods for coordinative and collaborative multi-agent heterogeneous systems. The framework should allow the possibility of using heterogeneous and homogeneous robots coordinating and collaborating amongst themselves.

The more specific goals of this project are the following:
- Development of generic sensor, data and strategically communication languages for optimum world modeling and coordination.
- Study and development of evolution programming and machine learning techniques to increase the performance of multi-agent systems learning procedures.
- Development of simple and complex individual decision making mechanisms using machine learning methods.
- Development a framework for opponent modeling; Opponent could be environment in rescue and search missions or could be opponent team in soccer playing domains.
- Development of a layered learning system based on the results of previous steps to obtain a flexible coordination among robots to achieve the collective goals.
- Adaption the framework to simulation and real environments.

The methodologies developed will be tested in different scenarios including robotic soccer leagues (simulation 2D, simulation 3D, SPL and middle size) and rescue simulation leagues (agent and virtual robots).

4.5. Descrição detalhada
4.5. Detailed description

In this section the work schedule will be presented together with work methodologies and project modules, including the objectives for each task.

Task 1: Literature Review

To begin with, all the existing related work on cooperative robotics learning should be studied carefully and organized into different possible approaches.

Task 2: Study and development of machine learning techniques

High-level programming of mobile robots in complex, dynamic, partially observable and stochastic environments, like the ones provided by the RoboCup soccer and Robocup Rescue Simulation competitions, is still a fundamental step for effective cognitive robots. This is an extremely difficult task, because the human developer is not able to predict the many possible situations that the robot will encounter, thus limiting its adaptively to the real environment. Machine learning techniques can help to create more robust behaviors and reduce the need for defining complex models of the systems in use. In this task various machine learning algorithms like reinforcement learning, neural networks and optimization algorithms will be studied.

Task 3: Agent Software Architecture

To enable a team to perform cooperative robotic tasks in a partially cooperative, partially adversarial environment a lot of knowledge is needed. Also robots must be able to represent some sort of world state that allows them to cooperate with each other. In this task the definition of a general world model architecture that can cope with the coordination of robotic teams with different capabilities and operating in distinct environments will be defined. Additionally, representation structures for this type of multi-level knowledge will be investigated and an appropriate knowledge representation structure will be implemented.
This architecture will define the set of rules that all cooperating agents must fulfill to operate in the coordination framework to be developed in the context of this project. Internal details of the agent architecture may be substantially distinct, as may be the case, for example, for agents originally developed by different teams, but all agents should comply with the general set of rules defined for the general World State Architecture. This architecture will be able to cope with the cooperation of heterogeneous agents within the same team and with the cooperation in completely distinct environments.

Task 3: Perception, Action, Communication and Supervisor Languages

Based on previous work developed by the FC Portugal team, several languages will be created to enable team cooperation. Initial versions of the four languages have already been created and will be improved in the context of this project with emphasis on the supervision language.

Task 3.1: Perception Language

A perception language will be created to enable the communication of different sensorial parts with the common framework. This perception language will enable high-level description of robots' perception, including moving objects and known stationary objects and their distances, directions, dimensions and other useful parameters. The language will enable the description of the perceptions both in absolute and relative coordinates and the inclusion of confidences in this perception information.

Task 3.2: Action Language

We intend to develop a language for action that will enable the common framework to send high-level commands to the robot actuators. These commands will consist mainly of behavior commands (dribble, pass, move to point, etc.), movement commands (rotations, translations, etc.) and object interaction commands (grab, push, pull, etc.). Robot's specific parts will translate these high-level commands into robots actuators low level commands (depending on the robots specific hardware and dynamical models).

Task 3.3: Communication Language
A more specific language will be implemented to enable robot communication for cooperative tasks in adversarial environments. This language will enable the communication of robots knowledge, world state and useful coordination events to other robots (like the beginning of a given task or a task swap between two robots). This communication language will be based on content languages presently used in the Multi-agent research domain adapted to the cooperative robotic domain. It will enable a robot to communicate with a single robot, with a selected part of the team or with the whole team at the same time.

Task 3.4: Supervision Language
The Supervision Language enables the agent to inform the supervisor of its perception and action capabilities and the supervisor to give instructions to the agent about the strategy to be used and coordination task to be achieved. Agents will be able to tell the supervisor of their perception and action capabilities. This information is essential for the supervisor as some of the coordination methodologies might have pre-requisites that may be fulfilled by some robots and lacking in others (an example is the precise self-positioning ability).
Domain knowledge, including the relevant skills for performing a given robotic task will be given to the agents by the supervisor, using a specially devised multi-resolution supervisor language inspired in Coach Unilang (a standard language for coaching a soccer team). The supervisor language will deal with concepts like tactics, formations, situations, tasks, positions and other spatial and time concepts. It will also enable to parameterize robot's cooperative decisions, robot's individual decision making and robot's action.

Task 4: Developing a decision making unit to integrate the deliberative behaviors of the robot

To provide the opportunity for the robot to decide how to act a framework is needed to organize the different skills at different times. RoboCup soccer and rescue simulation scenarios are good testbeds for this aim. For example in 3D soccer simulation league, each player has a defined role during the game and different tasks may be executed by each role. Each player may have its own hierarchy of behaviors, where the top of hierarchy provides the more abstract behaviors, such as Score and low-level behaviors may contain primitive behaviors such as move a specific joint to a specified angle. The whole behavior system can be seen as a layered system, just like a hierarchically structured system for the overall control of a robot. In higher levels a robot player may even be able to recognize its own role, such as attacking or defending by some predictions of the opponent behavior such as opponent modeling. Studied machine learning methods will be used in this task.

Task 5: Coordination methodologies for a team of robotic agents

This task will consist on the development of coordination methodologies for a team of robotic agents. Applications obtained from previous tasks, will be used to give support to this coordination aiming at producing a team of robots capable of coordinate their actions in order to reach a common goal. The developed methodologies will be integrated and tested in the context of RoboCup soccer leagues and rescue simulation leagues in the context of FC Portugal robotic teams.

Task 6: Layered Learning methodologies for team coordination

This task will consist on the development of learning methodologies, mostly based on reinforcement learning and on the authors previous research work and its application to individual decision making and team cooperation problems for FC Portugal distinct teams.

Task 7: Adaptation of Test beds to the Framework.

In this task, for Robocup soccer leagues and rescue simulation leagues, software will be developed and implemented in order to make them compliant with the defined framework.

Task 8: Real and Simulated Environment Experiments.

This task is aimed at testing the framework, starting with simple tests and finishing with robot cooperation experiments. A battery of tests will be planned and executed in order to test the different robots interactions. The tests will start with only one robot and as the coordination mechanisms are fined tuned, the number and heterogeneity of the robots will gradually increase. Simple soccer tasks, defined using the supervision language defined and executed with the aid of the communication language defined will be executed enabling to evaluate the languages, coordination methodologies and decision mechanisms developed.

The learning methodologies developed will be applied to all behaviors, decision making and team cooperation mechanism and tested in distinct problems/domains, e.g. distinct RoboCup leagues including robotic soccer leagues (simulation 2D, simulation 3D, SPL and middle size) and rescue simulation leagues (agent and virtual Robots).

Task 9: PhD Thesis Writing.

The PhD thesis will be completed with all the relevant data gathered during the doctoral programme and final result analysis. Throughout all the work plan execution, papers for relevant international conferences and journals will be written and submitted.

4.6. Anexos
4.6. Attachments

Nome Name	Tamanho Size
cronogram.pdf	**30,75Kb**

4.7. Referências
4.7. References

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