Universitat de Girona

A FORMALIZATION FOR MULTI-AGENT DECISION SUPPORT IN COOPERATIVE ENVIRONMENTS. A FRAMEWORK FOR SITUATED AGENTS

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A Formalization for Multi-agent Decision Support in Cooperative Environments

A Framework for Situated Agents

Doctoral Thesis

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May 2008

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A dissertation presented to the University of Girona in partial fulfilment of the requirements for the degree of DOCTOR OF PHYLOSOPHY

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ABSTRACT

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This thesis proposes a framework to decision support suitable for supporting the distributed performing of cooperative actions in dynamic and complex multi-agent environments. Decision support is a process aiming to improve the decision-making performance in cooperative scenarios. Simply stated, decision-making is the process of selecting a specific action out of multiple alternatives. This process occurs continuously in daily life. Humans, for instance, have to take decisions about what cloths to wear, what food to eat, etc. In this sense, an agent is defined as anything that is situated in an environment and acts, based on its observation, its interpretation and its knowledge about its situation on such environment to fulfil a particular action. Therefore, to take decisions, agents must get knowledge that allow them to be aware on what actions can or cannot perform. Here, such process takes three information parameters trying to embody an agent in a typically physical world. This set of information is known as decision axes, which it any agent must take into account to decide if it can perform correctly the task proposed by other agent or human. Agents can make better decision by considering and representing properly such information. Decision axes, mainly based on the agents' environmental condition, the agents' physical knowledge and the

agents' trust value, provide multi-agent systems a reliable reasoning for achieving feasible and successful cooperative performance.

Currently, many researches tend to generate news advances in agent technology to increase the intelligence, autonomy, communication and self-adaptation in open and distributed agent scenarios. In this sense, this research aims to contribute to the development of a new path to impact on both individual and cooperative decisions in multi-agent environments. In this light, the thesis was used to implement the concrete actions involved in the robot soccer both in simulated as in real scenarios. It emulates a soccer game where agents must communicate; interact and cooperate among them to perform complex actions within a dynamic and competitive scenario, both to drive the design of the involved actions' requirements as to demonstrate its effectiveness in cooperative jobs. Therefore, the thesis has obtained results, both on simulation and on real experimentations, showing that the framework to decision support for situated agents presented is capable to improve the interaction and the communication, reflect in a suitable and reliable agent's team-work within an unpredictable, dynamic and competitive environment.

The experimentation also showed that the selected information to generate the decision axes to situate agents are useful when these agents must perform the proper action or made sure commitments at each moment in order to reach successfully a goal. Conclusions emphasizing the advantages and usefulness of the introduced approach, in the improvement of multi-agent performance in coordinated task and task allocation problems are presented.

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Dedicated to my lovely family…

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Chapter 1

Introduction

The search of elements that allow obtain the needed knowledge to achieve multi-agent cooperation constitutes the main objective of this thesis. This chapter provides an introduction to the work presented in this dissertation. Specifically, an overview in the research area, the pursed aims and the main contributions are briefly described. Finally, the organization of this document is presented at the end of the chapter.

1.1 Overview

Most of the research into cooperative systems to date has concentrated on how to obtain desired dynamics interaction between agents [Tang and Parker, 07]. In this sense, to solve complex problems, multi-agents systems require knowledge about each agent and their skills to perform individual actions in distributed and cooperative environments. In this context, a distributed and cooperative environment refers to a world in which entities share goals and their actions are beneficial to their team-mates [Parker, 08]. So, the above knowledge allows multi-agent systems to know the skill of each to work performing both individual as collective actions. In this light, several recent efforts in multi-agent systems are related to building computer-controlled systems able to solve some well-know cooperative challenges [Haldemann et al., 07], [Benson et al., 07], [Walker et al., 05], [Huhns et al., 05]. High levels of cooperation, control, coordination and autonomy are looked for in distributed, asynchronous and networked environments. However, the recent approaches have a great deal of complexity that makes them less applicable to real-life problems.

Methods for cooperative multi-agent decisions are therefore, in most cases, intensive software applications and highly sophisticated algorithms that use advanced design technologies. Moreover, these systems have generally requirements that go beyond single disciplines (*form control engineering to computer sciences*). Over the past decade, there has been some work towards combining artificial intelligence (*AI*) approaches with traditional control theories to obtain intelligent systems. Despite several researches in multi-agent systems (*MAS*), important theoretical aspects of cooperation have been untreatable [Parker, 00b]. In this direction, the advances of the *AI* community in planning, adaptation, learning, logic-based theories and knowledge representation together with other techniques as well as control theories [Murray et al, 03] [Sanz et al., 04], societal metaphors [Esteva et al., 01], [Rodríguez-Aguilar, 01] or bidding methods [Busquets et al., 02] has present a fresh path for further progress.

In particular, some research trends have led to managing complex and cooperative problems using agents. Agents are defined as computer systems capable of flexible and autonomous actions in dynamic, unpredictable and typically cooperative environments [Luck et al., 05]. In this sense, several results have been obtained for coordinated actions using agent technology [Parker, 00], [Stone and Veloso, 00]. Agent technology helps to solve complex problems in real multi-agent scenarios by means of its cooperative problem-solving paradigm. However, these agents lack an appropriate reasoning on the needed kind of information that will be useful in the agents' decision-making, aiming to improve cooperative actions' performance.

Indeed, this information is closely related to the agents' environmental conditions, the agents' knowledge about its physical features and the agents' social relationship with other agents, and is used when they must solve complex problems. In this sense, theses three aspects arise as information elements in ***decision axes*** with the purpose of ***situate*** an agent considering all the agents' knowledge involved in the execution of any proposed action in a real cooperative scenario. For thus, this thesis proposes the information of the ***decision axes*** being directly related to:

- *the agents' environmental conditions directly involved in the performance of a cooperative action.*

- *the agents' physical features meaning the specification, the structure and other relevant details related to the agents' dynamic.*

- *the agents' trust value relates to the capability of an agent to interact and to work together with other agents.*

Several results have been obtained where agents have analyze someone of the proposed ***axes*** to increase their knowledge base and to use such information in their decision-making to perform cooperative actions [Quintero et al., 07a], [González et al., 07], [Duffy, 04], [Busquets et al., 02]. However, some approaches lack of an appropriate reasoning on these kinds of elements, especially when such elements can joint in the agents' decision-making.

Moreover, such relevant knowledge is not appropriately reflected and communicated by the agents. These deficiencies do not allow agents to make feasible collective decision when these are requested. Obviously, lack of the appropriate reasoning on these knowledge results in a lower cooperative performance between agents, mainly in coordinated tasks and task allocation problems where a proper managing of such knowledge is quite relevant to achieve sure and trustworthy commitments. In this sense, achieving cooperative agents is desirable for many considerable reasons, such that:

- *many agents application are inherently distributed in space, time or functionality, thus requiring a distributed solution.*

- *there are more possibilities that many applications could be solved much more quickly if the goals can be performed by a number of agents working at the same time pursuing the benefit of the agents-group.*

- *exploiting the chance of allocate determinate actions for an agent knowing its individual skills.*

Although achieving cooperative agents is still a challenging, because of many issues must be addressed in order to develop a working cooperative team, such as task allocation, conflict of interest, communication, etc. So, such cooperative agents systems often work in dynamic, unpredictable, hazardous and risky environments, requiring the agents-team members to respond robustly, reliably, adaptively to unexpected environmental changes, failures in the communication and modification in the agent system configuration due to failures, learning of new skills or by directly human intervention. In particular, cooperative agent systems are characterized by distributed control of heterogeneous agents. So, this thesis argues that in the near future, any autonomous system (e.g., cars, aircrafts, mobile robots, house artefacts) controlled by agents will only complete its tasks correctly and make proper decision, if it is able to reflect, consider and communicate its situation taking into account the information provided by the ***decision axes*** aforementioned.

Therefore, explicit reasoning on the managing of the ***decision axes*** in the agents' decision-making will prevent, most of the time, undesirable situations. As it has been mentioned before, each agent could represent in different ways these elements modifying its behavior to execute any proposed action. Here, agents are then proposed to be aware on the set of information involved in the ***decision axes***. In this sense, computer engineers need practical tools for developing this new type of agents and their coordinated method, taking into account the proposed information for the ***decision axes***. Similarly, cooperative agents and humans working jointly in search and rescue operations [Quintero et al., 07a], [Murphy, 04], [Davids, 02] could optimize their multi-agent team-work coordination if the agents know and they are able to reflect and communicate their knowledge on their limitations or capabilities related to the information involved in the ***decision axes***.

In summary, agents do not reflect on their knowledge related to their ***situation*** on the environment and, this knowledge is not currently properly taken into account in the agents' decision-making. This thesis then claims that reflection on the information involved in the ***decision axes*** is an interesting agent-oriented perspective implemented in multi-cooperative and controlled scenarios. In particular, such perspective makes it easier for agents to manage and communicate the execution of cooperative actions in controlled systems aiming at making physically feasible decihsion. Such decisions aim to improve the multi-agent performance in cooperative scenarios.

Physical agents are particular examples of controlled agent systems [De la Rosa et al., 07] for coordinated actions. Here, physical agents are understood as physical and encapsulated entities with control architectures that satisfy the agent design metaphor. In recent years, mobile robots one typical representation of physical agents, have become progressively more autonomous and cooperative. So, mobile robots are used in this approach without loss of general applicability. Such autonomous mobile cooperating robots must then have reliable self-knowledge if they are to improve their performance when executing cooperative and collective actions. This self-knowledge must be based on an appropriate agent-oriented representation of the ***decision axes*** in agents' knowledge bases. With this representation, any physical agent could reflect and consider appropriately its ***situation*** in some environment whenever it is committed to carry out a task or assume specific behavior in a multi-agent scenario. Thus, a physical agent is an intelligent entity, and its actions and cooperation with other agents or humans, to achieve the desired goals in a real environment, are restricted and conditioned by the consideration of the knowledge involved in the ***agents' situation***. In this light, the above knowledge constitute a feasible and trustworthy path towards improve cooperative actions inside dynamics, unpredictable and totally distributed scenarios.

The main objective of this research is to propose a formal framework to the decision support for situated agents, providing agents with the cognitive ability for reasoning if they are able to perform a determinate task or if they can assume a specific behavior, aiming at making feasible decisions and getting reachable and physically grounded commitments to improve the overall system performance. To that end, a reflection on the proposed ***decision axes*** guarantees an appropriate and proper explicit agent-oriented representation of coordination and commitments. As will be shown, the research on support decisions for situated agents in physical multi-agent systems proves the impact of this agency property, and its effectiveness in cooperative intelligent systems.

1.2 Objectives

The research addressed in this dissertation is focused on including the knowledge of the ***decision axes*** to embody the ***agent's situation*** in their decision-making. Such challenge has been worked from a cooperation viewpoint.

In this sense, the main objective of this thesis consists of improving the agents' collective performance within cooperative environments. An effective cooperation is one actions performed by two or more agents which is performed successfully. The success of such action depends on the capability of the agents to seek for useful knowledge about the ***decision axes*** and reflect it in a proper way when they must decide if they are able or not to perform an action or agree a commitment.

For thus, this thesis presents an appropriate framework to include the three ***decision axes*** in the physical agents' decision-making, and to represent explicitly such information in the agent's knowledge's bases. In fact, this thesis looks for then to bridge the gap between the high abstraction level of agents' cooperation and the low abstraction level of the environment's information sources.

In order that this objective can be achieved was necessary to fulfil the following goals to achieve the aim of the thesis:

- *To define relevant information of the decision axes related to the physical agent to obtain reliable level of knowledge to use in the high level of cooperative decisions.*

- *To establish a formal coordinated framework to perform cooperative actions within multi-agents systems.*

- *To demonstrate the utility and feasibility of the overall proposed approach on several examples of coordination in physical multi-agent environments.*

1.3 Contributions

This thesis is the result of a re-examination of intelligence and intelligent cooperation, with the aim of insight into how cooperative systems may be constructed. For thus, this thesis makes the following contributions:

- *A consideration of the three decision axes to situate a physical agent within real cooperative environments.*

- *A formal design of a framework for coordination of physical multi-agent systems using the information of the decision axes.*

- *An agents' decision making tool as a bridge to the gap between the actions' requirements and the agents' capabilities to perform the proposed action.*

- *A taxonomy for classification of approaches related to coordinated activities both in physical multi-agent systems as in multi-robot systems.*

1.4 Outline of the Thesis

Following is a general description of the contents of this thesis:

Chapter 1 presented a motivational introduction and overview of the thesis, its motivation, objectives and contributions.

Chapter 2 provides a general overview of background information regarding artificial intelligence, agent technology, robotics and decision support which is required to follow the approach described in section 4 and 5.

Chapter 3 is devoted to relevant related work and state-of-the-art on the field of cooperative agents and multi-agent systems as well as to autonomous robots.

Chapter 4 describes the formal aspects of the novel framework to decision support for situated agents presented in this dissertation.

Chapter 5 presents the implementation and results on several test bed of the framework proposed in chapter 4. The chapter also contributes to complete the description of such proposal.

Chapter 6 discusses and analyses the obtained results, summarizes the conclusions of this thesis and outlines the most promising directions for future works. The chapter also includes a list of publications and conference contributions.

Appendix A presents some results which complement the results presented in Chapter 5.

Appendix B describes the robots used in the real experimental phase depicted in Chapter 5.

Chapter 2

Background Information

This chapter introduces and reviews general concepts of agents, multi-agent systems and robotics, such that an architecture for physical multi-agent systems is proposed and discussed later.

2.1 Agent Technology

In recent years, agents technology is one of the most relevant and useful contribution in the Information Technology (*IT*) world. Agent-based systems emerge as an appropriate alternative to improve the traditional computing and current algorithms and software applications especially in dynamics and open environments, where heterogeneous systems must interact effectively to achieve specific goal. In this sense, agent-oriented developments are seen as fundamental to enable systems to respond in a suitable, effective and reliable way to changing conditions while trying to achieve the objectives for which they were designed.

The agent paradigm has found currency in several sub-disciplines of information technology, including computer networks, software engineering, artificial intelligence, human-computer interaction, distributed and concurrent systems, mobile systems, telematics, computer-supported cooperative work, control systems, decision support, information retrieval and management, and electronic commerce [Luck et al., 05].

In particular, agent technology offers fundamentally new ways of design, standardization and support for *IT* applications through distinct and independent software components interacting to provide better performance and valuable functionality. In such context, agent technology constitutes a proper way to conceptualise and implement the present and future computer systems.

2.2 Agent Concept

In the current literature is very difficult to find some definitions that represent and introduce the concept of agent in a precise and technical manner. The agent concept, in such case, is a general abstraction appropriated to a large range of applications. However, several criteria allow distinguishing between what is an agent and what is not at an engineering level. Such criteria are based on a reasonable model of the agents' features and behaviors. In this sense, some to the most cited definitions are highlighted.

Agent can be defined as computer systems capable of flexible and autonomous actions in dynamics, unpredictable and typically multi-agent domains [Luck et al., 05]. More specifically, agents can be defined as autonomous and problem-solving computational entities capable of effective operation and flexible autonomous actions in dynamics, unpredictable and open environments. Agents are often deployed in environments in which they interact, and maybe cooperate, with other agents that have possibly conflicting aims. Such environments are known as multi-agents systems [Luck et al., 03].

In addition, an agent denotes a software-based computer systems that has several properties as autonomy, social ability, pro-activeness, reactivity, mobility, rationality, etc., which is capable of independent actions to achieve some goals or desires [Wooldridge, 02].

In summary, agents are [Jennings and Bussmann, 03]:

1. Clearly identifiable problem-solving entities with well-defined boundaries and interfaces.

2. Situated (embedded) in a particular environment over which they have partial control and observability.

3. Designed to fulfil a specific role, they have particular objectives to achieve.

4. Autonomous, they have control over both their internal state and their own behavior.

5. Capable of exhibiting flexible problem-solving behavior in pursuit of their design objectives, being both reactive (able to respond in a timely way to changes that occur in their environment) and proactive (able to opportunistically adopt goals and take the initiative).

To avoid confusions with other agents meaning and contexts, the above agents are also commonly known as ***software agents***.

2.3 Agent Metaphor

Agent technology finds a stronger applicability when is used as a design metaphor of well-structured approaches for solving real-life *IT* challenges. ***Currently, agents provide software designers and developers an appropriate way of structuring software tools and applications around autonomous, communicative, situated and problem-solving entities to achieve the required design goals*** [Jennings, 01]. In this sense, the ***agent concept offers a promising route to the development of computational systems, especially in open and dynamics environments of several real-world domains*** [Luck et al., 05]. In addition, the ***agent concept provides elegant tools/methods for abstraction and encapsulation*** [Quintero, 07].

2.4 Agent Architectures

The internal structure of an agent is determined by its control architecture. The architecture determines the mechanisms used by an agent to interact under external and internal conditions, given some specification of its desired behavior.

There are several control architectures that allow describing the internal structure of an agent. However, four main perspectives can be mentioned: the deliberative (think hard, then act), the reactive (don't think, react), hybrids of the above two (think and act independently, in parallel) and a behavior-based strategy (think the way you act). Deliberative and reactive architectures embrace two basic ideas related to the agent concept respectively: the need of deliberation for long term reasoning based on a symbolic knowledge representation, and quick answers for suitable agent's behaviors according to the current situation.

A relevant deliberative architecture is the *BDI* (*Beliefs – Desires - Intentions*) architecture [Rao and Georgeff, 95]. The *BDI* model has been developed to provide solutions in uncertain and dynamic environments where agents have a partial knowledge of the problem and usually manage limited resources. Beliefs, desires and intentions constitute then important parts of the agents' state in these systems under the above conditions.

The ***beliefs*** represent the domain knowledge embedded in the agents. The ***desires*** represent the objectives or the expected set of actions that agent must do, representing the final state. Additionally, it is necessary to define a planning mechanism that allows identifying the agents' intentions to reach the pursued objectives taking into account the current beliefs. In this sense, the plans involved to the attainment of objectives constitute the ***intentions***. The type of modelling used by a deliberative agent us usually very elaborate.

However, the associated problem to a symbolic representation has led to the study of more effective models for the knowledge representation. In this sense, reactive architectures are an alternative. Subsumption [Brooks, 91] is a relevant reactive architecture. Such architecture is based on the hypothesis that "intelligence" is an emergent property of some complex systems and it allows generating suitable behaviors without symbolic models or any internal representation of the environment. Agents react to the current sensory information in a "stimulus-response" manner. This allows agents to respond very quickly to changing and unstructured environments. The Subsumption architecture manages a hierarchy of tasks for defining the agent's behavior and they are usually organized in layers from a low to a high abstraction level. A great amount of applications of this type of architecture is found in the development of controllers in robotics. In this sense, Subsumption architecture for mobile robots is based on a given priority to different controllers under different circumstances. Here, robots can be considered as real or physical agents that act in a environment favours the adoption of reactive architectures. Limitations of this approach are that such robots, because they only look up actions for any sensory input, do not usually keep much information around, have no memory, no internal representation around them, and no ability to learn over time.

In addition, there have been some proposed hybrid architectures [Wang et al., 07], [Jeong-Ki et al., 06], [Yong and Bo, 06], aimed at combining aspects related to deliberative and reactive architectures and to overcome their limitations. Such architectures adopt a layered organization generally distributed in three abstraction levels [Mas et al., 05]: Reactive (low level) is related to decision-making based on real time environments conditions. Knowledge (intermediate level) is related to the domain knowledge based on a symbolic representation of the environment. Social (high level) is related to social aspects in the environment, exchange information between agents, etc. The agent's global behavior is the defined by the interaction between all the above levels. However, such interaction could be different for different hybrid architectures.

On the other hand, behavior-based approaches [Weyns et al., 04] [Farahmand et al., 04] are an extension of reactive systems that fall between the purely reactive and the planner-based extremes. The behavior-based approach is a methodology for designing autonomous agents and robots [Arkin, 98]. The behavior-based methodology imposes a general biological inspired, bottom-up philosophy, allowing for a certain freedom of interpretation. It goal is to develop methods for controlling artificial systems (usually physical robots, but also simulated robots and other autonomous software agents) and to use robotics to model and better understand biological systems. In behavior-based approaches, the decomposition f the control system is performed in a task-oriented manner. Unlike reactive systems, behavior-based systems are not limited in their expressive and learning capabilities: behaviors themselves can have a state (internal and particular view of the world), and can form representation when networked together.

2.5 Multi-agent Systems

Several approaches, where a number of entities work together to cooperatively solve problems, fall into the area of distributed systems. The combination of distributed systems and artificial intelligence is collectively known as Distributed Artificial Intelligence (*DAI*). Traditionally, *DAI* is divided into two areas [Stone and Veloso, 00]. The first area, distributed problem solving (*DPS*), is usually concerned with the decomposition and distribution of a problem-solving process among multiple slave components, and the collective construction of a solution to the problem. The second area, ***Multi-Agent Systems*** (*MAS*), emphasizes the joint behaviors of agents with some degree of autonomy and the complexities arising from their interactions [Panait and Luke, 05]. In recent years, multi-agent systems have been studied by several research groups. There are also several multi-agent systems definitions. The most widely accepted definitions are here summarized.

Multi-agent systems are systems with a varying number of interacting, autonomous agents that communicate with each other using flexible and complex protocols, in order to achieve particular goals or perform some set of tasks. In multi-agent systems "the intelligence" arises from the aggregation of simple competitions as well as the task assigned to every individual is as important as the collective task [Weiss, 99].

According to the distributed artificial intelligence, a multi-agent system is a network of entities able to solve problems, working jointly to find answer to problems that are beyond the capacity and the individual knowledge of each entity. Thus, in multi-agent environments, agents must generally coordinate their actions and they must communicate the proper knowledge and information. In addition, there are constraints in a multi-agent environment such that agents may not at any given time know everything about the world that other agents know [Panait and Luke, 05].

In summary, the multi-agent system term is used to define all types of systems with multiple autonomous components that have the following elements and features [Jennings et al., 98]:

- A common environment.
- Agents.
- Interaction among agents.
- Interactions among agents and dynamic environment.
- Each agent has the capacity to solve the problem partially.
- There is no a global control system.
- The data are not centralized.
- The computation is asynchronous.

Three common types of interactions are described:

- Cooperation: working together towards a common goal.
- Coordination: organising problem solving activities so that harmful interactions are avoided and beneficial interactions are exploited.
- Negotiation: coming to an agreement which is acceptable to all the parties involved.

Agents interact to share information and achieve the proposed tasks and objectives in cooperative environments. In this sense, the interaction is understood as a mechanism to articulate the cooperation, coordination and negotiation between agents. In this light, several authors [Wajid and Mehandjiev, 06], [Far, 04], [Prouskas and Pitt, 04] define three key elements to achieve a good level of interaction within multi-agent environments:

- A common language and communication protocol.
- A common communication format.
- A shared ontology.

2.6 Agents' Interaction

In the past, several researches in agent technology were focused to achieve more autonomous and robust single agents systems, however, currently the recent efforts of the *AI* community are aimed on how improve the cooperation among intelligent, autonomous and heterogeneous entities [Stone and Veloso, 00] (i.e., *agents*). In this sense, agents' interaction is recurrent in order to share information to perform cooperative problems; due to the agents' interaction skill is the main characteristic of agents [Parker, 08]. From a practical perspective, when agents interact, first they analyse their skills to know their actions capabilities, then they made commitments to perform the proposed tasks and definitely they recur to the coordination to know how they can achieve their goals. In this sense, is possible to see how by means of coordination methods (e.g., cooperation, negotiation, and collaboration) agents are able to interact with other with a major feasibility aiming to improve the performance of the actions that they do at group.

Other point of view is given by the assumption that agents are, intentionally, designed with some differences (e.g., size, shape, weight, etc). This fact emphasises the problem from other perspective of interaction. It means, agent not only must to be able to interpret knowledge from their situation on the environment but they must capable to interact involving this new perspective.

2.6.1 Coordination

Coordination is interested in fully cooperative multi-agent systems in which all agents share a common goal and their actions are beneficial for the whole system. In this light, agents can select the actions they can execute singly, in a suitable way. A key aspect in such systems is therefore the problem of coordination: the process that ensures that the individual decisions of the agents result in optimal decisions for the group as a single unit.

Coordination refers to ensuring that the actions of independent agents in an environment are coherent in some way [Luck et al., 05]. The most widely accepted definition of coordination has its origins in the organization theory. In this sense, ***coordination is the management of dependences between organizational activities*** [Malone and Crowston, 94]. Taxonomy of such dependences and a set of coordination actions assigned for each dependence must be established according to the multi-agent system's features. [D'Inverno and Luck, 04] presents a formalization of possible different relations between agents in multi-agent environments. Thus, the coordination process is related to the attainment of two main tasks: to establish the dependences and to make decision on which coordination action must be performed. A coordination mechanism determines the way of how one or several agents perform the above tasks [Hongru et al., 06].

From a practical perspective, ***it is possible to understand the coordination as an effort to manage the interactions between agents*** [Busi et al., 01], [Gerkey and Matarić, 03]. From a design perspective, the challenge is how agents can interact in an appropriate way to solve the dependences and make the related decisions. There are several approaches in the literature on the matter [Scerri et al., 04]. Multi-agent scheduling, negotiation, organizational structures, norms, trust, etc., are some of them. The aim of the above approaches is to determine the interaction space. The applications of these mechanisms depend on the characteristics of the coordination problem.

2.6.2 Cooperation and Collaboration

Cooperation refers to coordination with a common goal in mind [Luck et al., 05]. Cooperation between agents has been widely studied in the distributed artificial intelligence field. There are several works related to cooperation [Mayoh, 02] [Watson et al., 02] [Jennings, 00]. These works address the problem from a deliberative architectures viewpoint, though the cooperation has been also studied in reactive agents [Molina et al., 04]. However, there is not a global vision about cooperation and all the current contributions are related to the cooperation advantages from a perspective aimed at answering of how cooperation can be performed, or how agents must interact to cooperate. ***Cooperation embraces the allocation and coordination of tasks***. They are key factors in order that the cooperation arises. In this sense, there are studies focused on methods to allocate tasks between agents in a set of synchronized actions in time and resources. In addition, ***collaboration refers to a suitable allocation of information, tasks and resources between agents in multi-agent systems*** [Ferber, 99]. Such allocation must take into account the agents' capabilities, the tasks' nature and the social structure of the system. In fact, difference between commitment and cooperation is measured by the level of autonomy of the involved agents. Cooperation happens when an autonomous agent generates a goal taking into account the goal of other autonomous agent.

2.6.3 Negotiation

Agents in a multi-agent environment typically have conflicting goals and not all agents may satisfy their respective goals simultaneously. In this sense, ***agents will need to negotiate with each other to resolve conflicts*** [Luck et al., 05], [Far et al., 06]. Recently, several efforts have been devoted to negotiation protocols, resource-allocation methods, and optimal division procedures based on ideas from computer science, artificial intelligence and socio-economic sciences. Negotiation is then, a key coordination mechanism for interaction that allows to a group of agents to reach an agreement according to their beliefs, goals or plans. The negotiation process can be performed of different ways as auctions, contract net, etc. However, this fact is a bit confused, because to the agents' complexity or the great variety in the interaction mechanisms must be added the complexity of the different contexts that prevail inside a negotiation [Beer et al., 99]. The negotiation consists therefore in reaching an agreement between agents that benefits them when each one has its own interest.

2.6.4 Commitments

A commitment refers to an acquired obligation when an agent interacts with others [Mallya et al., 03]. A need of finding suitable ways to fulfil such commitment then arises. Therefore, agents will base their actions on their capabilities, the capabilities of others and the developed work framework. There are coordination mechanisms that allow an organized way to perform actions in group. Thus, an agent decides to commit to others when it is able to fulfil the proposed tasks, to interact with other agents and to communicate with its action partners.

2.7 Agents & Robotics

Robotics is a research field where the agent concept can be directly applied. There is a direct equivalence between robots and agents in a rigorous sense. A robot is a real or physical agent situated in a real environment unlike an agent who just is a software entity. ***Physical agents are then understood as physical and encapsulated entities with control architectures that satisfy the agent design metaphor.***

An agent's architecture in robotics is equivalent to a robot's control architecture [Matellán and Borrajo, 01]. It is necessary to identify a set of actions (agent's capabilities) that allows robot to interact within the environment in all control architectures. The set of capabilities needs different hierarchic levels (grouping of capabilities to achieve a goal) in the control structure [Oller, 02]. Such control levels depend on the features of the tasks to perform and the available resources. There are then mainly two control levels following the above considerations. The high level performs long term reasoning and task planning while the low level performs the easiest tasks, solving the more immediate problems that not need planning. In summary, the fact that a robot is autonomous and physically independent has driven to the utilization of the agent technology as something slightly natural.

2.7.1 Mobile Robotics & Multi-robot Systems

In particular, mobile robotics refers to the application field of robotics where the essential feature of robots is the ability of autonomous motion [Oller, 02]. The motion allows the robot the accomplishment of movements in more or less structured environments and forces it to be equipped with specific sensors to know the environment's state.

On the other hand, the study of multiple-robot systems naturally extends research on single-robot systems [Parker, 00a]. ***Multiple-robot systems can accomplish tasks that no single robot can accomplish*** [Arai et al., 02]. Multiple-robot systems are also different from other distributed systems because of their implicit "real world" environment, which is presumably more difficult to model and reason.

There are three general problems to study in the mobile robotics that are relevant in this thesis [Parker, 00a]:

- The movement control of the mobile robot like an individual entity.
- The control of a system composed by diverse robots: the cooperation.
- The planning of the actions to perform, depending on the temporal and spatial restrictions.

A more deep and extensive analysis of related works on multi-robot systems and mobile robotics, focused specifically on the research topics addressed in this thesis, is presented in future sections of the chapter 3.

2.8 Decision Support Systems

A suitability fulfilment of cooperative team-work is largely dependent on the quality of the available information used to make an appropriate decision. In this light, some problems arise when the quantities of available information are huge and nonuniform (i.e., coming from many different sources or knowledge categories) and their quality could not be stated in advance. Another associated issue is the dynamical nature of the problem. For thus, Finlay [Finlay, 94] and others introduce decision support systems (*DSS*) rather broadly as ***"a computer-based system that aids the process of decision making"***. Turban [Turban, 95] defines it more specifically as ***"an interactive, flexible, and adaptable computer-based information system, especially developed for supporting the solution of a non-structured management problem for improved decision making***". It utilizes data, provides an easy-to-use interface, and allows for the decision maker's own insights". Nevertheless, according to Power [Power, 02], the term decision support system remains a useful and inclusive term for many types of information systems that support decision making. To the end, the term decision support system (DSS) has been used in some different ways [Harrison et al., 07], and has been defined in various ways depending upon the author's point of view [Liping, 05].

In a recent study, distributed decision support systems offer a methodology which can be used to combine distributed and heterogeneous models and problem solving processes under a single unified framework. ***They (DSS) improve the effectiveness of decision-making rather than its efficiency; they attempt to combine the use of models or analytical techniques with traditional data access and retrieval functions; they specifically focus on features that make them easy to use by noncomputer people in an interactive mode; and they emphasize the flexibility and adaptability to accommodate changes in both the approach of the decision maker and the environment in which he acts*** [Adla and Zarate, 06]. In this sense, a group of entities (e.g., agents, robots, intelligent artefacts) using a decision support system (GDSS) technique refers to a system based on the integration of knowledge, communication and decision taking into account the experience and capabilities of all its members. So, such members are able to reach individual decision aiming to achieve a beneficial behavior for the expectations of the whole group.

2.8.1 Characteristics and Capabilities

Because there is no exact definition of decision support system, there is obviously no agreement on the standard characteristics and capabilities of decision support system. In this light, in [Turban et al., 05] constitute an ideal set of characteristics and capabilities of decision support system. The key decision support system characteristics and capabilities are as follows:

- Support individuals and groups.
- Support managers at all levels.
- Support for interdependent or sequential decisions.
- Support intelligence, design, choice, and implementation.
- Support variety of decision processes and styles.
- *DSS* should be adaptable and flexible.
- *DSS* should be interactive and provide ease of use.
- Effectiveness balanced with efficiency (benefit must exceed cost).
- Support modelling and analysis.

2.8.2 Benefits of Decision Support Systems

Current decision support systems are highly complex and effective. They generally have a large number of interacting entities. Such systems aim to improve the cooperative metaphor of multi-agent systems by means of their mechanism to support both individual as collective decisions. Agents systems are invariably described in terms of "cooperating to achieve common objectives". For thus, they look for the indicated tools that allow to reach and to improve their decision-making structure especially when they must cooperate with other in order to achieve a common goal. In this light, decision support systems arise as a strong alternative to increase in sure and trustworthy way the choices in multi-agent systems. So, a list of possible benefits obtained in the application of the decision support technology in cooperative multi-agents environments is described as follow:

- Improving Personal Efficiency

- Expediting Problem Solving
- Facilitating Interpersonal Communication
- Promoting Learning or Training
- Increasing Organizational Control

2.9 Final Remarks

The aim of this chapter was to introduce and standardize the most transcendental theoretical topics addressed in this thesis. In this sense, a review of several definitions has been presented according with the most celebrated definition published until now.

The present background information on current works and definition about agents, multi-agent and multi-robot systems shows how some aspects involved in these technologies are yet in development. However, the references cited have been useful to illustrate the general concepts aimed on this thesis.

Chapter 3

Cooperative Agents

This chapter presents an overview of the main works focused in the topics addressed in this dissertation.

3.1 Autonomous Mobile Agents

Multi-agents systems are computational systems in which two or more autonomous agents are able to work jointly aiming to improve the overall systems performance. In this sense, this thesis presents an extension of these systems by means of the ***physical agent paradigm***. One typical implementation of physical agents is autonomous mobile cooperative robots. In fact, a physical agent makes its decisions based on the physical capabilities of its body. Likewise, a Physical Multi-agent Systems (*PMAS*) are assumed in the literature by implementing Multi-robot System (*MRS*) due to the physical embodiment of these systems is the main factor to operate in real cooperative environments. In this sense, ***physical multi-agent systems*** have been proposed in the last decade in a variety of settings and frameworks, pursuing different research goals, and successfully applied in several cooperative domains. Special attention has been given to *PMAS* developed to operate in dynamics and unpredictable environments where uncertainty changes can happen due to the inherent presence of other agents and external factors that could affect in the decision process of the cooperative systems.

Generally speaking, *PMAS* can be characterized as a set of physical agents operating in the same environment, in particular, physical agent may range from simple perception of intentions (i.e., in its cognitive representation), acquiring and processing knowledge both from the agent interaction as directly from the environment, able to interact with the world in fairly complex ways. Indeed, it is not easy to give a definition of the level of autonomy that is required for a physical agent in order to be considered as the physical representation of one entity acting in some environment, capable to be reactive and to be pro-active to the events that could happen in such environment. For that reason, the physical agent paradigm arises as the consideration of an intelligent agent who must handle a physical body and so, it must take its decisions based on the knowledge about the features of such physical body and its satiation on the environment. Here, such interpretation is devoted to analyse three kinds of information related to: the agents' world representation, the agents' awareness about their physical capabilities and the agents' interaction [Ibarra et al., 07b]. These set of information aims to provide physical agent with knowledge related to its situation involved in the execution of any action in a world therefore, agents are able to know "which" actions can or cannot perform in a suitable way.

Moreover, a significant amount of work on *PMAS* has been essentially originated from coordination ideology, where these systems are designed and implemented to improve the effectiveness of robotic systems [Parker, 08]. In fact, *PMAS* are useful not only when the agents can perform different actions, but also when they can perform the same actions in different ways by showing heterogeneity [Stone and Veloso, 00]. In this sense, heterogeneity refers to the fact that multiple entities, with different capabilities (i.e., *physical features*) and skills (i.e., *communicative agents*) should co-inhabit and, operate collectively to achieve the correct fulfilment of complex problems in real environments. Although these entities could be similar (i.e., manufactured with the same parts, at the same place and at the same time) they can act in a diverse way by representing both cognitive aspects such as:

- *internal representation of the state, social attributes, experiences, etc.*

as physical factors such that:

- *energy consumption, actuator, sensor, shape, size, response time, etc*

Besides, even when a single physical agent can achieve any given task, the possibility of deploying a physical agents' team can represent a significant improvement in the performance of the overall systems. A huge single robot, no matter how powerful it is, will be spatially limited while smaller robots could achieve a given goal more efficiently [Gulec et al., 06]. Another interesting development of *PMAS* stems from the studies on bio-inspired systems or complex models arising in cognitive science and economics (see for example [Busquets et al., 02], [Esteva et al., 01]). This thesis takes an engineering perspective, although it also looks at a few bio-inspired approaches. In addition, the increased availability of complex solutions on cooperation is nowadays a transcendent factor which represents a new challenge to present a classification on *PMAS* according to the current trends. Thus, it gives the guaranty to use solutions where a single action could be, in some cases, improved by using coordination among several physical agents because is feasible the assumption that multiple agents are able to solve problems more efficiently that a single agent [Jung, and Zelinsky, 98]. In this direction, several approaches to cooperation in *PMAS* consider the control of the actions of an individual agent separately from the actions of a cooperative group. Indeed, ***this thesis argues that cooperative behavior at group level emerges from individual agents' interactions***. Therefore, the study of *PMAS* applications is particularly relevant and significant for further investigation [Østergaard et al., 02].

Finally, *physical multi-agent systems* have been applied in several test beds (i.e., foraging, box pushing, clean tasks and exploration) and recently a significant boost to the work on such systems has been given also by robotics competitions, such as RoboCup[1] and FIRA[2]. In fact, the development of *PMAS* is regarded as one of the major scientific challenges and robotic contests, extremely useful for comparing and analyzing different strategies [Østergaard et al., 02] and techniques by providing a common test bed for experiments. Likewise, these competitions offer new challenges in the design of *PMAS*; for example in soccer domain the *PMAS* are tested against other teams, the environment is highly dynamic and present external factors, such that: light problems, noise in the radio frequency, etc. In this sense, the complexity both the systems and the applications domains requires more and more sophisticated alternatives for coordination. While some points on coordination are still open to discussion, here, physical multi-agent systems are presented by the consideration of intelligent entities that are embodied by considering their ***situation*** in the environment. Such ***situation*** refers to: the purely agents' perception of their environment, the knowledge about the agents' physical bodies and the relationship among agents, as a set of parameters that agents use to make decisions aiming to cooperate between them in order to achieve successfully the solution of complex problems.

3.2 How can cooperation benefit Agents?

The control and coordination of multiple mobile agents is a challenging task; particularly in environments with multiple, rapidly changing conditions and agents

[1] http://www.robocup.org
[2] http://www.fira.net

[Xu et al., 07]. So, a number of reasons exist for which cooperation among agents is necessary, and numerous issues have to be tackled to achieve efficient coordination. In fact, the objective of the cooperation is to maintain maximum utilization of multi-agent resources while ensuring job performance at the highest productive level. In this sense, the purpose of cooperative multi-agent systems is to increase the system performance in dynamic environments. But, a general theory of cooperation for multi-agents domains remains elusive [Ostergaard et al., 02]. However, the research effort into multi-agent systems is given by the assumption that multiple agents have advantages over single agents for the solution of some problems. In particular, this thesis argues that significant reliability and computational benefits may be had by employing multi-agent cooperative systems for tasks that could be achieved with a single robot. In this light, the most obvious advantage for multi-agent systems is that some tasks cannot be accomplished by a single agent. For example, one of the most cited examples is the *pushing a box* test bed, where two or more agents must work together to carry out the proposed actions (i.e., move a box from one point to other), or performing tasks that must be accomplished quickly (i.e., make a pass between soccer players).

In recent years, cooperation in multi-agent systems is an increasingly and essential element for managing systems with enormous amount of data to process and communicate, providing high performance, high confidence, and reconfigurable operation in the presence of uncertainties [Murray et al., 03]. Although multi-agent systems provide many potential advantages, they also present many difficult challenges inherent both in design as in the implementation of such systems, such that:

– *how to formulate, describe, and allocate problems among a group of physical agents?*

– *how to enable agents to interact? how can heterogeneous agents interoperate? what and when can they communicate?*

– *How to find useful agents in an open environment?*

– *how to ensure that agents work coherently in making decisions or assume a commit?*

– *how do enable individual agents to represent and reason about the actions, and knowledge of other agents to coordinate with them; how do reason about the state of their coordinated process (for example, initiation and completion)?*

In this sense, the solutions to these problems are interrelated. For example, different cooperative schemes of an individual agent can constrain the range of effective coordination regimes; different procedures for communication and interaction have implications for behavioral coherence [Sycara, 98]. Coherence is a global (or regional) property of the multi-agent systems that could be measured by the efficiency, quality, and consistency of a global solution (system behavior). In this sense, the more transcendent topics for this dissertation are ***coordinated task*** and ***task allocation***.

3.2.1 Coordinated Task

Agents can improve cooperation by planning the execution of complex problems. Planning for a single agent is a process of constructing a sequence of actions considering only goals, capabilities, and environmental constraints. However, planning a coordinated task in an multi-agent environment also considers the constraints that the other agents' activities place on an agent's choice of actions, the constraints that an agent's commitments to others place on its own choice of actions, and the unpredictable evolution of the world caused by other agents or changes occurred during the action's process. Most early work in *Distributed Artificial Intelligence (DAI)* has dealt with groups of agents pursuing common goals (e.g., Jung [Jung and Zelinsky, 98]; Simmons [Simmons et al., 02]. In this sense, ***agent interactions are guided by cooperation strategies meant to improve their collective performance.***

Most work on multi-agent cooperative planning assumes an individual sophisticated agent architecture that enables them to do rather complex reasoning. Several recent works on distributed planning took the approach of complete planning before action. To produce a reasoned plan, the agents must be able to be aware of sub-goal interactions and avoid them or resolve them. Another direction of research in cooperative multi-agent planning has been focused on modelling team-work explicitly. Explicit modelling of team-work is particularly helpful in dynamic environments where team-members might fail or be presented with new opportunities, such in [Matellán and Borrajo, 01]. In such situations, it is necessary that teams monitor their performance and reorganize based on the situation. Agents within a multi-agent scenario need to have wide-ranging knowledge to improve their decisions and to achieve sure commitments within an agent society. For instance, reference [Oller et al., 99] introduces dynamical aspects that consider a physical body in the design of agents. Empirical results are obtained when the physical agent systems try to solve dynamic-world problems using knowledge about their physical bodies' capabilities.

Other related examples of this approach are presented in [Quintero et al., 04a] [Quintero et al., 04b] [Quintero et al., 04c] [Quintero et al., 04d] where the agents are able to analyze their physical bodies using introspective reasoning techniques to know which tasks they can perform with their physical capabilities. Some results are drawn to show how these approaches are effective when a team of agents must achieve cooperative actions.

Since Brooks proposed the Subsumption architecture [Brooks, 86], many other coordination mechanisms for robotic systems have been proposed. This fact demonstrates that coordination mechanisms for autonomous robots are necessary to improve the performance of the above systems. Such mechanisms allow these systems to perform cooperative tasks to improve their interactions and make sure decisions within an agent cooperative system. In this direction, several authors have studied the problem to cooperative actions planning, especially in multi-robot environments, based on different kinds of coordination mechanisms. However, an approach based on the proposed decision axes has not been completely carried out. For instance, architecture to explicitly coordinate actions for multiple robots is presented in [Simmons et al., 02] where market-based techniques are used to assign tasks at the planning level. In particular, this architecture describes a multi-robot extension to the traditional three-layered architecture allowing direct communication with its peer layers in other robots.

Reference [Jung and Zelinsky, 98] proposes architecture for behavior-based agents. This architecture provides a distributed planning capability with task-specific mechanisms to perform cooperative joint-planning and communication in heterogeneous multi-robot systems. In particular, the architecture above expresses the behavior of a system by implementing two modules which represent an agent's knowledge both in terms of the agent's position and the physical agent's capabilities.

Reference [Langley, 05] presents an adaptive architecture in an in-city-drive example domain that involves cognition but in which "perception and action" play central roles. This approach is concerned with intelligent behavior in physical scenarios. In the same way, authors such as: [Behnke et al., 00], [Goldberg and Matarić, 02], [Chaimowicz et al., 01] and [Gerkey and Matarić, 01], show similar alternatives to perform the coordination process of their systems. Moreover, in [Busquets et al., 02] a multi-agent approach is implemented in a navigation system. This approach proposes a model of cooperation and competition based on a bidding mechanism. Thus, the agents must coordinate among themselves to manage resources and information such as motion and vision for the navigation system.

Reference [Aylett and Barnes, 98] shows a multi-robot architecture for planetary rovers. It is designed to be able to accommodate diverse and usually conflicting behavior related to physical robot capabilities and the relationship among them.

Results are presented using two real robots to perform a cooperative task (i.e., transport an object from one point to another avoiding obstacle).

Reference [Duffy, 04] presents architecture to express robot social embodiment in autonomous mobile robotics. In particular such architecture address the issue of embodiment in two distinct robots attributes: the internal representation of beliefs, desires and intentions; and the external consideration of the physical agent on the environment.

In references [Parker et al., 01], [Bredenfeld and Kobialka, 00] knowledge regarding to the agent's situation inside the environment has been vaguely implemented. In particular, these approaches use the geographical current position of the agents at moment in which such agents decide the actions that they might perform. Some results are present to show how these systems response due to the changes that happen in the environment conditions. In addition, in [Simmons et al., 00] a software architecture to coordination of heterogeneous robots is presented showing result with three robots in a high-precision docking tasks. Such robots are able both to interact with the other robots as to identify its physical configuration. Other related approach is implemented in [Castelpietra et al., 00] where agents' interaction and physical agents' capabilities are the information that the agents have used to express a certain level of awareness to perform cooperative behavior.

Reference [Wegner, 99] is focused on systems of cooperative autonomous robots in dynamics environments. In fact, it is discuses that both the explicit communications among agents as the representation of a model of the world are needed into systems that cooperate only through environmental interaction. This approach presents its main conclusions by implementing a RoboCup soccer system.

Architecture that allows teams of heterogeneous robots that dynamically adapt their actions over time is present in [Zweilge et al., 06]. In this sense, the robots are able to perform their actions over long periods of time requiring the robot ability to be responsive to continual changes in the capabilities of its team-mates and to changes in the state of the environment or the proposed goals.

Early work by [Falcone et al., 04], [Ramchurn et al., 04], [Carter and Ghorbani, 03] have present approaches focused on the design and implementation of models of trust to multi-agent systems. In fact, agents may operate jointly because they are able to relate with other agents using information involved in the result of their above interactions.

The afore-mentioned works present suitable approaches to represent and to include the knowledge related to physical features of agent systems. However, it is still difficult to choose the needed and enough information to include in the agents' decision-making. In this light, it is possible to assume that such knowledge must be directly related to the information of the three decision axes previously introduced:

- *The agents' environment conditions that directly affect in the performance of their selected actions.*

- *The agents' physical knowledge related to the physical features and dynamic of their bodies when they take decision.*

- *The agents' trust value allowing them to work jointly with other team-mates.*

Thus, reliable information must be extracted from the ***decision axes*** to obtain an appropriate knowledge of the ***agents' situation***. In this sense, such knowledge can be represented by means of specific features focused mainly on the ***decision axes*** as it will be show in the next chapters.

3.2.2 Task Allocation

Task allocation is the problem of assigning responsibility and problem-solving resources to an agent. Minimizing task interdependencies has two general benefits regarding cooperation: First, it improves problem-solving efficiency by decreasing communication overhead among the problem-solving agents. Second, it improves the chances for solution consistency by minimizing potential conflicts. In the second case, it also improves efficiency because resolving conflicts can be a time-consuming process. The issue of task allocation was one of the earliest problems to be worked on in Distributed Artificial Intelligence (*DAI*) research. On the one extreme, the designer can make all the task assignments in advance, thus creating a non-adaptive problem-solving organization. This approach is limiting and inflexible for environments with a high degree of dynamism, openness, and uncertainty. However, one can do task allocation dynamically and flexibly.

In this sense, several authors have been studied the problems related to task allocation, especially in multi-agent environments, based on utility/cost functions. These approaches mainly take into account domain knowledge in the agents' decision-making. However, an approach based on decision axes features has not been completely carried out. For instance, [Krothapalli, 03] presents a distributed allocation of dynamically arriving interdependent tasks to the agents. Such agents are partners in a heterogeneous multi-agent system and they must to perform task allocation to achieve cooperation within an uncertain and dynamic environment using knowledge of their interactions.

Reference [Gerkey and Matarić, 02] presents the MURDOCH system for the allocation of tasks using auctions. Regarding metrics, it only states that "it should represent the robot's fitness for a task" and that "it could perform any arbitrary computation". It gives as examples of metrics: a) the cartesian distances from the robot's position to the goal position, and b) the offset of an object in the robot's camera image.

Reference [Fatima and Wooldridge, 01] introduces an adaptive organizational police for multi-agent systems that allows a collection of multiple agent organization to dynamically allocate tasks and resources between themselves in order to efficiently process an incoming stream of task request. It main contribution is intended to cope with environments in which tasks have time constraints. Likewise, in reference [Goldberg and Matarić, 00] is presented a behavior-based controller for a multi-robot collection task that is easily modifiable to obtain new controllers. However, it does not perform any controller/agent selection.

A learning method that uses decisions trees to learn pass advices from observation of players' actions in the simulated robot soccer test bed is presented in [Bou et al., 06]. This approach uses an online coach-agent who acts as advice-given agent. A coach-agent aims at improving a team's performance by providing advices of the players, which refer to environmental knowledge.

A short review of different task allocation methods, analyzing their efficiency (solution quality versus computation and communication costs) is provided in [Gerkey and Matarić, 04]. It defines utility as the difference between the *quality* of task execution and the *cost* of executing the task. However, it does not indicate how this quality and cost should be computed. The approach presented in [Dahl et al., 04] uses Q-learning to establish task utilities (which task is the most profitable among a set of possible tasks) in a multi-robot transportation scenario. This utility is computed as the reward (fixed) obtained by executing the task (weighted according to the execution time), and is used to decide which.

The afore-mentioned works present suitable approaches to task/action selection where the criteria to bid in such multi-agent task allocation are usually classified by: cost/function (i.e., spatial/temporal) and embodiment (i.e., agents' physical features, actuator and preceptor capabilities, etc), social ability (i.e., communication between agents) and environmental conditions (i.e., the current setting of the environment). In this sense, such basic utility/cost functions are only related to the physical elements of the physical agents where aspect such as their social ability, their dynamics or their current environmental conditions are not taken into account at all, within the agents' decision-making. However, the next chapters show how these three decision axes contribute to a more suitable task allocation by considering the ***agents' situation*** in a better and more reliable way. Such consideration is directly related to the representation of such information performed by the physical agents within dynamical and unpredictable environments. Thus, appropriate representation of knowledge must be extracted by the agents from by perception of the current environmental state, the features of their physical bodies, and the result of previous interaction among themselves. Finally, the representation of such knowledge applied in the execution of cooperative actions contributes to satisfy then the above challenges in multi-agent systems.

3.3 Cooperative Decisions in Multi-agent Environments

Research in multi-agent systems is concerned with the study, behavior, and construction of a collection of possibly preexisting autonomous agents that interact with each other and their environments [Sycara, 98]. According to [Wooldridge, 02] an agent is an entity that is situated within some environment and is capable of solving problems through autonomous actions to achieve its goals in typically cooperative environments. Therefore, multi-agent systems can be integrated by a group of autonomous agents with different capabilities such that the ability to communicate among themselves and to make collective decisions aims to improve cooperative agents' performance in dynamical and unpredictable environments. In fact, multiple cooperating agents hold the promise of improved performance and increased fault tolerance for large-scale problems such as planetary survey [Haldemann et al., 07] and habitat construction [Howard, 05]. Reach cooperative decisions in multi-agent coordination, however, is a complex problem. Along this thesis will show such problem in the framework of multi-agent dynamic tasks allocation (i.e., coordinated tasks) and tasks planning under uncertainty. According to this, the study on multi-agent systems (*MAS*) focuses on systems in which intelligent agents should interact with each other [Tang and Parker., 07], [Vlassis, 03], [Ostergaard et al., 02], is due to ***all agents in a multi-agent system can potentially influence each other, it is important to ensure that the individual actions selected by the agents result in optimal decisions for the group as a whole***.

In this sense, scientific research and practice in cooperative multi-agent systems, which in the past has been called *DAI* focuses on the development of computational techniques and methods for constructing, describing, implementing and analyzing the patterns of interaction and coordination in both large and small agent societies [Benson et al., 07]. In this sense, distributed intelligence on computer science is, currently, focused to generate systems of software agents, robots, sensors, computer systems, and even people that can work together with the same level of efficiency and expertise as human teams [Parker, 08].

In brief, the main difficulty of the coordination problem addressed in this dissertation is that each agent can select an individual action, but that the outcome of its actions is directly beneficial to their team-mates. It means, if an agent forget its mission or cannot fulfil a commitment such effect is reflected on the performance of the whole system. Fortunately, in most of the cases, to perform an action an agent does not depend on the action performed by other agents. In fact agents are able to select and to perform any actions without involve other agents' action. For example, in many real-world domains only agents which are spatially close have to coordinate and to share their goals, and agents that are positioned far away from each others can act independently. Coordination then enables agents' groups to solve complex problems more effectively. For thus, the agents' group must be able to take decisions related to who agents must perform any action and when, as well as to define to whom they must communicate the result of their actions. In summary, even though the use of multi-agent systems technology is still in its development and the number of fielded commercial applications to date is small, there is tremendous potential and an exciting research agenda for the field. The field has already developed a rich set of concepts and mechanisms, both theoretical and practical, which will provide a solid base for future work. The challenge is determining how best to properly design the system so as to achieve global coherence trough the local interaction of individual entities [Parker, 08]

3.4 Final Remarks

An important element of the multiple agent research is the development of a system that supports the ability of each agent to be able to interact between periods of limited and unlimited communication in a cooperative environment. In this direction, agents must know the implications of the commitments with other agent-based entities or humans and they must know if they can carry out them. To that end, it is necessary to have some physical knowledge of the system to know what it is physically possible to perform and what it is not possible. For thus, physical inputs and outputs towards and from the environment must be integrated to the agent's knowledge base. This is due to the fact that the agent is contained in a physical body (embody and situated) which it must cooperate by means of collective decisions.

The approaches presented in this chapter summarize the recent effort development on the field of Physical Multi-agent System and Multi-Robot Cooperation, especially on those approaches that are focused to specific tasks, actions, skills, environments, and motivated by engineering consideration. Specifically, the thesis has remarked such approaches aiming to emphasising the coordinated features on the earliest proposals. For that reason, the thesis has defined a set of awareness levels [Ibarra et al., 07a] for the classification of the approaches introduced (see Fig. 3.1). Such classification arises from the binary combination of the three proposed ***decision axes*** which has been explained throughout this chapter. Indeed, the combination describes the usefulness of each axis in the agents' reasoning process. In summary, the Fig. 3.1 provides a classification of the revised approaches according to the consideration (or not) of the ***decision axes*** into their decision-maker. To the end, the analysis of the recent works in the literature shows that for more complex tasks (e.g., soccer, rescue mission, etc), in unpredictable, uncertain and hazardous environments, systems require both a very suitable performance and high robustness, for thus; more complex coordination capabilities are required.

This thesis has identified some limitations of the current architectures, but these suggest in turn some natural extensions which will let that the classification cover a wide range of intelligent knowledge that, it believe, will prove difficult to achieve in a traditional architectural background. In recent efforts on large scale systems, heterogeneity is often chosen in order to exploit different agents' capabilities and reduce the cost of the overall system. In conclusion, the analysis of the literature indicates that the problem of coordination will be decentralized when the physical agents are able both to has an individual perception of its ***situation*** in the world as to use this knowledge in their decision-making to perform cooperative actions within a typically cooperative environment. In summary, agents can achieve a successful coordination by mean of the consideration of the three decision axes. Such information promise to be useful in the agents' decision-making aimed to improve the performance of the overall system. ***Improving the cooperative multi-agent performance is the main research goal pursued in this doctoral dissertation.***

Table 3.1. Classification of Agents' Awareness Level based on a combination of the Decision Axes.

Awareness Level	Agents'			Other Approaches
	Environmental Conditions	Physical Knowledge	Trust Value	
0 (0,0,0)	0	0	0	All reference takes at least one of these parameters.
1 (0,0,1)	0	0	1	[Patel, 05], [Falcone et al., 04], [Krothapalli, 03], [Ramchurn et al., 04] [Carter and Ghorbani, 03], [Lesser, 99]
2 (0,1,0)	0	1	0	[Quintero et al., 04a], [Quintero et al., 04b], [Quintero et al., 04c], [Quintero et al., 04d], [Goldberg and Matarić, 00], [Oller et al., 99]
3 (0,1,1)	0	1	1	[Simmons et al., 00], [Castelpietra et al., 00], [Aylett and Barnes, 98]
4 (1,0,0)	1	0	0	[Gerkey and Matarić, 02], [Parker et al., 01], [Bredenfeld and Kobialka, 00]
5 (1,0,1)	1	0	1	[Tang and Parker, 07], [Bou et al., 06], [Zweilge et al., 06], [González and Torres, 06], [Simmons et al., 02], [Busquets et al., 02], [Wegner, 99], [Veloso et al., 97]
6 (1,1,0)	1	1	0	[Langley, 05], [Duffy, 04], Goldberg and Matarić, 02], [Matellán and Simmons, 02] [Fatima & Wooldridge, 01], [Jung and Zelinsky, 98], [Parker, 00b], [Behnke et al., 00], [, [Chaimowicz et al., 01], [Gerkey and Matarić, 01]
7 (1,1,1)	1	1	1	[De la Rosa et al., 07], [Quintero et al., 07a] [Quintero et al., 07b]

Chapter 4

Decision Support for Situated Agents

Improving Cooperative Actions is reachable when agents can successfully interact among them based on their situation. This chapter presents the formalization of the framework to decision support for situated agents proposed in this dissertation to provide agents with a cognitive ability for reasoning on decision axes, aiming at making physically feasible cooperative actions and to get reachable and physically feasible commitments that maximize the overall expected performance in multi-agent systems. The main definitions, formalization aspects and information provided by the decision axes used in this work are introduced in this chapter.

4.1 Situated Agents

The main challenge involved in this thesis is focused on the agent's lack on the appropriate awareness of their ***situation*** mainly related to its perception involved in the knowledge that influence them to work jointly when they must execute a collective action in a physical world. In particular, ***agents' situation*** refers to all the information that an agent has to decide if can or cannot execute any proposed action. Specifically, these information elements are directly estimated from three points of view, called ***decision axes***.

- *Agents' environmental conditions (world), composed by information about the state of the environment, directly involved in the performance of a cooperative action.*

- *Agents' physical knowledge (awareness) meaning the specification, the structure and other relevant details related to the agents' physical skills and characteristics.*

- *Agents' trust value (interaction) related to the capability of an agent to communicate, to interact and other relevant details to work together with other agents.*

Explicitly, the lack of the appropriate reasoning on the information provided by the ***decision axes*** reflects in a lower cooperative performance between agents, mainly in complex problems performed in situations, such as, coordinated task or task allocation. In this sense, a proper alternative is that agents can communicate such information aiming to achieve a successful cooperative agents' performance. Indeed, such lack represents a significant impediment to reduce complexity and to achieve appropriate levels of coordination and autonomy in multi-agent systems.

Otherwise, an analysis of the recent works in the literature [Parker, 08], [Tang and Parker, 07], [Halderman et al., 07], [Jeong-ki et al., 06], [Duffy, 04], shows that for more complex tasks (e.g., soccer, rescue mission, etc), where unpredictable, uncertain and hazardous environments requires both a very suitable performance as well as a high robustness, more complex coordination capabilities will be required. For instance, in [Parker, 08] is claimed that if a large number of robot are too expensive or are not available to be applied to, say, planetary exploration, then more purposive interaction (i.e., cooperation) is required to achieve the goal of the mission. Of course, it indicates that a complex problem will be decentralized when agents will able both to have an individual perception of its ***situation*** in the world as to use such information in their decision-making aiming to make sure decisions and to achieve trustworthy commitments in cooperative environments. In this light, the expected agents' performance depends on the information that they can acquire about their ***situation*** on the environment before to take a decision. Therefore, agents within a multi-agent scenario need to have a wide-range of knowledge which allows them to reach good decisions and to achieve sure commitments within an agents' group. In this sense, the fact of receiving and sending the right information related to ***agents' situation*** is essential for an appropriate agents' collective performance and to reach a coherent agents' behavior to achieve the expected system performance. For thus, to include appropriately the knowledge about the ***agents' situation*** in their decision-making, a suitable representation of the elements involved in the ***decision axes*** must be first developed to include such information in the agents' knowledge base which is general, accessible, understandable, comparable and computationally tractable for these agents. In particular, such agent's knowledge base means the embodiment of the agents representing their ***situation*** within a cooperative physical environment.

In summary, the thesis argues that the framework to decision support for situated agents based on the information elements of the decision axes makes then easier for agents to reflect such knowledge in their knowledge bases, aiming at making physically feasible and safer decision, getting more secure and reachable commitments, avoiding undesirable situation that could affect the collaboration, achieving a better cooperative levels.

4.2 Multi-agent Decision Support

Along the history of the artificial intelligence (*AI*), and until these days, several researchers in artificial intelligence have dealt with developing theories, techniques, and systems to study and understand the behavior and reasoning properties of a single cognitive and intelligent virtual entity (i.e., *an agent*). Artificial Intelligence (*AI*) has advanced, and it tries to attack more complex, practical, and large-scale problems, essentially when these problems are beyond the capabilities of an individual agent. So, the skills of an agent are limited by its knowledge, and the perspective of its ***situation*** on an environment, especially when those entities must to coordinate among them.

If a problem domain is particularly complex, large, or unpredictable, then the only way it can reasonably be addressed is to develop a number of functionally specific and nearly modular entities (i.e., *multi-agents*) that are specialized at solving a particular problem aspect [Sycara, 98]. Such segmentation allows each agent to use the most appropriate paradigm for solving its particular problem. Aside, when interdependent problems arise, the agents in the system must coordinate with one another to ensure that interdependencies are properly managed.

In this light, ***"multi-agent systems are computational systems in which two or more autonomous agents interact or work together to perform some set of tasks or to satisfy some set of goals"***. These systems may be comprised of homogeneous or heterogeneous agents. Therefore, before an agent starts a task, it should make a plan for how to reach a given goal. Such planning requires that agents have: knowledge about their perception of the current environmental conditions (*world*), knowledge about their physical capabilities to execute an action (*awareness*), and knowledge about the result of previous interactions between themselves (*interaction*), to represent such set of information in their knowledge bases. It means that the representation of such information (i.e., *knowledge*) internally represented in an agent is usually known as its knowledge bases [Quintero, 07]. Such knowledge allows agents to be able to reason about their ***situation*** in the environment and it is useful in the agents' decision-making, especially when they must work together with other agents or humans. In this sense, the methods, mechanisms or techniques that allows an agent to be "aware" about the fact that they must plan their actions before to take a decision or make a commitment is knows as ***decision support***. It aims to achieve more suitable cooperative performance in the overall system.

4.3 Decision Axes

Decision making is a vital component of multi-agent systems success. Decisions that are based on a foundation of knowledge and sound reasoning can lead agents into long-term cooperation; conversely, decisions that are made on the basis of flawed knowledge or incomplete information can quickly put an agent system out of commission (indeed, bad decisions can cripple even robust agent systems over time). Ultimately, what drives cooperative agents' success is the quality of decisions, and their implementation. ***"Good decisions mean good performance"***.

In this sense, problem-solving also sometimes referred to as problem management and it can be divided into two parts: ***process and decision***. The process of problem solving is predicated on the existence of a system designed to address issues as they crop up. In many cases, cooperative systems are apparently content to operate with an ultimately fatalistic manner ***"what happens, happens"***.

Experts in the area [Parker, 08], [Matarić, 00], [Stone, 00], [Lesser, 98] contend that such attitude is simply unacceptable, especially for autonomous cooperative agents that wish to expand, let alone survive. The second part of the problem management equation is the decision (or choice) itself. Several sets of elements are needed to be considered in looking at the decision process. Such set of elements refers to the rationales used for the agents to reach decisions. Others emphasize the setting, the scope and level of the decision, and the use of procedural and technical aids.

Models of decision-makers have adopted a variety of styles in their decision making processes [De la Rosa et al., 07], [González et al., 07], [Duffy, 04], [Jung and Zelinsky, 98]. For example, some approaches leaders embrace processes wherein every conceivable response to an issue is examined before settling on a final response [Patel, 05], while others adopt more flexible philosophies [Quintero, 07]. The legitimacy of each style varies in accordance with individual realities in such realms as competitive environments, dynamic task allocation, etc. Special attention must be paid to cooperative scope and organizational levels in multi-agent systems. Cooperative problems of large scope need to be dealt with high levels of organization. Similarly, problems of smaller scope can be handled with lower levels of organization. The final step in the decision-making process is the implementation of the decision. This is an extremely important element of decision-making; after all, the utility/benefits associated with even the most intelligent decision can be severely compromised if implementation is slow or imperfect. In addition, several factors in deficient decision-making are commonly cited by several experts [Luck et al., 05], [Wooldridge, 02] including the following: limited cooperative capacity; limited information; interdependencies between agents' skills and tasks requirements; the robustness of the system(s) to be analyzed; and the diversity of forms on which cooperative decisions actually arise. Moreover, time constraints, agents' distractions, low levels of decision making skill, conflict over individual goals can also have a deleterious impact on the decision making capacities of a cooperative multi-agent system. In this sense, this thesis proposes three decision axes (*world*, *awareness*, *interaction*) that mean information parameters which try to help agents to achieve a more suitable decision-making process. These axes are the embodiment of an agent on the environment dealing with information that represents all the knowledge that an agent has involved in the execution of any proposed action. It means the agent's knowledge base characterizes all the information that an agent can acquire to execute an action or to assume a commitment in a real cooperative world. In (Fig. 4.1) is showed the scheme of the decision axes.

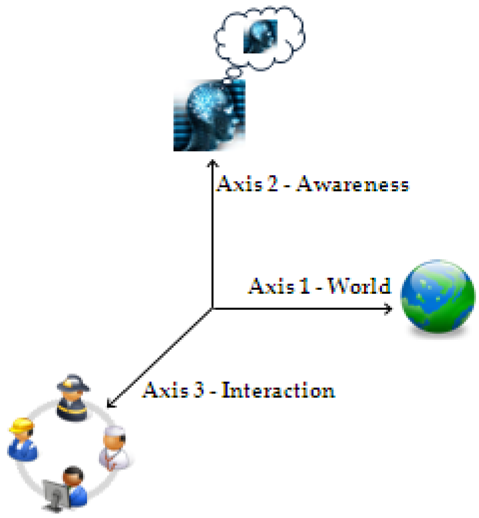

Fig. 4.1. General scheme of the proposed Decision axes.

4.3.1 Axis 1 – World. The Environmental Conditions

Previous studies [Gulec et al., 06] revealed that one of the main problems in cooperative systems is to avoid the collisions of the robots with obstacles as well as with other members of the group (i.e., *other agents*). For thus, physical systems must attempt to consider prevalent sources related to the current environmental state which represents the situation both the "objects" (i.e., walls, obstacles, etc) as the "conditions" (i.e., lights, noise, etc) that reproduces the real world situations. In this sense, a set of environmental conditions refer to the information available from the environment. In other words, the representation of the information is considered as the embodiment of all the knowledge that has influence (e.g., in god or bad ways) in the reasoning process (i.e., *perception*) of a physical agent. Besides, physical agents may at times, be working on different parts of the higher goal, and thus may at times have to ensure that they share the workspace without interfering with each other [Parker, 08]. Agents must be therefore, capable to analyze the information of their workspace before to take a decision about to perform an action or to assume a commitment [Bolander, 03] in real environments. In fact, this knowledge helps agents in their decision-making modelling the current setting that could affect in the correct development of their expected actions. If agents are not able to abstractly represent their environment then their actions' performance could be lower due to the fact of does not take into account the setting and features of their work space. However, although, it is possible to find many kinds of helpful information from the environment; it is import to define and to restrict as far as is possible to consider the information involved in a real cooperative scenario. In particular, environmental conditions aim to guide the agents' decision-making about what information must take into account from the environment at moment to decide if they have an opportunity to execute an action achieving the required performance.

4.3.2 Axis 2 – Awareness. The Physical Knowledge

When agent interaction exists in a real cooperative environment, each entity of the agent group must be able to be physically differentiated from others. These agents require a sense of themselves as distinct and autonomous individuals obliged to interact with others within cooperative environments (i.e., they require an agent identification) [Duffy, 04]. Such identification refers to the property of each agent to know who it is and what it does according to the knowledge of its physical representation (i.e., *its body*). For instance, before an agent commits it in the execution of an action, the agent should register the fact of knowing if it can or cannot perform the proposed action; it needs knowledge about the capabilities and skills of its physical body to reach at suitable decisions. In addition, to decide how well the agent is doing or will do the proposed action, an agent will also need this self-examination capability [Quintero, 07]. To express, self-examination reasoning, the agent should refer to its own knowledge as objects in its world. It means that there is a complete separation between the model (i.e., *the knowledge base*) and the reality being modelled (i.e., the environment). For that reason, although the agent possesses a body within a world, in its internal representation it is not part of the world, it only consider internally their capabilities and skills of its body. The knowledge base therefore contains sentences expressing those features (e.g., dynamic, skills) about its physical body that the agent takes to be true. In this sense, an agent is "aware" if it can reason about the actions that it can execute based on the knowledge (i.e., capabilities, skills) of its physical body. In particular, physical knowledge aims to guide the agents' decision-making in knowing on what actions can perform taking into account their physical skills and characteristics.

4.3.3 Axis 3 – Interaction. The Trust Value

Many computer applications are open distributed systems in which the constituent components are spread throughout a network, in a decentralised control regime, and which are subject to constant change throughout the system's lifetime [Ramchurm, 04]. In this sense, the need of considering risky situations in open multi-agent systems (i.e., situations in which cooperation between different autonomous entities is not assured by the mechanisms and protocols of interaction) requires to model decision-making tools into each single agent (i.e., to rely on other entities). For thus, open distributed systems can be modelled as open multi-agent systems that are composed of autonomous heterogeneous agents that interact with one another using particular mechanisms and protocols of coordination. However, their application on large-scale open distributed systems presents a number of new challenges. Thus,

- *The agents are likely to represent different stakeholders that each has their own aims and objectives.*
- *The agents can join and leave at any given time, this given that the system is open.*
- *An open distributed system allows agents with different characteristics to enter the system and interact with others.*

Specifically, the presented challenges characterize the key interaction problems. In this light, many researchers are focusing their efforts on formalizing social models that introduced interesting and promising interactions' models in virtual societies can base their interaction process on different manners [Patel, 05], [Ramchurn, 04], [Carter & Ghorbani, 02], [Falcone et al., 01]. Such models are often built over time by accumulating personal experience with others, and using this experience to judge how they will perform in an as yet unobserved and unknown situation. Generally speaking, there are two approaches to trust value in multi-agent systems. First, to allow agents to interact with others, there is a need to endow them with the ability to reason about the reciprocal nature, reliability, or honesty of their partners. The second approach concerns to design of protocols and mechanisms of interaction. It expects agents to interact using a particular way only if it can be trustworthy. In particular, a trust value aims to guide the agents' decision-making in deciding on how, and whom to interact with.

4.4 Electronic Institutions for Situated Agents

Computer-based systems are being to tackle increasingly complex problems in ever more demanding domains [Parker, 08]. The most important paradigm to face this situation is to decompose the problem into smaller and more manageable components which can communicate and cooperate at the level of sharing processing responsibilities and information. Over the years, one of the best-known and most influential contributions to the area of the agent theory is due to Cohen and Levesque in [Cohen and Levesque, 90]. In this light, problem-solving agents cooperate to achieve the goal of the individual and of the system as a whole [Jennings, 93]. Each individual is capable of a range of identifiable problem-solving activities, has its own aims and objectives, and can communicate with others. Typically, agents within a given system have problem-solving expertise that is related but distinct that has to be coordinated. Such interaction are needed because agent's actions and the necessity to meet global constraints and because often, no one individual has sufficient competence to solve the entire problem. In this sense, agents must be able to increase their ability to take more successful and trustworthy decisions. Because there are many approaches to problem-solving and due to the wide range of domains in which decisions are made, the concept of decision support is very broad. In such case, a cooperative multi-agent decision support can take many different forms. In general, it can say that a formalization of a multi-agent decision support is a computerized system for helping make collective decisions. A decision refers to a choice between alternatives based on previous analysis about the suitability rates of such alternatives. Supporting a decision means helping people (i.e., *agents*) working alone or in a group gathers intelligence, generate alternatives and make good choices. So, reaching cooperative agents is possible if they are "aware" on how perform their actions based on the knowledge that they have about their ***situation*** on a determined environment. Agents must know and must manage such information aiming to solve a complex problem inside particular regions of the environment.

Indeed, there are several approaches which establish cooperation between agents [Luck et al., 05], [Goldberg and Matarić, 00], [Jung and Zelinsky, 98]. Some kind of limitations are identified from the perspective that authors have focused in its implementation [Parker, 08], [Jennings, 04], [Mataric, 04] where their efforts are aimed to develop ad-hoc methodologies or frameworks to solve a particular problem [Sariel et al., 07], [Wang et al., 07]. So, one of the most recent efforts in cooperation and collaboration is based on approaches which base their organizational paradigm from human systems [Bou et al., 03], [Esteva et al., 02], [Busquets et al., 02]. In this sense, the electronic institutions (*e-Institutions*) have arisen as a proper answer to solve the cooperative agents paradigm when these agent form temporal groups. Some approaches using *e-Institutions* have been tested in different scenarios [Esteva et al., 02] and applying diverse artificial intelligence techniques to introduce cooperative behavior in open agent systems with a large number of successful results. In fact, *e-Institutions* [Esteva et al., 02] are organizations formed by autonomous agents in which is necessary the declaration of certain types of lineaments that allows estipulate the conduct, which determines how a group of agents could work jointly (i.e., ***"the rules of the game"***). Such lineaments must be respected and must provide agents as the ways to express individual behavior and so, to reach cooperative behavior.

In this light, according to [Esteva et al., 02] an *e-Institution* is identified with four basic elements which allow cooperating agents to work jointly: dialogic framework, scenes, performative structure and norms. The ***dialogic framework*** refers to the valid communication and inter-change of information among agents. Likewise, the dialogic framework defines which are the roles that participating agents may play within the institution. The ***scenes*** model a particular multi-agent dialogic activity (i.e., a meeting among agents). In this sense, any agent participating in a scene has to play one of its roles. The ***performative structure*** is, in general, defined as a collection of multiple, concurrent scenes. Agents navigate from scene to scene constrained by the rules defining the relationship among scenes. Performative structure is then a specification that must be regarded as networks of scenes. The ***norms*** which govern an organization are one of the key sources of trust for potential participants, since they define the commitments, obligation and right of participating agents. In fact, the norms are, in effect, local. Finally, in any *e-Institution*, the ***roles*** define the pattern of behavior and, particularly, any agent within an institution is required to adopt some of them. In this sense, the adaptation of these features is sometimes unsuitable or must be re-defined. For instance, in this thesis, the set of actions that must be executed by the participating agents are grouped in sets of goals which represent the expected intentions for the multi-agent systems. Such goals are, in general, related to a specific region of the environment. The ***first difference*** is then, the ideology of the roles formalism. Aside, based on the dialogic framework definition, a communication language and a decision algorithm are needed to describe the way in which agents will be able both to converse among them and to make sure collective commitments. The ***second difference*** is therefore, how agents participating can inter-act and can work together aiming to increase the cooperative levels of a complex problem. On the other hand, here, the scenes are meeting areas where autonomous agents must satisfy particular requirements to participate in the scene's jobs. Similarly to the *e-Institutions*, each agent must play a role (i.e., *to execute an action*) inside a scene whenever agent can ensure the correct execution of its role. It is the ***first equality*** with the traditional *e-Institution* methodology. The transition of agents from scene to scene depends on the ***situation*** of the agents related to their capabilities to execute in suitable way the actions involved in such scenes. It means, the agents navigate between the scenes (and goes to the scenes) constrained by the agents' knowledge about what they should supposedly doing and under what conditions and constraints must work in a determined scene. In this sense, the ***third difference*** is that agents can change of scene depending on their capabilities to fulfil the issues' requirements in this scene. Finally, the norms concept is taken to define a set of condition that any agent must attend before to start an action. The ***fourth difference*** is that agents must obey the stipulated norms to achieve a sure and effective cooperative performance. Besides, the norms will be in effect, local to the scenes. The ***second equality*** has been introduced. The main objective of re-defining the traditional concepts of *e-Institutions* is to do that these ideas are more suitable for the formalization of the framework to decision support that will be described in this dissertation. Such adaptation supposes some useful concepts for manage agent interaction in populated and dynamics environments. These ideas also provide solutions aiming to enhance the level of autonomy and cooperation in open and distributed multi-agent systems. In order to stressing the adaptation of the *e-Institution* methodology performed in this dissertation, in (Fig. 4.2) is drawn a comparative between the traditional model of the *e-Institutions* methodology and the proposed adaptation.

Electronic Institutions Features	The Proposed Adaptation
Agents and Roles	The Roles (i.e., actions) are defined as goals.
Dialogic Framework	A communication language and a decision algorithm are designed.
Scenes	The scenes are defined as agents-meetings areas.
Performative Structure	Agents change from scene to scene depending on their capabilities to operate in such scene.
Normative Rules	A set of conditions that agents must attend before to execute an actions or to assume a commitment.

Fig. 4.2. Adaptation of the e-Institution methodology.

In this sense, a situated agent can cooperate throughout a formal framework based on the *e-Institution*, where the main factor to perform cooperation will be the information that embodies the agent's situation regards to the proposed action. Thus,

Definition 1: *Agents' Situation refers to the agents' capability to perceive, interpret, and include all the information related to their job's capabilities and can introduce in their knowledge bases.*

In particular, this thesis classifies agents into two categories. Such classification allows differentiating the information that each agent processes, and the range of actions that agents can execute, such that: supervisor agents (*SA*) and physical agents (*PA*) describe the intelligent entities that constitute a cooperative multi-agent system. Agents are then differentiated among them and such classification is helpful to the cooperative process due to agents are able to include their own information on their knowledge bases. Such differentiation allows to classify the job of each agent can execute on the environment, avoiding that agents confuse whom are they and what they can do. Thus,

Definition 2: *Physical Agent (PA) refers to an intelligent entity that has a physical representation on the environment and through which the multi-agent systems can introduce physical changes in a real cooperative environment. Such physical agents are embodied by considering the information parameters of the three decision axes within its knowledge base.*

Physical agents are then the connection between the real world and the cognitive cooperative representation of the agent world paradigm. In some cases, such physical agent might need a particular supervision of a more perceptual and cognitive entity introduced as an omniscient and omnipresent centralized intelligent supervisor agent [Stone, 00]. Thus,

Definition 3: *Supervisor Agent (SA) refers to an intelligent entity that is in-charge of informing and supervising the successful fulfilment of the actions in a specific region of the environment. Such supervisor agents are characterized by considering the set of requirements involved in the region supervised by them. Such information represents the supervisors' knowledge bases.*

At this context, both physical as supervisor agents must reach agreement in cooperative groups by properly including the information involved in the agents' situation on their knowledge bases. Thus,

Definition 4: *Agent's knowledge base refers to the set of information that an agent has linked to its perception regards to its situation on the environment. Such situation allows* *systems be aware about the cognitive perception of the problem (i.e., the required requirements) and the physical perception of the problem (i.e., the expected actions).*

Therefore, physical agents must be "aware" on their knowledge bases to decide if they are capable or not to execute an action in a suitable way to achieve a collective solution. On the other hand, supervisor agents interpret the information of its supervised region to know the requirements of the involved problems in order to ensure the right development of the actions in such region in a typically multi-agent environment. Due to the nature that multi-agent systems are composed by autonomous and distributed entities that must interact, decisions will reached only if agents are capable to carry on a reasoning process on how they must perform a determine action in order to fulfil their individual actions to achieve the global goal. In this light, human interactions very often follow conventions, that is, general agreements on language, meaning, and behavior [Esteva et al., 02]. In this case, all the agents who co-inhabit the systems must respect a proposed set of rules that govern the way in which agents must collaborate. Such rules attempt to be useful as a defined reasoning through which agents can get reliable commitments with their agent-mates. Therefore, to imitate the ideology of the *e-Institutions* (i.e., *e- Institutions* use a set of regulations to manage the execution of multi-agent tasks), the agents' decision-making structure must be able to endow agents with the needed skill to define how they could work jointly to reach collective behavior, taking as a main decision factor their ***situation*** related to the execution of any proposed action. Then, in order to adapt in a suitable way the *e-Institutions* features, let us to define a *scene* (*S*) as a spatial region which represents "a meeting area" where a set of actions (with requirements) are expected and must be performed to fulfil the intentions of the scene. Thus,

Definition 5: *Scene is a spatial region where agents must interact and cooperate to perform some set of action in order to satisfy the system goals.*

In this sense, to ensure the correct interaction and well-execution of the actions, agents-meting (i.e., scenes) requires norms, which define how agents can interact and the manner in which agents must work to look for the benefit of its particular agents-group. In particular, such norms stipulate the set of terms and conditions that agents must respect to play a role in a determinate scene in order to collaborate with other agents. In other words, such norms are useful when different organizational units (i.e., agents) must coordinate their actions for joint benefit. So, a norm is considered as one of the most critical requirements stated in cooperative organizations. For thus,

Definition 6: *Norms refer to the set of rules which determine how agents must perform an action on a specific scene. In this case, the rules are in effect, locals.*

4.5 Formalization Aspects

Let us suppose that a supervisor agent *sa_a* is part of a cooperative group *Gsa*. A cooperative group must generally involve more than one supervisor agent for the execution of the system's goals (see Fig. 4.3). That is,

$$\exists sa_i, sa_j \in Gsa \mid sa_i \neq sa_j \quad \text{and} \quad Gsa \subseteq SA$$

$$\text{where,} \quad Gsa = \{sa_1, sa_2, sa_3, \ldots, sa_n\}$$

Where *SA* is the set of all possible supervisor agents in the environment.

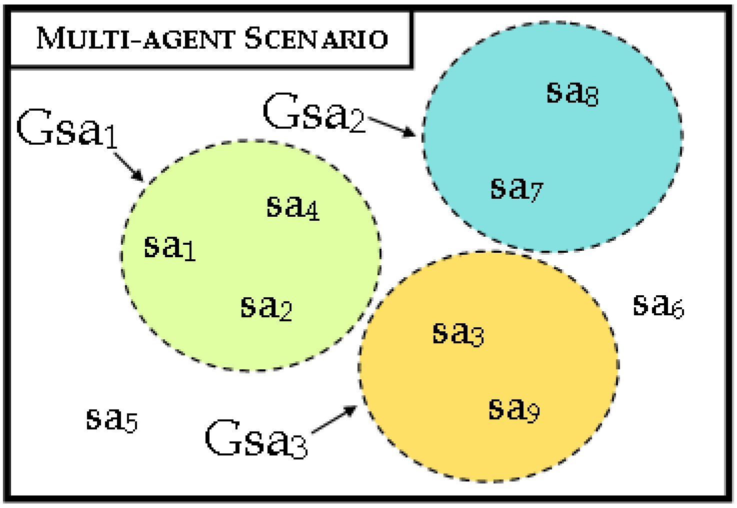

Fig. 4.3. General scheme of the supervisor agents within the environment.

One supervisor agent is in-charge to examine and evaluate a determined spatial region of the environment aiming to fulfil the greater sum of cooperative actions involved in such scene (see Fig. 4.4). In this sense, a supervisor agent has a pro-active behavior according to the agent metaphor [Wooldridge, 02] (i.e., it is pro-active because is continually checking which scene it must supervise). Besides, when a *supervisor* has identified its scene, it must claim the information involved in such scene in order to know which actions must be achieved in such area. It is defined as a *supervisor agent* sensitive to the events that happen and affect in a determinate way the process of the actions inside any spatial region of the environment. For thus,

Let us define that a scene *s_a* is a spatial region on the environment where agents have meetings and must interact to perform a set of actions involved in such space, such that,

$$\exists s_i, s_j \in S \mid s_i \neq s_j \quad \text{where,} \quad S = \{s_1, s_2, s_3, \ldots, s_n\}$$

Where *S* is the set of all possible scene in the environment.

Let us consider that a scene s_a is supervised by a supervisor agent sa_a such that,

$$\forall sa_i \in Gsa \, \exists \, s_i \in S \,|\, sa_i \rightarrow s_i \quad \therefore \, SA = S$$

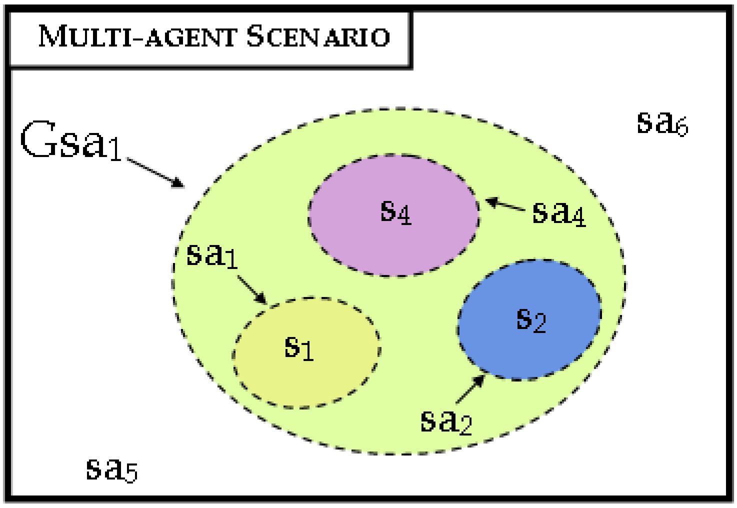

Fig. 4.4. General scheme of the Scenes within the Environment. Each scene is supervised by one supervisor agent.

Aside, studies about which actions are involved in a determined scene are required to provide and to define all the information involved in the execution of a complex problem, to facilitate the execution of the management of such region. Once a supervisor agent knows the region where it will develop its function, it must identify the goals to be accomplished in such spatial region, it must indicate the tasks that should be performed to achieve such goals, and what roles are necessary for the task achievement. All together, this set of information constitutes information which differentiates one supervisor from others. Thus, it is possible to considerer a heterogeneous group of supervisor agents trying to reach collective behavior to solve a global complex problem. Indeed, it is necessary to propose a priority index ω which represents the relevance of every cooperative issue (i.e., goals, task and roles) within determined region of the environment. In this sense, a *supervisor* will know both the sequence in which the goals and the tasks must be performed and the sequence in which roles will be executed according to its supervised scene. Such priority index will be established according to system requirements (i.e., robustness, timeline, etc) aiming to achieve a sure and effective accomplishment of the scene's aims.

Let us suppose that a goal g_γ is part of a set of cooperative goals involved in any determined scene. A scene must generally involve more than one goal for the fulfilment of the system's proposal (see Fig. 4.5). Thus,

$$\exists g_i, g_j \in G(s_\alpha) \,|\, g_i \neq g_j \quad \text{and} \quad G(s_\alpha) \subseteq G$$

$$\text{where,} \quad G(s_\alpha) = \{g_1, g_2, g_3, \ldots, g_o\}$$

$$\text{thus,} \quad \forall\, g_i \in G(s_\alpha)\ \exists\, \omega(g_i) \in \Omega(G(s_\alpha)) \mid 0 \le \omega(g_i) \le 1$$

Where G is the set of all possible goals in the environment, and $G(s_\alpha)$ is the set of goal involved in a determined scene s_α.

Where $\Omega(G(s_\alpha))$ is the set of the priority indexes defined for the relevance of the goals in specific scene, and $\omega(g_i)$ is the priority index of a specific goal.

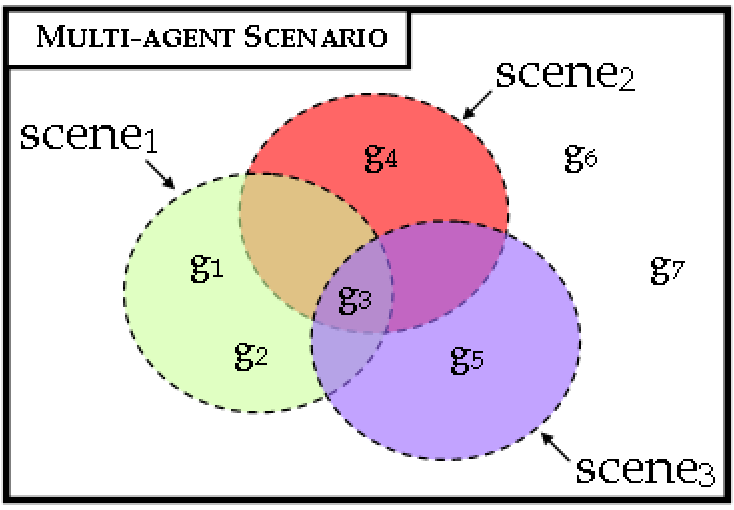

Fig. 4.5. General scheme of the goals within the environment.

Here, a *goal* refers to the set of issues that must be performed in any determined scene, aiming to achieve a particular system's target. Such goals then embody the system aims, according with the targets that must be reached as the outcome of the cooperation among agents.

Let us define that a task t_δ is part of a set of cooperative activities that must be performed to achieve a specific goal g_γ in any determined scene. A goal must generally involve more than one task for the achievement of the scene's proposal (see Fig. 4.6). Thus,

$$\exists\, t_i, t_j \in T(g_i) \mid t_i \neq t_j \quad \text{and} \quad T(g_i) \subseteq T(s_\alpha) \subseteq T$$

$$\text{where,} \quad T(g_i) = \{t_1, t_2, t_3, \ldots, t_p\}$$

$$\text{thus,} \quad \forall\, t_i \in T(s_\alpha)\ \exists\, \omega(t_i) \in \Omega(T(s_\alpha)) \mid 0 \le \omega(t_i) \le 1$$

Where *T* is the set of all possible tasks in the environment, and $T(s_\alpha)$ is the set of all possible task involved in determined scene, and $T(g_i)$ is the set of all possible tasks involved in the performance of a determined goal.

Where $\Omega(T(s_\alpha))$ is the set of the priority indexes defined for the relevance of the tasks in specific scene, and $\omega(t_i)$ is the priority index of specific task.

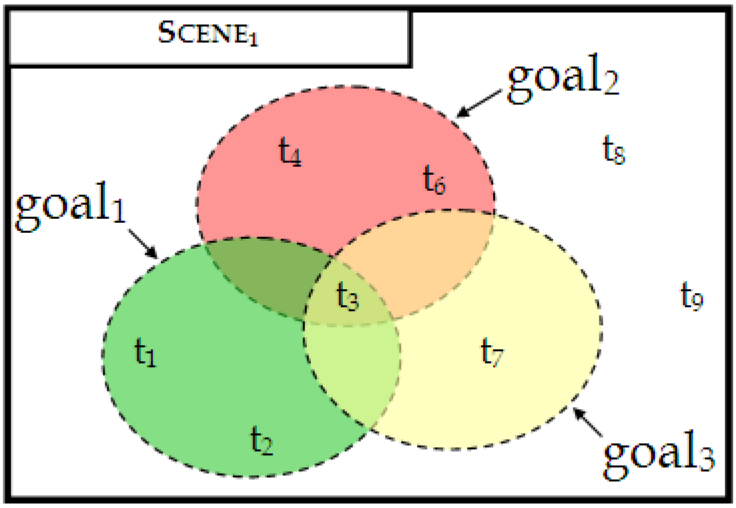

Fig. 4.6. General scheme of tasks within the environment.

A goal therefore could be achieved without the implicit needed of performing or assuming its entire involved tasks. In fact, the execution of one task is independent of other task execution, but their development and outcome could reflect in a positive or negative way the development and execution of other tasks (see Fig. 4.6). Here**,** a *task* refers to the set of action that must be performed in any determined scene aiming to achieve a particular goal.

Let us define that a role r_φ is part of a set of cooperative actions that must be performed to achieve a specific task t_δ in any determined scene. A task must generally involve more than one role for the achievement of the goal's proposal (see Fig. 4.7). Thus,

$$\exists r_i, r_j \in R(t_i) \mid r_i \neq r_j \quad \text{and} \quad R(t_i) \subseteq R(s_\alpha) \subseteq R$$

$$\text{where,} \quad R(t_i) = \{r_1, r_2, r_3, \ldots, r_q\}$$

$$\text{thus,} \quad \forall\, r_i \in R(s_\alpha)\ \exists\, \omega(r_i) \in \Omega(R(s_\alpha)) \mid 0 \leq \omega(r_i) \leq 1$$

Where *R* is the set of all possible roles in the environment, and $R(s_\alpha)$ is the set of all possible tasks involved in determined scene, and $T(g_i)$ is the set of all possible tasks involved in the performance of a determined goal.

Where $\Omega(R(s_\alpha))$ is the set of the priority indexes defined for the relevance of the tasks in specific scene, and $\omega(r_i)$ is the priority index of specific task.

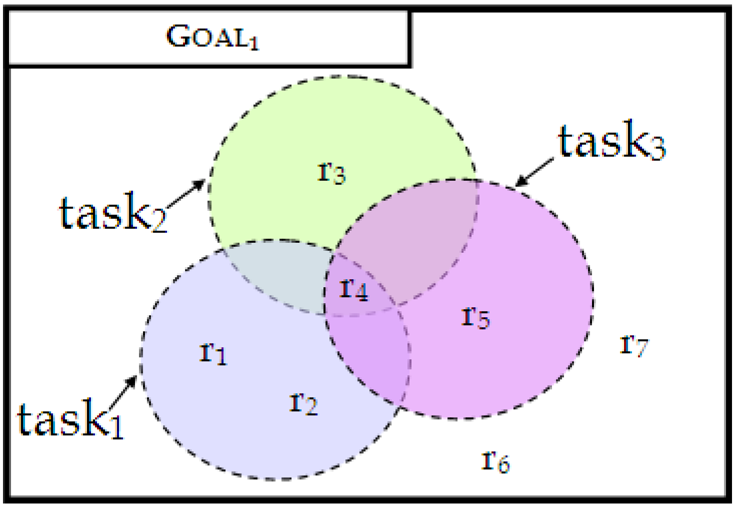

Fig. 4.7. General scheme of the roles within the environment.

A task then could be achieved without the implicit needed of performing or assuming its entire involved roles. In fact, the performance of one role is independent of other roles performance, but their development and outcome could reflect in a positive or negative way the development and performance of other roles (see Fig. 4.7). Here, a *role* refers to a specific action that must be executed by a particular physical agent in order to fulfil the performance of a determined task within the development of any scene's goals.

The information acquired by the supervisor agents usually constitutes their knowledge bases. Such bases have associated all the information about the requirements (i.e., the issues that must be solved) involved in a determined area. The overall set of information aims to provide supervisor agents with the enough knowledge allowing them to perform a sure and reliable fulfilment of a greater amount of cooperative actions involved in its supervised area. The supervisor agent's knowledge base *KB* (see Fig. 4.8) is therefore founded on the union both of the goals, the tasks and the roles implicated in the scene under its manage as is described in (4.1).

$$KB(sa_\alpha) = G(s_\alpha) \cup T(s_\alpha) \cup R(s_\alpha) \quad (4.1)$$

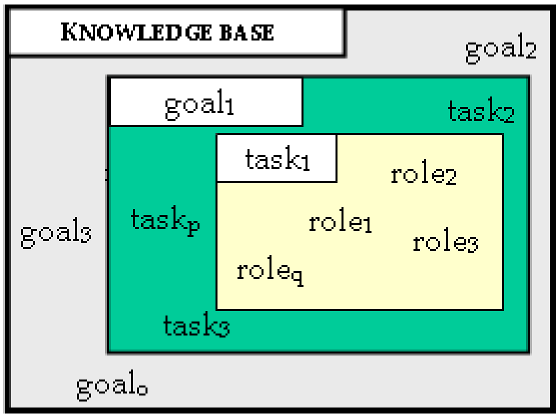

Fig. 4.8. General scheme of the supervisor agent's knowledge base.

In consequence, the supervisor agent's knowledge base allows each *supervisor* to be conscious about what it can do for the fulfilment of the global system's goal. Such information also keeps the systems "aware" about the requirements of its involved action, because of this; it is needed identify the capabilities of the *workers* (i.e., the physical agents) that operate within the environment. Thus,

Let us define that a physical agent pa_β inhabit in a real and typically cooperative environment. These agents have therefore the ability to consider their physical *situation* related to the execution of a particular action in such physical scenario. Although these characteristics could supposedly take a lot of "things" concerning the environment, this thesis argues to consider three kinds of knowledge looking for include information which could be useful for the perception of particular pa_β about its situation in the environment. So, the environmental conditions refer to knowledge involving the physical condition of an agent within an environment, the physical knowledge represents knowledge about the physical features of the agents and the trust value takes all the knowledge involved in the agent interactions. Thus,

Let us suppose that a physical agent pa_β is part of a cooperative mobile group *Gpa*. A cooperative mobile group must generally involve more than one physical agent for the execution of the actions in a scene (see Fig. 4.9). That is,

$$\exists pa_i, pa_j \in Gpa \mid pa_i \neq pa_j \quad \text{and} \quad Gpa \subseteq PA$$

$$\text{where,} \quad Gpa = \{pa_1, pa_2, pa_3, \ldots, pa_m\}$$

Where *PA* is the set of all possible physical agents in the environment.

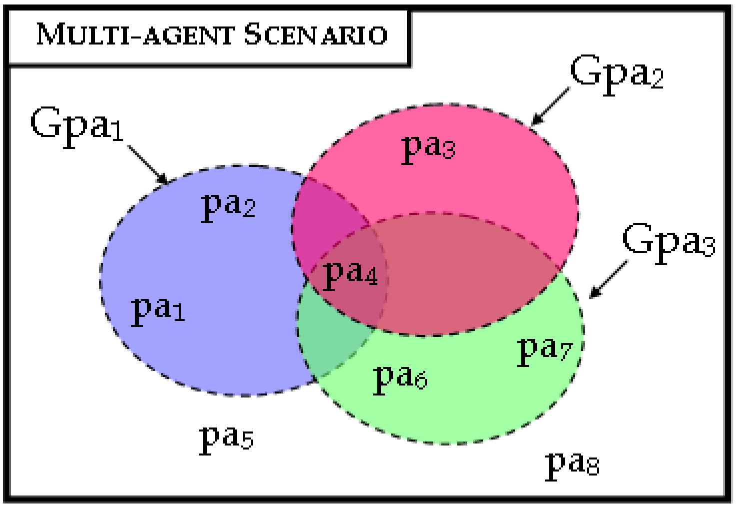

Fig. 4.9. General scheme of the physical agents within the environment.

Let us suppose that physical systems enhance prevalent knowledge regarding the current environmental state, trying to model the situation of the "objects" (i.e., walls, obstacles, ets) that reproduce the current world features in which physical agents operate and interact. Thus, physical agents could look for numerous kinds of helpful information from the environment; but here, such information only refers to the notion of environmental conditions as the needed information to describe the state of the environment which could influence the agents' reasoning process at moment to evaluate if they are capable or not to perform a proposed action.

Let us consider that physical agents' environmental conditions *EC* are composed by a set of environmental features *EF* (e.g., noise, lights, etc) and a set of environmental objects *EO* (e.g., walls, obstacles, etc) as is described by (4.6)

$$EC(pa_i) = EF(pa_i) \cup EO(pa_i) \quad (4.6)$$

$$\text{where,} \quad \exists ef_i, ef_j \in EF(pa_i) \mid ef_i \neq ef_j \quad \text{and} \quad \exists eo_i, eo_j \in EO(pa_i) \mid eo_i \neq eo_j$$

$$\text{This gives,} \quad EC(pa_i) = \{ef_1, ef_2, ef_3, \ldots, ef_u; eo_1, eo_2, eo_3, \ldots, eo_v\}$$

The environmental conditions of any selected physical agent for the execution of a specific role in a time in a determined scene are obtained, as in (4.7) taking into account the features and objects related to the proposed role such that (see Fig. 4.10):

$$\forall pa_i \in Gpa \, \exists EC(pa_i, r_\varphi)_{t_{s_\alpha}} = EF(pa_i, r_\varphi)_{t_{s_\alpha}} \cup EO(pa_i, r_\varphi)_{t_{s_\alpha}} \quad (4.7)$$

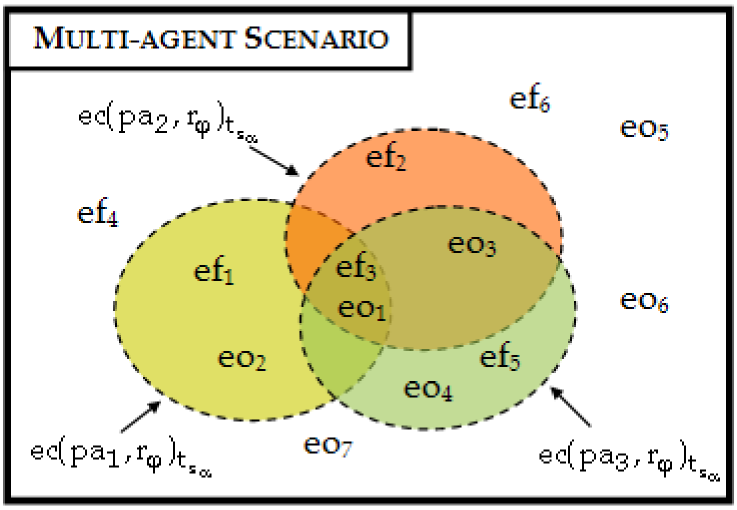

Fig. 4.10. General scheme of the physical agents' environmental conditions involved in a specific role within a determined scene.

In this context, environmental conditions refer to the well-defined information to describe the physical state of the environment. The environmental objects refer to the needed set of information that usually embodies the conditions of the environment.

Definition 7: *Environmental Conditions refer to the set of environmental knowledge that physical agents have to perform the proposed set of actions. Such domain representation is considered as the embodiment of the environment knowledge that represents all the physical information that has influence in the physical agents' reasoning process.*

Likewise, a physical agent could be any physical object "handled" by an intelligent agent or group of intelligent agents, (i.e., an autonomous robot, a machine or an electric device). So, such agents have aspects which represent their physical body features (i.e., their dynamic, their physical structure) usually when they must perform some task or must satisfy a specific behavior within a cooperative group.

Let us define that physical agent's physical knowledge *PK* is constituted by a set of movement skills *MS* (e.g., speediness, robustness, etc) and a set of body specifications *BS* (e.g., shape, size, wheels, etc) as is described by (4.4)

$$PK(pa_i) = MS(pa_i) \cup BS(pa_i) \quad (4.4)$$

$$\text{where,} \quad \exists ms_i, ms_j \in MS(pa_i) \mid ms_i \neq ms_j \quad \text{and} \quad \exists bs_i, bs_j \in BS(pa_i) \mid bs_i \neq bs_j$$

$$\text{This gives,} \quad PK(pa_i) = \{ms_1, ms_2, ms_3, ..., ms_w; bs_1, bs_2, bs_3, ..., bs_x\}$$

In particular, the physical knowledge of any selected physical agent is constituted for the movement skills and body specification involved in the execution of a specific role in a time in a determined scene (see Fig. 4.11) as is described by (4.5).

$$\forall\, pa_i \in Gpa\, \exists\, pk(pa_i, r_\varphi)_{t_{s_\alpha}} = MS(pa_i, r_\varphi)_{t_{s_\alpha}} \cup BS(pa_i, r_\varphi)_{t_{s_\alpha}} \quad (4.5)$$

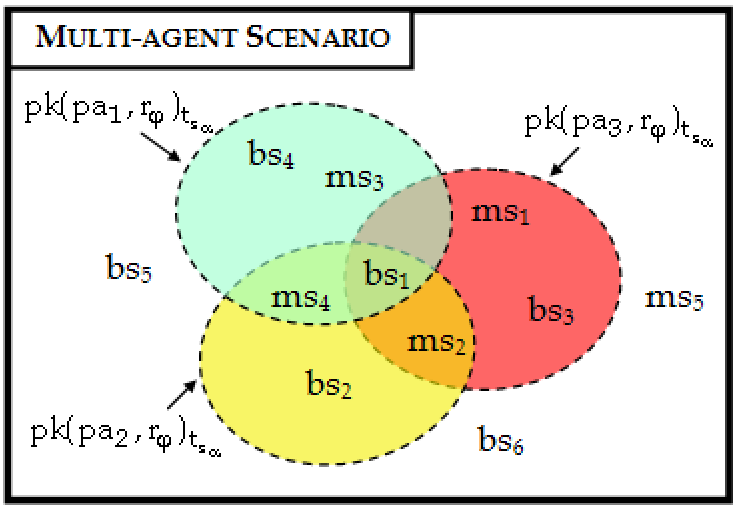

Fig. 4.11. General scheme of the physical agents' physical knowledge involved in a specific role within a determined scene.

In this context, the movement skills refer to specific knowledge to define the skills and characteristics of one physical agent have to perform a determined free movement trajectory. In addition, the body specifications refer to the needed set of information that usually embodies the body specifications of any physical agent.

Definition 8: *Physical knowledge refers to the set of physical self-knowledge that a physical agent has represented about its skills and physical characteristics to execute any proposed action. Such physical representation is considered as the embodiment of the physical features that constitute all the information that physical agents can include in their decision-making.*

Let us suppose that the set of information about the physical agent's trust value is given as the consequence of the previous interaction between them. Such knowledge provides physical agents the needed knowledge to assume a commitment or to perform an action with a high level of effectiveness and certainty.

Let us define that physical agent's trust value *TV* is constituted by a set of good feelings *GF* (e.g., honesty, certainty, fitness, etc) and a set of bad feelings *BF* (e.g., selfish, deceitful, disinterest, etc) as is described by (4.2).

$$TV(pa_i) = GF(pa_i) \cup BF(pa_i) \quad (4.2)$$

$$\text{where,} \quad \exists\, gf_i, gf_j \in GF(pa_i) \mid gf_i \neq gf_j \quad \text{and} \quad \exists\, bf_i, bf_j \in BF(pa_i) \mid bf_i \neq bg_j$$

$$\text{This gives,} \quad TV(pa_i) = \{gf_1, gf_2, gf_3, \ldots, gf_y;\, bf_1, bf_2, bf_3, \ldots, bf_z\}$$

Specifically, the trust value of any selected physical agent is made up for the good and bad feelings involved in the performance of a specific role in a time in a determined scene (see Fig. 4.12) as is described by (4.3).

$$\forall\, pa_i \in Gpa\ \exists\ tv(pa_i, r_\varphi)_{t_{s_\alpha}} = GF(pa_i, r_\varphi)_{t_{s_\alpha}} \cup BF(pa_i, r_\varphi)_{t_{s_\alpha}} \quad (4.3)$$

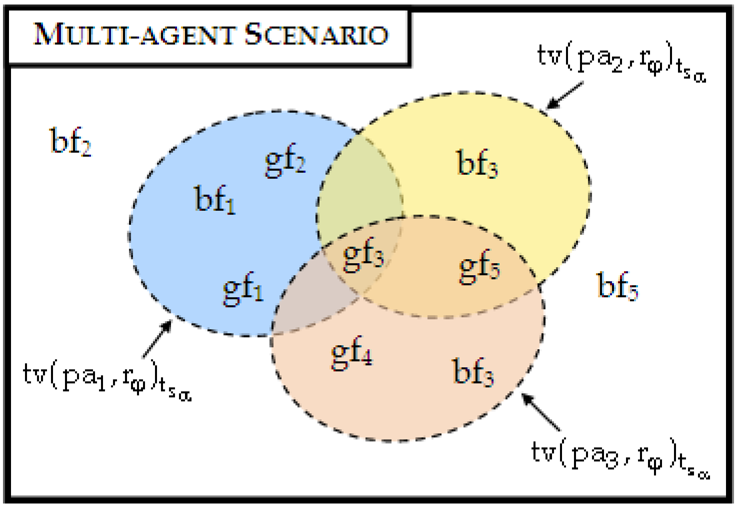

Fig. 4.12. General scheme of the physical agents' trust value involved in a specific role within a determined scene.

Here, good feelings refer to the proper knowledge, implicit in the nature of one physical agent to interact with other agents. Against, bad feelings refer to the negative disposition of one agent which could affect in the physical agent's interactions.

Definition 9: *Trust Value refers to the certainty that an agent wants to interact with other agents to assume a specific behavior with successful and high reliability to achieve any action proposed within any determined scene. Such information is useful in the interaction process of the agents because they can trust in other agents based on the result of their previous interactions.*

In this sense, the set of knowledge acquired by a physical agent usually constitutes its knowledge base. Such base therefore, involves the associated information about the rate that each physical agent has to perform a proposed action in a time in determined scene. Explicitly, such information aims to provide physical agents with enough knowledge that allows them to perform in a more successful and reliable way the execution of any proposed individual action at any scene.

The physical agent's knowledge base *KB* (see Fig. 4.13) is therefore founded on the combination of the environmental condition, the physical knowledge and the trust value implicated in the execution of an action as is described by (4.8)

$$\forall\, pa_\beta \in Gpa\ \exists\ KB(pa_\beta) = EC(pa_\beta) \cup PK(pa_\beta) \cup TV(pa_\beta) \quad (4.8)$$

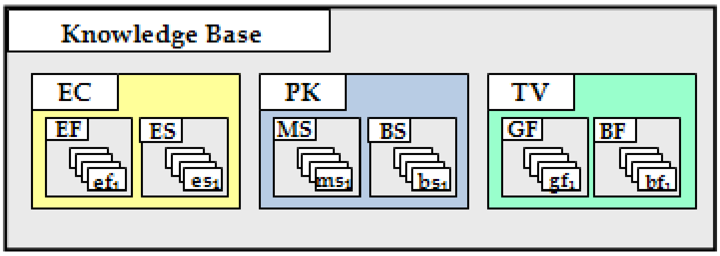

Fig. 4.13. General scheme of the Physical agents' knowledge base.

In particular the physical agent's knowledge base for the development of any specific role r_φ in a time t in a determined scene is given by (4.9).

$$kb(pa_i, r_\varphi)_{t_{s_\alpha}} = ec(pa_i, r_\varphi)_{t_{s_\alpha}} \cup pk(pa_i, r_\varphi)_{t_{s_\alpha}} \cup tv(pa_i, r_\varphi)_{t_{s_\alpha}} \quad (4.9)$$

At this context, the physical agents must agree among them to define which actions will play every one in a determined region (*scene*); where a supervisor agent checks and coordinates the physical agents' performance to ensure a successful development of the activities. In this sense, multi-agent systems present coordination at two meta-levels (i.e., supervision of the intentions and physical execution), thus, supervisor agents must coordinate among them to guide a predefined group of physical agent, aiming to achieve a sure and reliable performance of the goals' system (see Fig. 4.14).

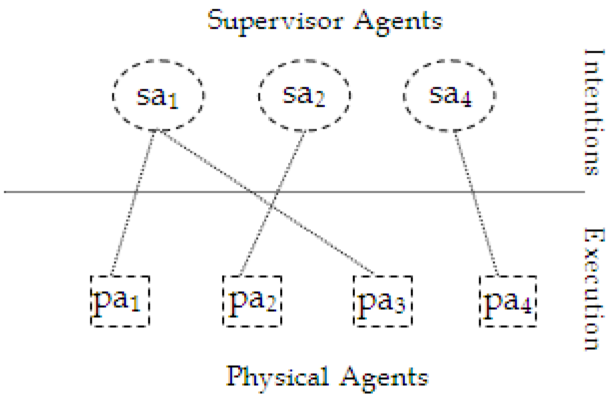

Fig. 4.14. General scheme of the meta-level of coordination within the multi-agent system.

In this sense, agents (both supervisor and physical) can achieve sure and trustworthy commitments within a specific scene; for thus, agents, both the supervisors as the physical, must attend to an implicit set of rules which establish the normative structure for develop a specific action within determined scene. Thus,

Let us define that a norm N_η is denoted as a rule that govern the way in which agents perform the actions in a scene. Besides, such rules must be respected by the physical agents while they try to keep behavior or to perform an action in such scene. Thus, the accomplishment of a norm N_η is denoted by the condition:

$$\text{if } (N_\eta) \text{ do / donot } \{\text{action}\}$$

$$\text{where,} \quad \exists N_i, N_j \in NN(s_\alpha) \mid N_i \neq N_j \quad \text{and} \quad NN(s_\alpha) \subseteq NN$$

$$\text{Thus gives,} \quad NN(s_\alpha) = \{N_1, N_2, N_3, \ldots, N_a\}$$

For instance, let us consider a group of two supervisor agents *Gsa* = {sa_1, sa_2} supervising the actions in a defined set of two scenes, such that, S = {s_1, s_2}, and a group of four physical agents *Gpa* = {pa_1, pa_2, pa_3, pa_4} aiming at solving a task allocation problem. The sa_1 supervises the s_1 and the sa_2 supervises the s_2. For sake of simplicity, each scene only has one goal, one task and two roles.

Firstly, it is assumed that supervisor agents agree between them to schedule their interaction with the group of physical agent. Such agreement is achieved when the *supervisors* inform to the other supervisors their rates of priority of their involved goals, following the norm N_1 as follow:

$$N_1 = \text{if } (\omega(g_i) > \omega(g_j)) \text{ do } \{\text{execute } (g_i)\text{else}(\text{execute} g_j)\}$$

The supervisor agents' decisions are achieved by following the N_1, such that:

$$G(s_1) = \{g_1\} \wedge \omega(g_1) = 0.76 \qquad G(s_2) = \{g_2\} \wedge \omega(g_2) = 0.81$$

$$\text{if } (\omega(g_1) > \omega(g_2)) \text{ then } (g_1 \text{ is performed}) \text{ else } (g_2 \text{ is performed})$$

In this sense, the g_2 is higher than g_1 therefore the sa_2 must start the communication with the physical agent for the execution of the task involved in the g_2. In this sense, as the goal g_2 only has one task (t_2) the supervisor agent only must allocate (for this case) the involved roles of the task t_2, such that:

$$N_2 = \text{if } (\omega(r_i) > \omega(r_j)) \text{ then } \{(\text{the allocated order is } r_i, r_j)\text{else}(\text{the allocated order is } r_j, r_i)\}$$

$$T(g_1) = \{t_1\} \wedge \omega(t_1) = 0.76 \quad R(t_1) = \{r_1, r_2\} \wedge \omega(r_1) = 0.45, \omega(r_2) = 0.54$$

$$T(g_2) = \{t_2\} \wedge \omega(t_2) = 0.56 \quad R(t_2) = \{r_3, r_4\} \wedge \omega(r_3) = 0.67; \omega(r_4) = 0.74$$

According with the given values the r_4 must be the first one to be executed and the r_3 must be allocated after it. For instance, let us to suppose that pa_1 and pa_2 are the more suitable agents respectively for this case, then the allocation will be, such that:

$$r_4 \text{ is allocated to the } pa_1 \quad \text{and} \quad r_3 \text{ is allocated to the } pa_2$$

After this, the remaining supervisor agent (sa_1) can perform the same process to interact with the remaining physical agents (i.e., pa_3, pa_4) and allocate its roles (i.e., r_1, r_2) following the same rules.

4.6 Influence Degree. A suitable way to obtain the utility of the agents

Multi-agent utility is a unifying, if sometimes implicit, concept in economics [Esteva, 02], game theory [He et al., 06], and operations research [Endo et al., 06], as well as multi-robot coordination [Fang and Parker, 07]. The main idea of such utility is therefore, that each agent can somehow internally estimate and evaluate its capability of executing a proposed action. In the literature [Simmons et al., 02], [Goldberg and Matarić, 00], the notion of utility of the agents has received various names according to its application, such that: fitness, valuation, and utility/cost. Utility/cost functions provide a natural and advantageous framework for achieving self-optimization in distributed autonomic computing systems [Weyns et al., 04]. In this sense, an exact and practical formulation varies from system to system; this thesis now gives a useful and general, yet practical, definition of utility for multi-agent cooperative systems.

In particular, this thesis assumes that each physical agent (i.e., *a robot*) is capable to evaluate its aptitude for the execution of any proposed action. Such estimation is performed by including two aspects, which allow the agents to self-calculate their suitability rate for any proposed action, such as,

- *the capabilities of the physical agents (i.e., their situation) taking into account the information parameters of the decision axes, to perform any proposed action.*

- *the influence degree that every axis has as requirement to the selection/allocation of any determined action.*

Influence Degree Ψ refers to the relevance that the ***decision axes*** has over the execution of any determined action in a particular scene. Such influence aims to provide the awareness needed to determine the suitability of a physical agent to execute any action in a successful and reliable way. In this sense, such influence degree is represented as is described by the tupla (4.10).

$$\Psi_{R(s_\alpha)} = [\Psi(\mathrm{EC}) \quad \Psi(\mathrm{PK}) \quad \Psi(\mathrm{TV})] \quad (4.10)$$
$$\text{where,} \quad \Psi(\mathrm{EC}), \Psi(\mathrm{PK}), \Psi(\mathrm{TV}) \in [0,1]$$

Where $\Psi(EC)$ is the relevance of the environmental conditions, $\Psi(PK)$ is the relevance of the physical knowledge and $\Psi(TV)$ is the relevance of the trust value. In particular, the influence degree for the development of any specific role within any determined scene is given by (4.11).

$$\forall r_i \in R(s_\alpha)\ \exists\ \psi_{r_\varphi, s_\alpha} \in \Psi_{R(s_\alpha)} = [\psi(EC)_{r_\varphi, s_\alpha} \quad \psi(PK)_{r_\varphi, s_\alpha} \quad \psi(TV)_{r_\varphi, s_\alpha}] \quad (4.11)$$

In such case, the suitability rate of any physical agents is obtained by a match function ξ which works as a **capabilities/requirements** function.

4.6.1 Formalism

Let us suppose that a physical agent pa_i is capable of executing a role r_j with a suitability rate ξ_{pa_i, r_j} as is described in (4.12).

$$\xi_{pa_i, r_j} = \left(\frac{\sum_{b=1}^{3} kb(pa_i)_{(b)} * \psi(r_j, s_\alpha)_{(b)}}{\sum_{b=1}^{3} (\psi(r_j, s_\alpha)_{(b)})} \right)_{t_{s_\alpha}} \quad (4.12)$$

Suitability rate ξ refers the range of certainty that a physical agent has to perform any proposed action in a time in a scene. In fact, the suitability rate provides physical agents a reliable measure of its capability for the execution of specific role in determined scene. For instance, let us to suppose a group of three physical agents, such that, $Gpa = \{pa_1, pa_2, pa_3\}$ and four roles in a determined scene $R(s_a) = \{r_1, r_2, r_3, r_4\}$, and it is established, for illustrative reasons, a decision threshold (th=0.7), which establish the minim value of suitability required for the execution of any action. For sake of simplicity, the influence degree for all the roles is: $\Psi = [0.4 \quad 0.6 \quad 0.5]$.

In the example, physical agents use the information of their knowledge bases (see Fig. 4.15) to self-calculate their suitability rate for each proposed role. In this sense, each physical agent can classify its estimation in a decreasing order and discard those actions in which it has not opportunity. Therefore, using this classification, the agents are able to agree among them to define which action executes each. In this sense, when more than one physical agent can execute the same action, the elected agent will be the agent with the higher suitability to execute the actions (see Fig. 4.16, decision trial 1).

Then, the remaining agents agree between them to discuss what action executes which one. In this case, each agent can execute different role with higher suitability rate (see Fig. 4.16, decision trial 2) taking into account the proposed decision threshold (th).

KB(pa_1)			
Roles	EC	PK	TV
r_1,s_1	0.51	0.648	0.32
r_2,s_1	0.557	0.82	0.74
r_3,s_1	0.75	0.638	0.792
r_4,s_1	0.679	0.82	0.463
a)			

KB(pa_2)			
Roles	EC	PK	TV
r_1,s_1	0.51	0.84	0.71
r_2,s_1	0.77	0.813	0.57
r_3,s_1	0.66	0.743	0.661
r_4,s_1	0.476	0.71	0.43
b)			

KB(pa_3)			
Roles	EC	PK	TV
r_1,s_1	0.793	0.32	0.64
r_2,s_1	0.539	0.806	0.89
r_3,s_1	0.294	0.66	0.476
r_4,s_1	0.68	0.732	0.698
c)			

Fig. 4.15. Empirical Knowledge bases.

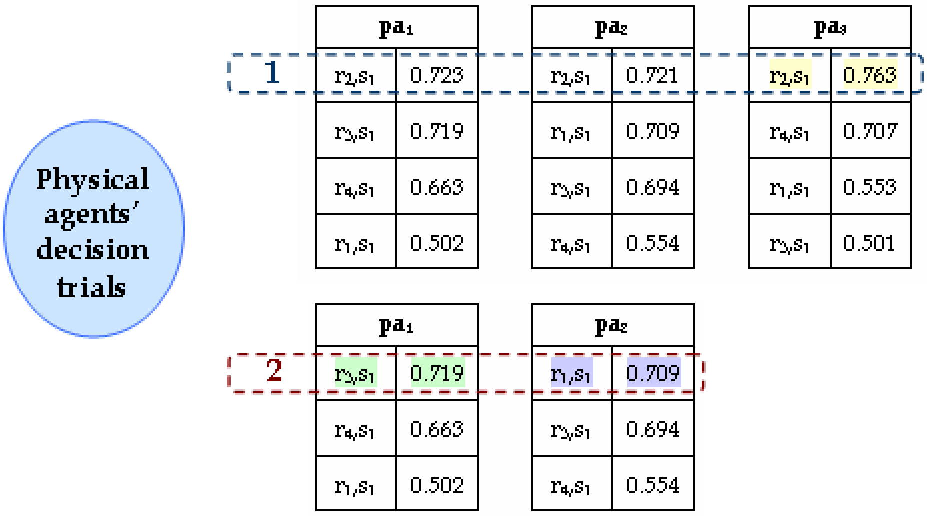

Fig. 4.16. General scheme of a coordination process performed by physical agents to execute the proposed actions.

To the end, in two decision trials (see Fig. 4.16) the group of physical agents has agree which one is the most suitable to execute each role taking into account their suitability rates for the proposed set of roles, such that, ($pa_1 \rightarrow r_3$, $pa_2 \rightarrow r_1$, $pa_3 \rightarrow r_2$). However, in this example the role r_4 is not selected by any physical agent due to fact that all the agents have estimated a low suitability rate for such role (it means that their suitability rates are not enough to perform correctly such role).

4.7 Decision Algorithm for Multi-agent Coordination

The diffusion of information or ideas in a common format (i.e., *language*) to make sure and reliable agreements between humans is one of the most important aspects of the interaction. Likewise, artificial intelligence has several approaches showing advantages by applying such process in the agents' coordinated processes [Mudasir et al., 07], [Yong and Bo, 06], [Luck et al., 05] aiming to increase the multi-agent interaction's performance. One of the most important physical agents' jobs is therefore to make decisions, that is, to commit to execute a particular action. In this sense, an important criterion for the development of any complex problem within cooperative environments is therefore, that agents are capable to transfer the proper information (i.e., *their situation*) in an appropriate and common way. In this sense, to accomplish a collective action, a group of agents must establish communication to coordinate them. On such coordination agents must "converse" among them to agree who is who within the group. To the end, agents must agree to define who agent is the best to execute a certain action. The use of a communication language is then needed to strengthen the interaction between agents. Such language aims to be useful improving the communication between supervisor agents by divulging information about their desires and allows reach common agreements. Also, it is useful for the physical agents due to allows them inform their suitability to execute any proposed action, and so, they can reach community agreements. For thus, following the *BDI* philosophy [Shoham, 93] and the *KQML* specification [Finin et al., 97] a model of language is described as follow:

$$\mathrm{request}(A_i, A_j, \Phi, s_\alpha)$$

Where an agent A_i (or group of agents) proposes to other agent A_j (or group of agents) its beliefs Φ to solve a complex problem in a scene s_α.

$$\inf \mathrm{orm}(A_j, A_i, \Theta, s_\alpha)$$

Where an agent A_j (or group of agents) tells to other agent A_i (or group of agents) its answers Θ about the proposition before proposed.

Once defined the language, it is necessary determine how agents can reach agreements among them. Such event occurs when agents have a structure which allow them estimate the way to reach an efficient cooperation. To that end, this thesis argues that an effective way to achieve successful and reliable coordinated performance can be reached by using a decision algorithm. A decision algorithm is based on a communication among agents in which they can compare and analyze their *situation* in the environment and by which can reach decision that benefit the overall systems performance. Such algorithm aims to improve the agents' choice which allows them to agree which is the most suitable agent to execute the proposed action. In this sense, along this chapter has been devoted to study the effect of the cooperation based on the agents' situation in two collaborative scenarios, this thesis has defined decision algorithm to solve complex problems at two kinds of coordination, such that, coordinated task and task allocation. To follow, a brief description about how agents (both supervisor and physical) can reach agreements in each scenario is presented.

4.7.1 Coordinated Task problem-solving Algorithm

The execution of a coordinated task performed by multi-agent systems estimates will be inexact for a number of reasons, including interaction faults, general uncertainty and environmental change. These unavoidable characteristics of the multi-agent scenarios will necessarily limit the efficiency with which coordination can be achieved. For illustrative reasons, let us to consider an agreement between a cooperative group of two supervisor agents, such that, $Gsa = \{sa_1, sa_2\}$, supervising the scenes s_1 and s_2 respectively, aiming at performing a set of actions to a cooperative group of three physical agents, such that, $Gpa = \{pa_1, pa_2, pa_3\}$, to solve a complex problem as is depicted in (Fig. 4.17). To follow, the scheme of the coordinated task algorithm is concisely explained.

Definition - The sa_1 sends to sa_2 its higher goals (based on the priority indexes of its goals). Then, the sa_2 analyzes the information dispatched by sa_1 and evaluates this proposal (comparing the priority of its goals with the information provided by sa_1). In case that sa_2 has a higher goal than sa_1, sa_2 informs a new proposal for sa_1. So, sa_1 analyzes and evaluates this proposal. This process assumes that sa_1 agree that sa_2 will selected. In this sense, sa_1 informs its decision to sa_2 and sa_2 continues with the decision algorithm.

Proposition – Once the sa_2 knows it is the elected supervisor, it must analyses which tasks must execute. sa_2 schedules their involved tasks according with the priority of each task. So, the tasks in each scene are scheduled. In this sense, each task involves several roles for its fulfilment. Therefore, sa_2 uses the priority of the roles to schedule the execution of them. Once, sa_2 defines the roles must be executed, informs this items (i.e., the roles) in order of relevance, to the group of physical agents.

Decision – Here, it is assumed that each physical agent can self-calculates its suitability rate for every one of the informed roles of which it can play in the current scene. With the suitability rates, each physical agent is able to generate its knowledge bases, it means, the physical agents can internally establish, in a decreasing order, the roles they can play. In this sense, a physical agent could be capable execute more than one role, but it only execute those roles for which it is the most suitable physical agent. To the end, using the information of their knowledge bases, each physical agent informs to the other *physicals*, the suitability rates for the roles it can plays. So, each *physical* evaluates who is the most suitable agent to execute each role.

Agreement – When the *physicals* have agreed which role will play each one, each physical agent informs to the supervisor sa_2 of the current scene s_2 which role has to execute. In addition, the *physical* that cannot execute any role in the current scene must also inform such event. So, the sa_2 can communicate that there are some physical available to the remaining supervisor sa_1. So, sa_1 must begin the process to inform the involved roles for its supervised scene s_1.

Execution & Supervision – The *physicals* that has agreed to play a role, must execute such role. At the same time, while physical agents execute the adopted role, the supervisor of the scene must supervise to evaluate if each physical agent has execute in a positive way the selected role.

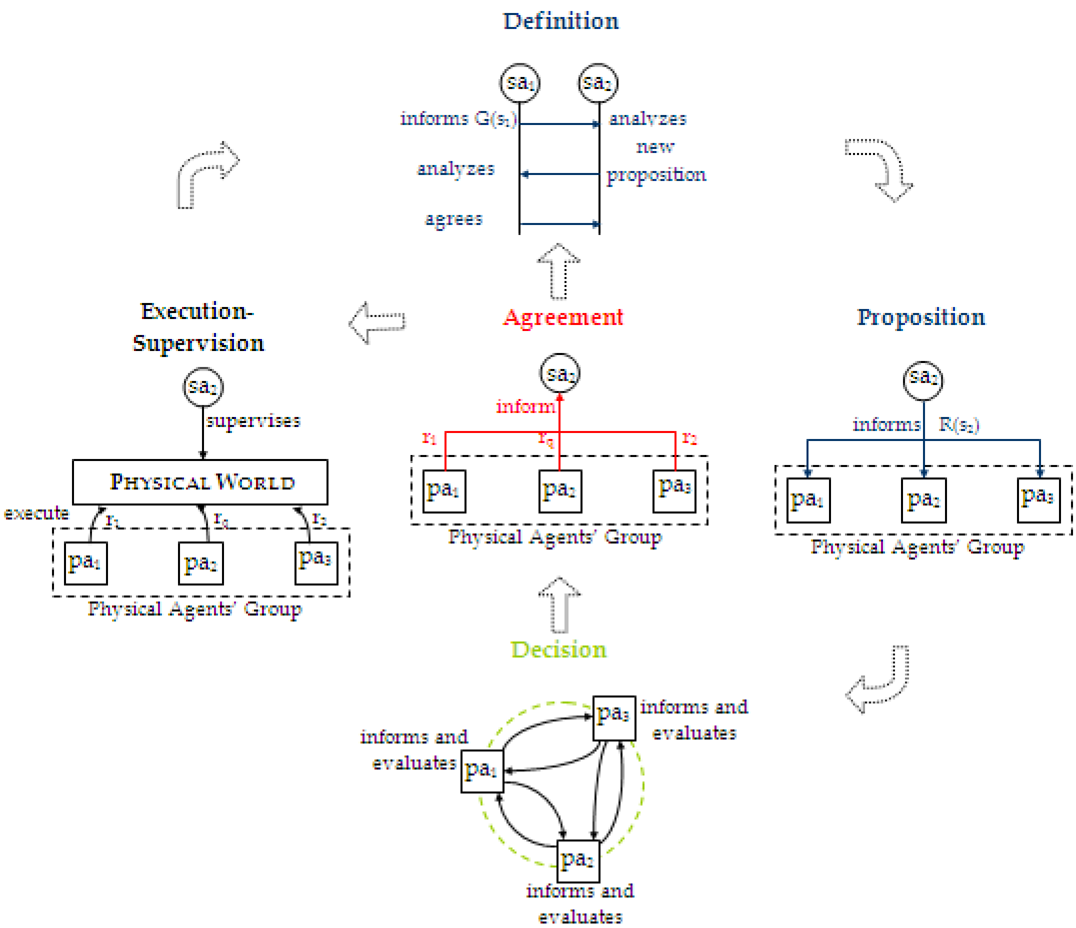

Fig. 4.17. General Scheme of the coordinated task solving-problem algorithm.

4.7.2 Task Allocation problem-solving Algorithm

Multiple tasks allocation is nowadays, one of the problems more studied by the researches focused on cooperative multi-agent systems [Tang and Parker, 07], [Gerkey and Matarić, 03], [Krothapalli, 03], [Matarić et al., 03]. Such approaches mainly are based on utility/cost functions to achieve simple task allocation using domain knowledge in the agents' decision-making. In this sense, such approach lacks of an appropriate reasoning on others agents' sources that define more detailed the *agents'* *situation*. So, a group of agents must analyse their capabilities and knowledge to decide if they are able to perform the proposed action. In fact, agent must communicate such self-analysis to other agents in order to achieve a collective agreement to work jointly in the development of a collective task. To facilitate such process, the decision process executed by the agents for the execution of a particular set of action in a task allocation scenario is performed as is described in (Fig. 4.18). For instance, let us to consider a cooperative group of two supervisor agents, such that, $Gsa = \{sa_1, sa_2\}$ aiming at allocating an amount of action to a cooperative group of three physical agents $Gpa = \{pa_1, pa_2, pa_3\}$, to solve a cooperative problem.

Definition - The sa_1 sends to sa_2 its higher goals (based on the priority indexes of its goals). Then, the sa_2 analyzes the information dispatched by sa_1 and evaluates this proposal (comparing the priority of its goals with the information provided by sa_1). In case that sa_2 has a higher goal than sa_1, sa_2 informs a new proposal for sa_1. So, sa_1 analyzes and evaluates this proposal. This process assumes that sa_1 agree that sa_2 will selected. In this sense, sa_1 informs its decision to sa_2 and sa_2 continues with the decision algorithm.

Proposition – Once the sa_2 knows it is the elected supervisor, it must analyses which tasks must execute. sa_2 schedules their involved tasks according with the priority of each task. So, the tasks in each scene are scheduled. In this sense, each task involves several roles for its fulfilment. Therefore, sa_2 uses the priority of the roles to schedule the execution of them. Once, sa_2 defines the roles must be executed, sends a request for the each physical agent, of the group of physical agents, in order to obtain the suitability rates of each physical agent to execute each role.

Answer – Here, it is assumed that each physical agent can self-calculates its suitability rate for every one of the requested roles of which it can play in the current scene. With the suitability rates, each physical agent is able to generate its knowledge bases, it means, the physical agents can internally establish, in a decreasing order, the roles they can play. In this sense, a physical agent could be capable execute more than one role, but it only execute those roles for which it is the most suitable physical agents. To the end, the physical agents inform this information to the supervisor of the scene.

Decision – Analyzing the information provided by the physical agents, the **supervisor** can evaluate and choose who physical agents is the most capable to execute each role. Such chooses are performed allocating the roles for the physical agent with higher suitability rate for each role.

Agreement – Insomuch as the supervisor has chosen, it must to inform the allocated role for each selected physical agent. On the other hand, the supervisor also must inform to the *physical* that cannot execute any role in scene under its supervision. In this sense, such physical agents must to inform to the remaining supervisor sa_1 that some physical agents are available to interact with it. So, sa_1 must begin the process to inform the involved roles for its supervised scene s_1 (proposition).

Execution & Supervision – The *physicals* that has agreed to play a role, must execute such role. At the same time, while physical agents execute the adopted role, the supervisor of the scene must supervise to evaluate if each physical agent has execute in a positive its role.

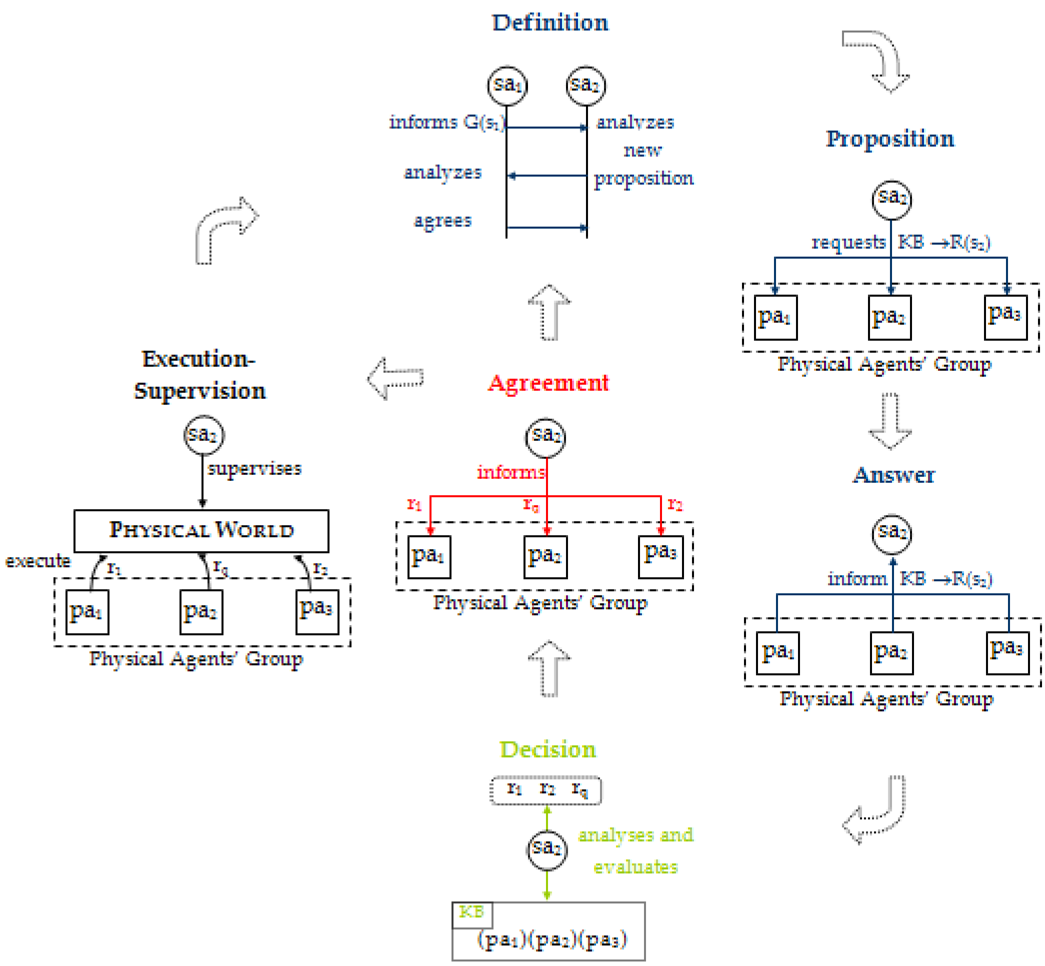

Fig. 4.18. General Scheme of the task allocation solving-problem algorithm.

4.8 Final Remarks

This chapter has been focused on the basic questions argued in this thesis to embrace the formalization of a framework to decision support for situated agents (see Fig. 4.19). Such formalization undertakes cooperation, to solve complex problems in dynamics and competitive environments, using the adaptation of the *e-Institution* methodology. The formal notions discussed in this chapter aims to formalize a decision support that empower autonomous agent to achieve cooperative behavior over temporal meeting (i.e., scenes) in typically dynamic and cooperative environments. In this light, the thesis argues the need for a formal representation of the ***agents' situation*** for physically situated agents (i.e., *physical agents or robots*) based on the information provided by the three ***decision axes***. In this sense, the thesis claims the relevance of the knowledge introduced in the ***decision axes*** for the correct fulfilment both individual and cooperative decision between groups of agents. Here, such axes have been related to embody the situation of the physical agents in order to provide them with the needed and useful knowledge to solve any proposed action. Therefore, environmental conditions (*world*), physical knowledge (*awareness*) and trust value (*interaction*) arise as a new paradigm to lead intelligent agent system in direction of reaching sure and trustworthy collective commitments, to prevent and to avoid undesirable situation, which could reflect in a lower overall system performance.

To make safer decisions, each physical agent must base its decision (both individual as collective) mainly in the knowledge of its ***situation*** related to the proposed actions. For this, each physical agent has its knowledge base, which means all the information which embodies it in a physical real environment. Therefore, physical agents can behave intelligently when they interact with other agents or humans. In this light, intelligence is understood as the appropriate exploitation of the knowledge about its *situation* involved in the execution of any proposed action, to perform better commitments and to enhance the performance and autonomy levels in multi-agent systems.

The chapter also considers an adaptation based on ***e-Institutions*** to state the manner in which agents with different aptitudes and capabilities can interact in a better way, increasing the performance of systems composed by diverse kind of agents. Likewise, the supervisor agent introduced by [Stone, 00] is, here, defined a software entity capable to perceive the intentions of a real environment and able to supervise the execution of such intentions both in coordinated approaches (where it is only an observer and communicator of the expected action) as in allocated approaches (where it has the ability to interact with physical entities in order to allocate the expected actions to increase the cooperative performance of any multi-agent systems placed on real environments). In this case, agents can at any time switch (i.e., choose) between different actions based on the external embodiment of their *situation* (based on the elements of the decision axes) and the requirement and constraints proposed for the execution of any determined action. Thus, it is reached by means of a "match" which allows agents compare critically their actions' capability rate for the execution of any action and the requirements and conditions under which action must be executed.

Coordination is then, the result of the different agents performing actions corresponding to their proposed role. Indeed, the role assignment also defines the coordination structure. So, the formalism presented in this dissertation is based on the ***agents' situation*** which defines the information of the ***decision axes*** that specify the needed kind of knowledge for a specific proposed cooperative and complex problem. This makes it helps to fulfil the aims of cooperative systems and also be a contribution to agent-based computing theory and practice. To the end, the following chapter presents the experimental phases, in which the main issues introduced in this dissertation has been implemented.

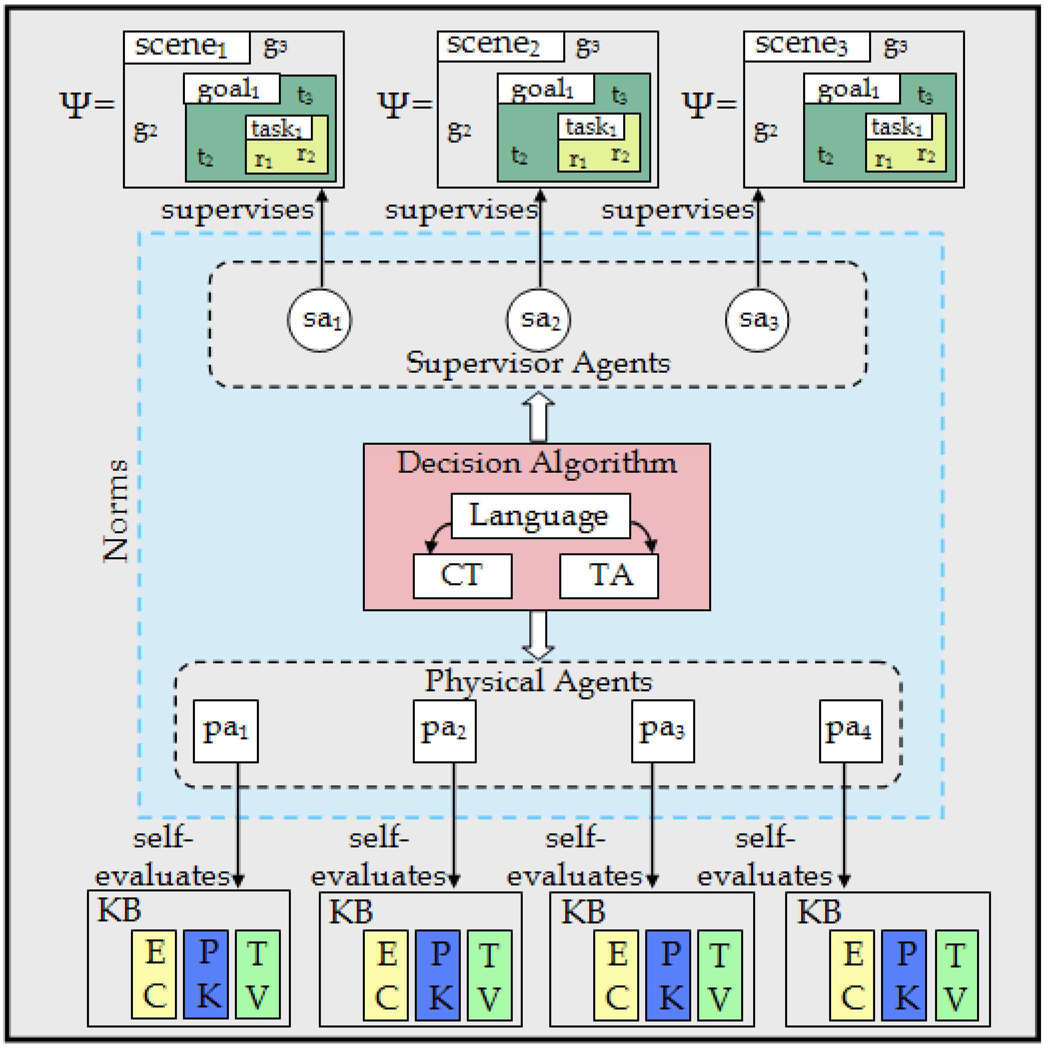

Fig. 4.19. General scheme of the Framework for Situated Agents

Chapter 5

Implementation and Results

This chapter is devoted to the application of the proposed approach on coordinated environments. It describes how multi-agent systems can work jointly to solve complex problems by mean of coordinated actions and task allocation on the robot soccer test bed. Specifically, these cooperative scenarios have been used as test bed to solve situations such as: the execution of dynamic actions and team-work problems. Finally, the chapter presents the empirical experiments and testing that have been carried out for the proposed test bed. The results depicted in this chapter demonstrate and corroborate the utility, feasibility and reliability of the overall proposed approach presented in the previous chapter.

5.1 The Test Bed

Autonomous, cooperating mobile robots represent multi-agent systems. The robot soccer test bed is a challenge for autonomous mobile cooperating robots [Burkhard et al., 02]. This test bed is a rich domain for the study of topics related to multi-agent systems [Kim and Vadakkepat, 00]. Robot soccer has many features found in a real world system such as complexity, dynamism, uncertainty and goal variability, together with both cooperating and competing robots [Oller et al., 97]. In addition, working with robot soccer is a great opportunity to deal with a lot of different kinds of technical subject areas. It is possible to deal with every technology, which is necessary for an autonomous system [Novak, 02]. The emergence of robot soccer competitions as *RoboCup* (http://www.robocup.org/) and *FIRA* (http://www.fira.net/) is then an interesting trend that agents' researchers have explored for developing new approaches. In this case, stronger links with the *AI* community should be explored, because that community is currently at the forefront of many of these applications [Murray et al., 03]. In particular, the agent paradigm is commonly proposed as a solution to controlling a robot community [De la Rosa et al., 97] [Rocher and Duhaut, 98]. The global behavior problem of a robot soccer team provides the opportunity to apply agent theory because of the distributed architecture of the mobile robots. The problem itself implies coordination, competition and cooperation by means of communication between the robot soccer players. Specifically, the multi-agent cooperative algorithm, in such active environment, must then comprise a low level kinematics and dynamics and high level decision-making. Robot soccer has been used as the main test bed for these reasons. Robots employed in disaster control and response operations, household activities, traffic control and industrial operations can profit from the results gained by researching and enhancing the game of these small mobile robots. In order to validate the decision support for situated agents presented throughout this research work, the thesis continue with the presentation of a set of implementation both in simulate as in real robot soccer scenarios.

5.2 Robot Soccer for Situated Agents

Robot soccer arises as initiative to generate and to enhance the research in the artificial intelligence and robotic areas [Mackworth et al., 95], turning this in a common challenge that allows to study and to develop new technologies [Kim and Vadakkepat, 00] with a performance at human level. Several authors [Johnson et al., 98], [Stone and Veloso, 00], [Kim and Vadakkepat, 00] affirm the idea that robot soccer test bed is a good benchmark for the study and implementation of artificial intelligence techniques, reinforcing the usefulness of the agent decision-making paradigm as a good tool to increase the correct execution of the actions within dynamic, unpredictable and competitive scenarios. In particular, this thesis argues that robot soccer is a powerful experimental environment for the evaluation and corroboration of its proposed aims. Aside, although the robot soccer is considered as a simple game, seemingly a toy-example; many real complexities are preserved from the comparative with the human soccer. In this light, a key aspect in the mentioned complexity refers to the need that agents should not only consider their physical body to execute one action, but also they should consider their environmental conditions and their interaction with other agents in order to execute the proposed action in a more suitable and reliable manner. Moreover, two cooperative scenarios from the robot soccer test bed have been selected to evaluate the proposed approach: coordinated tasks and task allocation.

Here, a coordinated task is focused to the process which allows to a group of agents agree among them to perform a defined set of action. On the other hand, a task allocation refers the process which a supervisor agent decides who is the most suitable physical agent to perform a proposed action. In this sense, these presented scenarios try to demonstrate the feasibility and utility of the proposed decision support for situated agents to perform the exposed actions in collaborative environment at different levels of cooperation.

5.2.1 Simulated Robot Soccer

A simulated environment has been selected as a test bed to evaluate and to corroborate the usefulness of the framework proposed in this dissertation. A simulated robot soccer game is a scenario where agents must interact and cooperate to achieve the expected system performance. In this light, the *simuroSOT* has been used to apply the main ideas of the formalization for multi-agent systems here proposed (see Fig. 5.1). Such simulator facilitates extensive training and testing for the proposal of this dissertation. Generally speaking, the *simuroSOT*[3] simulates soccer games where players (i.e., agents) must interact between them in order to reach the systems' goals. So, this simulator allows working with two teams constituted by five (5) physical agents (where one of them is the goalkeeper) which play in a simulated field along only one time of five minutes. The agents are currently represented by squares with a simple kicking device. *SimuroSot* also consists of a server which has the soccer game environments (playground, robots, score board, etc.) and two client programs with the game strategies. A 3D color graphic screen displays the match. Teams can make their own strategies and compete with each other without hardware. The 3D simulation platform for 5 vs. 5 and 11 vs. 11 games are available at FIRA[4] web site.

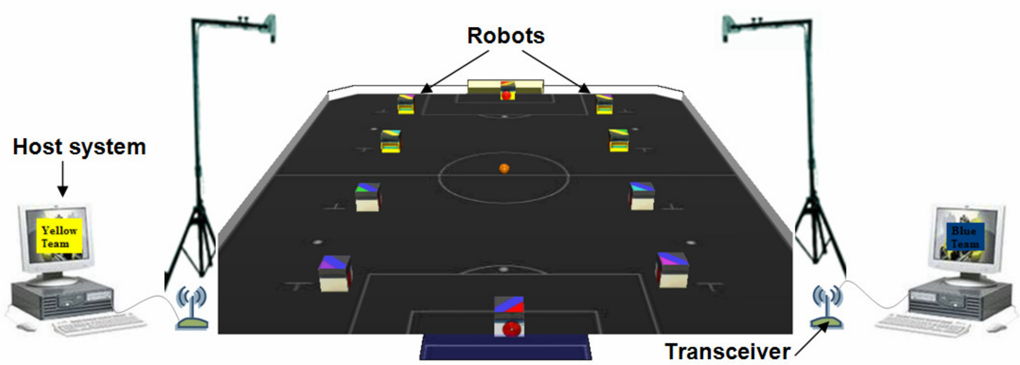

Fig. 5.1. Overall robot soccer system.

[3] http://www.fira.net/soccer/simurosot/overview.html
[4] http://www.fira.net/

5.2.2 Simulated Features for Soccer Implementation

The features for the simulated soccer tournaments are here described as follow: a group of three supervisor agents, such that, $Gsa = \{sa_1, sa_2, sa_3\}$ and a group of five physical agents, such that, $Gpa = \{pa_1, pa_2, pa_3, pa_4, pa_5\}$ are involved in the cooperative actions related to game a set of soccer matches. In this sense, each physical agent has an obstacle-free movement trajectory controller to move them in the environment. In addition, the supervisor agents must identify the spatial region that will supervise in the soccer environment. To the end, there are three (3) scenes, such that, $S = \{s_1$=attack; s_2=midfield; s_3=defense$\}$ which represent the zones in such environment as it shows in Fig. 5.2.

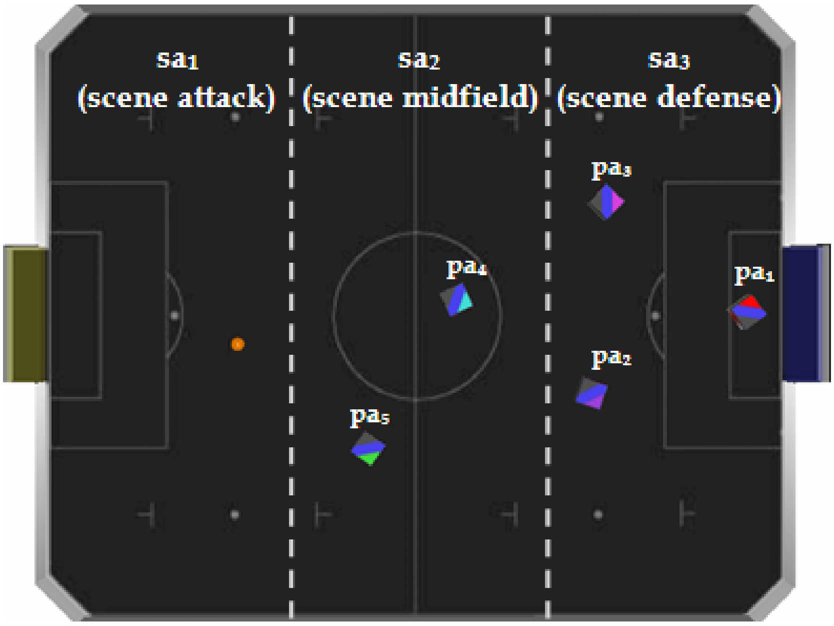

Fig. 5.2. Supervisor Agents, Scenes and Physical Agents in the simulated robot soccer scenario.

Here, a scene refers to any spatial region in the soccer field, supervised by a supervisor agent, where a group of physical agents must meet and must work jointly to execute a set of actions pre-defined in such scene. Therefore, a scene is established "active" when the current ball position is into the region assigned to this scene. For sake of simplicity, the main role that each physical agent must play in each scene is to kick the ball; however, other relevant roles will be defined more ahead in detail. To mention, the global goal in a robot soccer games is scoring the major amount of goals to win the match. The remaining actions are related to other specific targets (e.g., to move the ball towards the opposite goal; to defend their own goal, etc). In this sense, the defined supervisor agents must agree between them to establish the sequence in which they will solve the actions involved in their scenes. So, each *supervisor* is able to provide information to the physical agents, about the requirements involved in the scene under its supervision. Besides, the physical agents must coordinate between them by using several coordination parameters in their decision-making to agree among them, who is the most suitable *physical* to execute the most prior action based on the established strategy for the current scene. In addition, the physical agents that cannot execute any action in this scene must inform to the remaining *supervisors,* that they are available to play roles in their scenes. For illustrative reasons, in Fig. 5.3 shows an example of this simulated case study for the achievement of the "*kick the ball*" action.

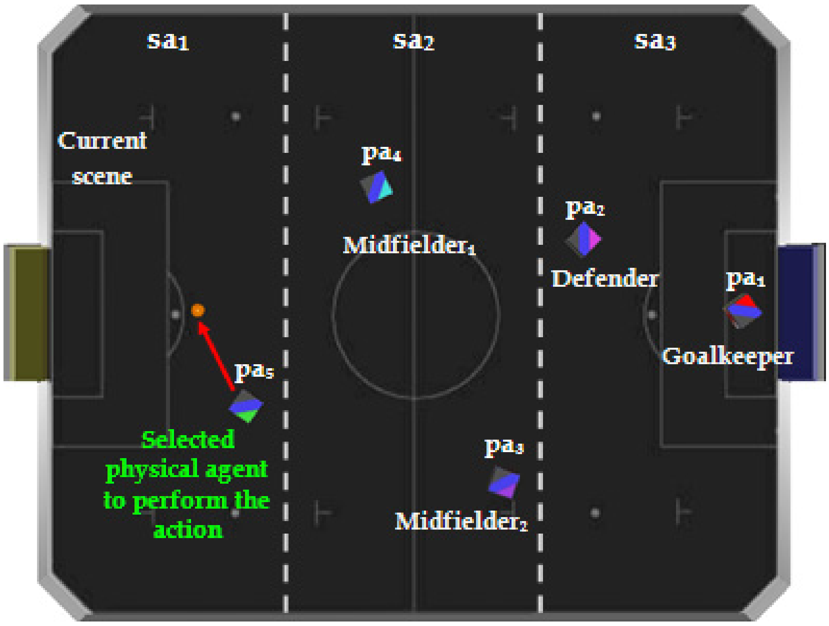

Fig. 5.3.Example of the execution of a cooperative action in the simulated robot soccer.

5.2.2.1 Scenario 1: Coordinated Task

Using the simulated features presented in Section 5.2.2 the coordinated task experiments are then developed using the coordinated task solving-problem algorithm (see Section 4.7.1) as is described in (Fig. 5.4). The first step in the execution of a coordinated task is when each supervisor agent, from the supervision agents' group, observes and analyzes the scene that it must supervise trying to get all the involved scene's issues (i.e., the supervisor agent's knowledge base) (see Fig. 5.4a). Thereby, each supervisor agent is able to generate its knowledge base, where additionally, each issue (i.e., the goals, the tasks and the roles) has assigned a priority index which defines the relevance in the execution of such issue. It means the sequence in which the supervisor agent solves the actions in the scene. Moreover, the group of *supervisor* must follow the stated norms to establish which supervisor has the more priority action (definition). In this sense, only a *supervisor* must be selected at the time, to begin the communication process with the group of physical agents in order to inform them the set of actions required for the current scene (see Fig. 5.4b). In this light, the selected supervisor agent only informs the roles (attending the priority indexes of every role); in order to advice to the physical agents the actions that must be performed and the sequence of them. In addition, the selected *supervisor* must inform (proposition) to each physical agent the result of its previous interaction. This information allows physical agent takes into account its relation with the supervisor, at the moment to generate its knowledge base and suitability rates for the roles proposed by such supervisor. To the end, the *supervisor* also informs the influence that each parameter from the decision axes, has over each role.

Once the *supervisor* advices such information, each physical agent from the physical agents' group is capable to generate its knowledge base to evaluate (i.e., to calculate the match) its situation related to the roles proposed by the *supervisor* agent in the *scene* that it supervise. So, each physical agent calculates and evaluates its suitability rates for all the proposed roles that it can play in the current scene. This fact allows physical agents to esteem if they have a chance or not to execute any action within the current scene. Such information is then represented as the ***situation*** of each agent meaning its suitability rate for the execution of the roles, and using these knowledge the physical agents can agree among them in order to decide which agent is the most suitable to execute each role (decision) within the hotness scene (see Fig. 5.4c). This process is carried out by using the communication process. So, each physical agent informs to the other *physicals* which roles can play and its suitability rate to perform each one of the mentioned roles. In this sense, each *physical* can discriminate among the roles that it cannot play in a suitable way. For thus, the physical agents can dispose what action perform each physical agent without the implicit intervention of the supervisor agent in the roles' selection process. To the end, the *physicals* must inform to the supervisor in-charge, which role will play each one. Besides, if some physical agent cannot do any role (due to a low estimation of their suitability rates for the proposed roles) in the current scene must to inform this to the active supervisor (agreement). In addition, such supervisor must inform to the other supervisors that there are some physical agents available to work in their scenes (see Fig. 5.4d). In this sense, the remaining *supervisors* must begin the process of the coordinated algorithm. To follow, each physical executes its selected role. Besides, the *supervisor* of the scene must supervise the performance of such role to validate if the tasks (and the goals) were fulfilment in a good way. Likewise, the *supervisor* must update its relation with the *physicals* that have work in its scene.

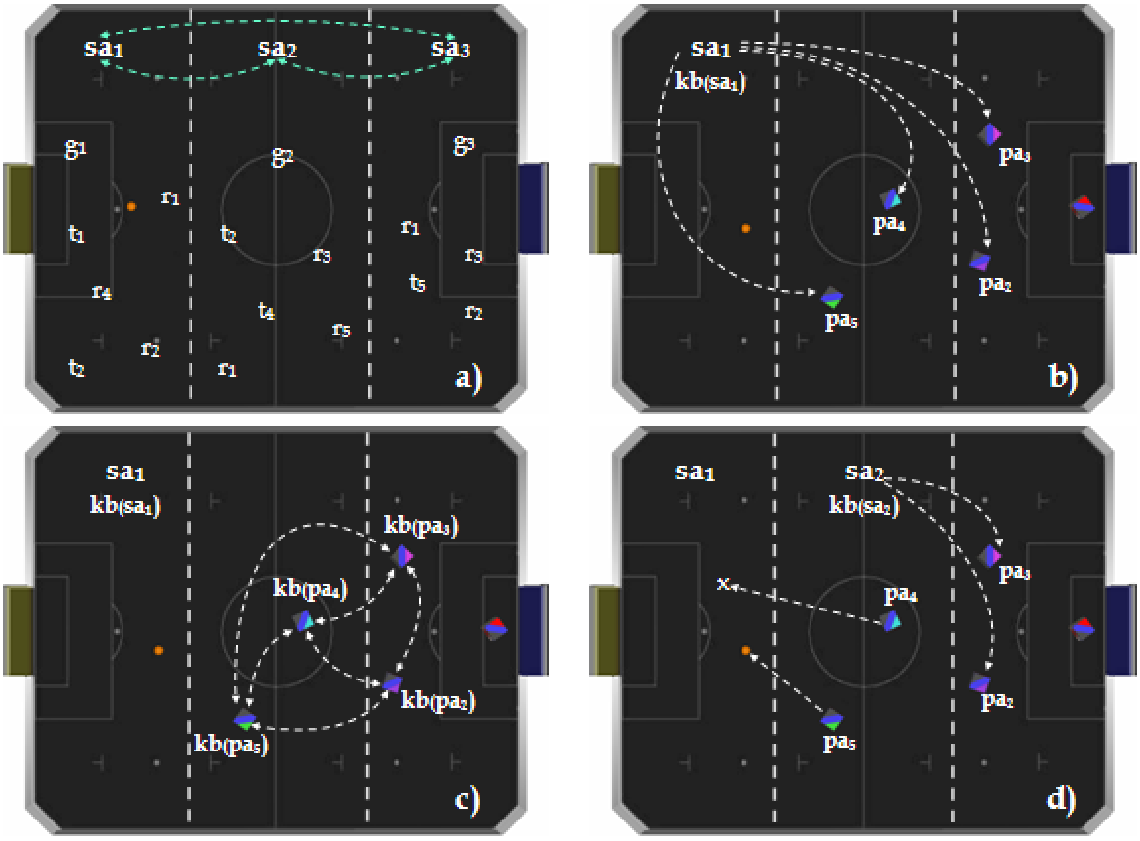

Fig. 5.4. General scheme of the execution of a set of coordinated tasks – simuroSOT.

5.2.2.2 Scenario 2: Task Allocation

The simulated features introduced in Section 5.2.2 have been used to face a task allocation experimental phase as is described in (Fig. 5.5) using the task allocation solving-problem algorithm described in Section 4.7.2. So, at the beginning of the execution, and similarly to the coordinated task algorithm, each supervisor agent, from the supervision agents' group, observes and analyzes the scene that it must supervise trying to get all the involved scene's issues (i.e., the supervisor agent's knowledge base) (see Fig. 5.5a). Each supervisor agent then generates its knowledge base, where additionally, each issue (i.e., the goals, the tasks and the roles) has assigned a priority index which defines the relevance of the execution of such issue. It means the sequence in that the supervisor agents solve the actions in the scene. Hereby, the group of supervisor agents must follow the stated norms to establish which supervisor has the more priority action (definition). In this light, only a supervisor must be selected at the time (see Fig. 5.5a), to begin the interaction with the group of physical agents in order to claim them their suitability rates for the set of roles involved in the current scene (see Fig. 5.5b). In this light, the selected supervisor agent only informs the roles (attending the priority indexes of the set of roles) in order to request the suitability rates of the physical agents to perform these particular roles (proposition). In addition, the selected *supervisor* must inform to each physical agent the result of its previous interaction. This information allows to each physical agent takes into account its relation with the supervisor, at the moment to generate its knowledge base and suitability rates for the roles proposed by such supervisor. To the end, the supervisor also informs the influence that each parameter from the decision axes, has over each role.

Once the supervisor advices such information, each physical agent from the physical agent group is capable to perform a self-analysis to generate its knowledge base (i.e., to calculate the match) its situation related to the roles proposed by the *supervisor* agent in the *scene* that it supervise. So, each physical agent calculates and knows its suitability rates for all the proposed roles that it can play in the current scene. This fact allows physical agents to esteem if they have a chance or not to execute any action within the current scene. Such information is then represented as the ***situation*** of each *physical* meaning its knowledge base. Unlike to the coordinated task process, in task allocation process the physical agents cannot self-select their actions. In this sense, physical agents must inform to the supervisor agent (answer) their suitability rates for the proposed roles (see Fig. 5.5c). So, each physical agent informs to the supervisor agent which roles can play and its suitability rate to perform each one of the mentioned roles. In this sense, each *physical* can discriminate among the roles that it cannot play in a suitable way.

Using the above information, the *supervisor* can decides and choose the most suitable *physical* to plays each role comparing the suitability rates of these agents for the same role in the *scene* under its supervision (decision). After it, the supervisor agent decides and allocates the roles for the better physical agents and informs to the remaining physical agents that they are no qualified (due to a low estimation of their suitability rates for the proposed roles) to execute any role in its scene (agreement). This process is carried out by the supervisor agents until finishing with the roles or that the physical agents with an appropriate suitability rate will not enough. To the end, the current supervisor must inform to the other supervisors that there are physical agents available to work in their scenes. In this sense, the remaining *supervisors* must begin the process of the allocated algorithm. To follow, each physical executes its allocated role. Besides, the *supervisor* of the scene must supervise the performance of such role to validate if the tasks (and the goals) were fulfilment in a good way. Likewise, the *supervisor* must update its relation with the *physicals* that have work in its scene.

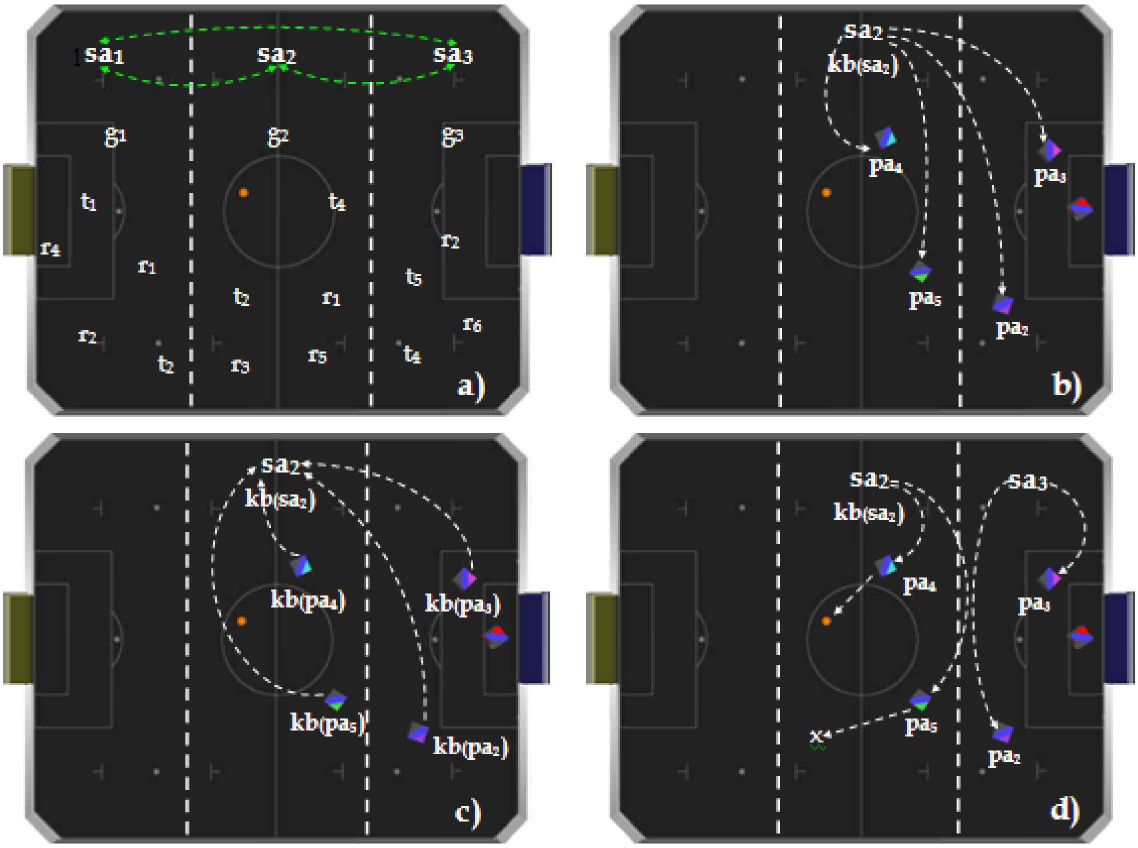

Fig. 5.5. General scheme of the execution of a set of task allocation – simuroSOT.

5.2.3 Simulated Features for the Passing a ball

The features of the passing a ball experiments are here described as follows: one supervisor agent (sa_1) and four physical agents, such that one of they must be the *passer* and three shooters, such that, $G_{shooter}$ = {$shooter_1$, $shooter_2$, $shooter_3$} are involved in the passing a ball task. Each physical agent has an obstacle-free movement trajectory controller to move in the environment. The supervisor agent must supervise the area of the zone where the passing a ball task will be performed. In this sense, there is only one (1) pre-defined scene, such that, S = {s_1: to do a pass}. In (Fig. 5.6) are showed the feature of the passing a ball task.

The passer must strike the ball towards the interception point (*ip*) in a suitable way. The shooters must intercept and shoot the ball with the intentions of scoring in the opposite goal. Thus, the shooters must coordinate them to execute the task successfully. Passing a ball is then represented as follow: the distance (d_{ball}) between the ball and the interception point (*ip*), the initial velocity of the ball (V_0) and the distance between each shooter (ds_1, ds_2, ds_3) and the *ip*. For sake of simplicity, the *passer* and the *shooters* are not moving at the beginning of the task. The *IP* is arbitrarily selected in a region near to the opposite goal. The V_0 determines the behavior of the ball and depends on the impact of the passer. Additionally, this task takes into account dynamic and non-holonomic constraints inherent to the physical agents' bodies, and movement constraints of the physical agents' control design. Time constraints are then considered because the environment's dynamics impose time limitations on passing a ball.

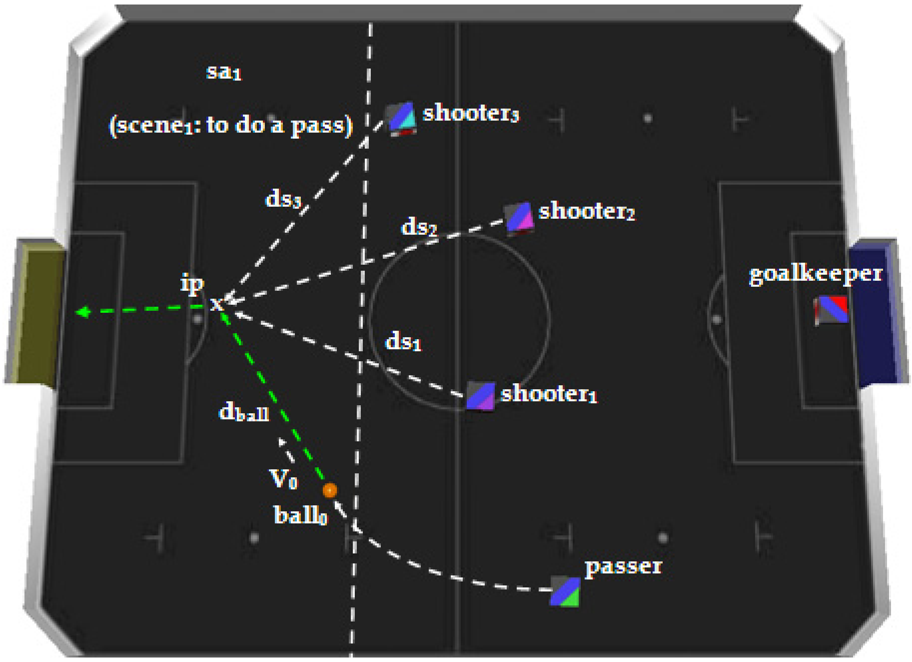

Fig. 5.6. General scheme of the simulated passing a ball features.

Here, the defined scene (i.e., *to do a pass*) refers to a spatial region on the opposite field where a group of physical agents must work jointly to execute the proposed actions (i.e., *passing the ball*) in a time *t* of the current scene s_1. In this sense, the *passer* strikes the ball towards the *ip* then; the *shooters* must self-calculate their suitability rate to try to kick the ball towards the opposite goal. Explicitly, only one *shooter* can try to perform the task, the remaining *shooters* do not any movement. In Fig. 5.7 is showed an example of a simulated case for the achievement of the "*passing the ball*" task.

For sake of simplicity, the strategy to execute the passing a ball task is is stated as follow:

$$G(s_{todoapass}) = \{g_1 = score\_in\_the\_opposite\_goal\}$$

$$T(g_1) = \{t_1 = passing\_the\_ball)$$

$$R(t_1) = \{r_1 = pass\_the\_ball, r_2 = kick\_the\_ball\}$$

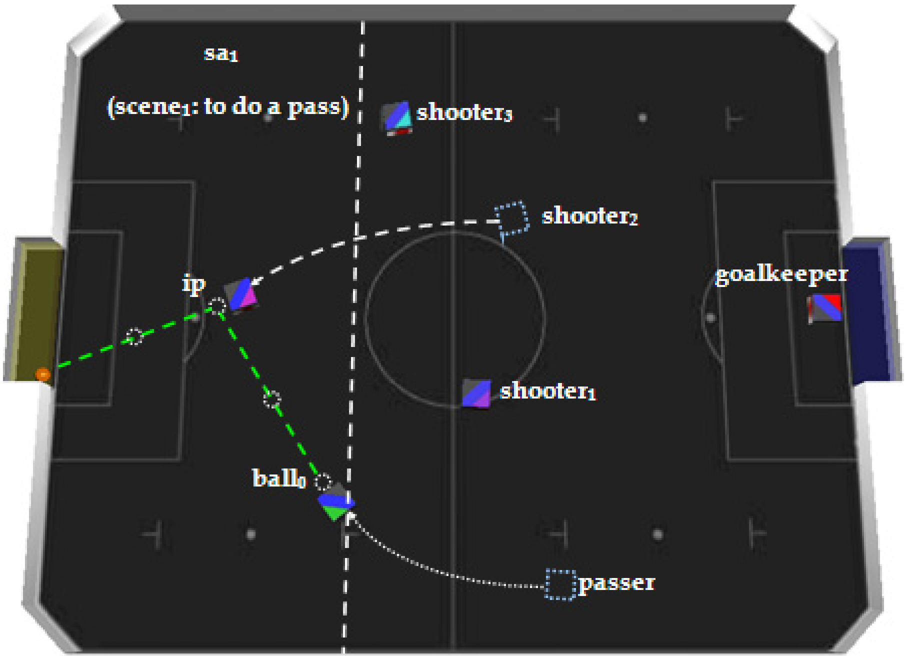

Fig. 5.7. Example of the execution of the passing a ball task in the simulated robot soccer.

To the end, the *passing a ball* execution both in the coordinated task as in task allocation scenarios is described as follow:

5.2.3.1 Scenario 1: Coordinated Tasks

Using the simulated features presented in Section 5.2.3 the coordinated task features performing the *passing a ball* are described in (Fig. 5.8). The *supervisor agent* must observe and analyze the scene that it must supervise trying to get all the involved scene's requirements (i.e., the supervisor agent's knowledge base) (see Fig. 5.8a). In this case, such requirements are the implicated events in the *passing a ball* problem, such that, the roles (e.g., *role*$_1$ and *role*$_2$) are defined to be executed in the established scheduling for the current scene. Therefore, the *supervisor* follows the stated norms to define what role has more priority, in this case, the events' scheduling to perform a pass between two physical agents. Then, the *supervisor* advices what physical agent will play the *role*$_1$ (see Fig. 5.8b). Likewise, the *passer* advices to the *shooters* group the *ip* and the *role*$_2$. Using the information provided by the passer, each *shooter* can self-calculate its *situation* (i.e., its suitability rate) to execute the proposed *role*$_2$. This fact allows *shooters* esteem if they have a chance or not to execute the proposed role in the current scene. Such information is then represented as the ***situation*** and, using this knowledge the *shooters* agree among them to choose which agent is the most suitable to play the proposed *role*$_2$ in hotness scene (see Fig. 5.8c), (i.e., to kick the ball towards the opposite goal). To the end, *shooters* have agreed who plays the *role*$_2$ (see Fig. 5.8d). In addition, the selected *shooter* informs to the supervisor that it plays the proposed *role*$_2$. So, the *shooters* can select the best *shooter* for this pass situation without the implicit intervention of the supervisor agent in the role selection process.

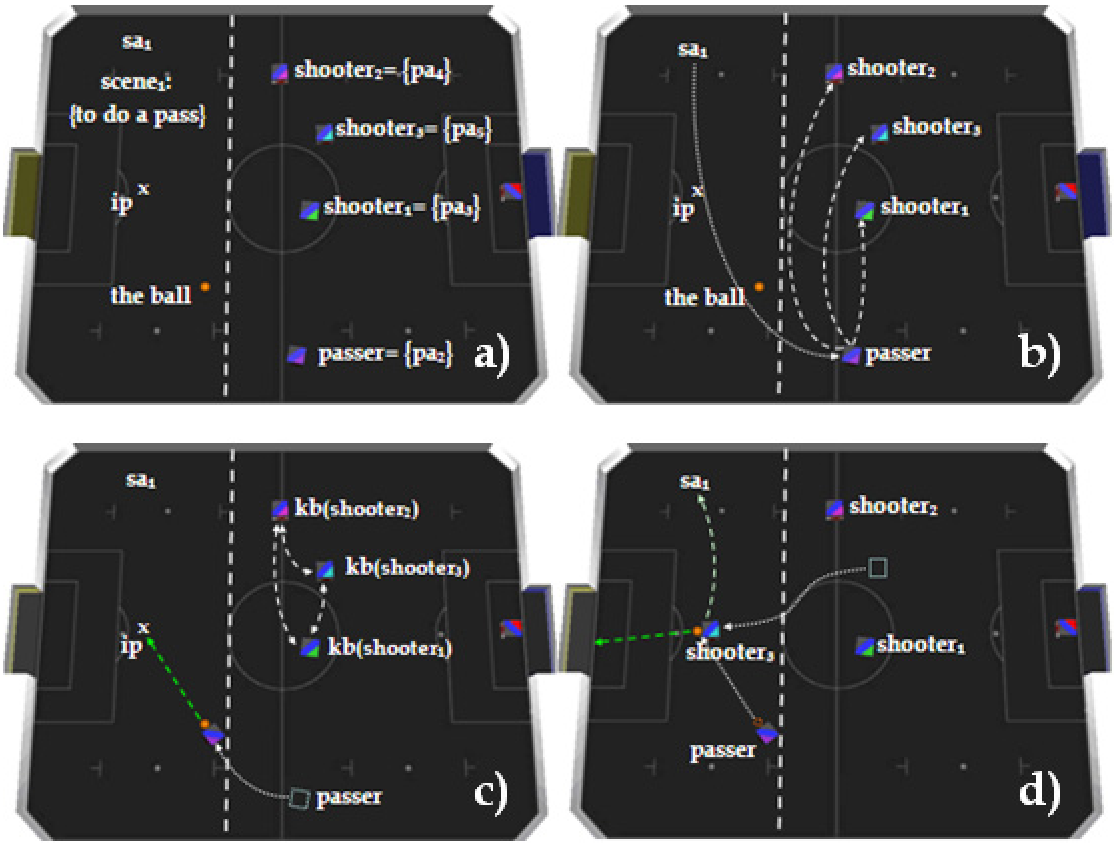

Fig. 5.8. General scheme of the passing a ball implementation as a Coordinated Task.

5.2.3.2 Scenario 2: Task Allocation

The simulated features introduced in Section 5.2.2 have been used to face a task allocation *passing a ball* experiment as is described in (Fig. 5.9). The *supervisor agent* observes and analyzes the scene that it must supervise trying to get all the involved scene's requirements (i.e., the supervisor agent's knowledge base) (see Fig. 5.9a). Such *supervisor* obtains then its knowledge base, where additionally; the roles (e.g., *role*$_1$ and *role*$_2$) are defined to be executed in an established scheduling for the current scene. To do this, the *supervisor* agent obeys the stated rules for the *passing a ball* task. Besides, the *supervisor* advices what physical agent will be the *passer*, in such case, the selected physical agent will plays the *role*$_1$ (see Fig. 5.9b). In this sense, the *passer* informs to the *supervisor* its *situation* to do the pass in a suitable way and then, the *supervisor* requests to the *shooters* their suitability rates to play the defined role$_2$. The *shooters* can self-calculate their suitability rates for the proposed *role*$_2$ and they inform this information to the *supervisor* (see Fig. 5.9c). So, the *supervisor* can choose the most suitable *shooter* to play the *role*$_2$. Once the *supervisor* chooses a *shooter*, it advices to the selected *shooter* that it must perform the proposed action (i.e., *kick_the_ball*). Finally, the selected *shooter* execute the action and the *supervisor* evaluates the result of the action (i.e., if the *shooter* scores in the opposite goal).

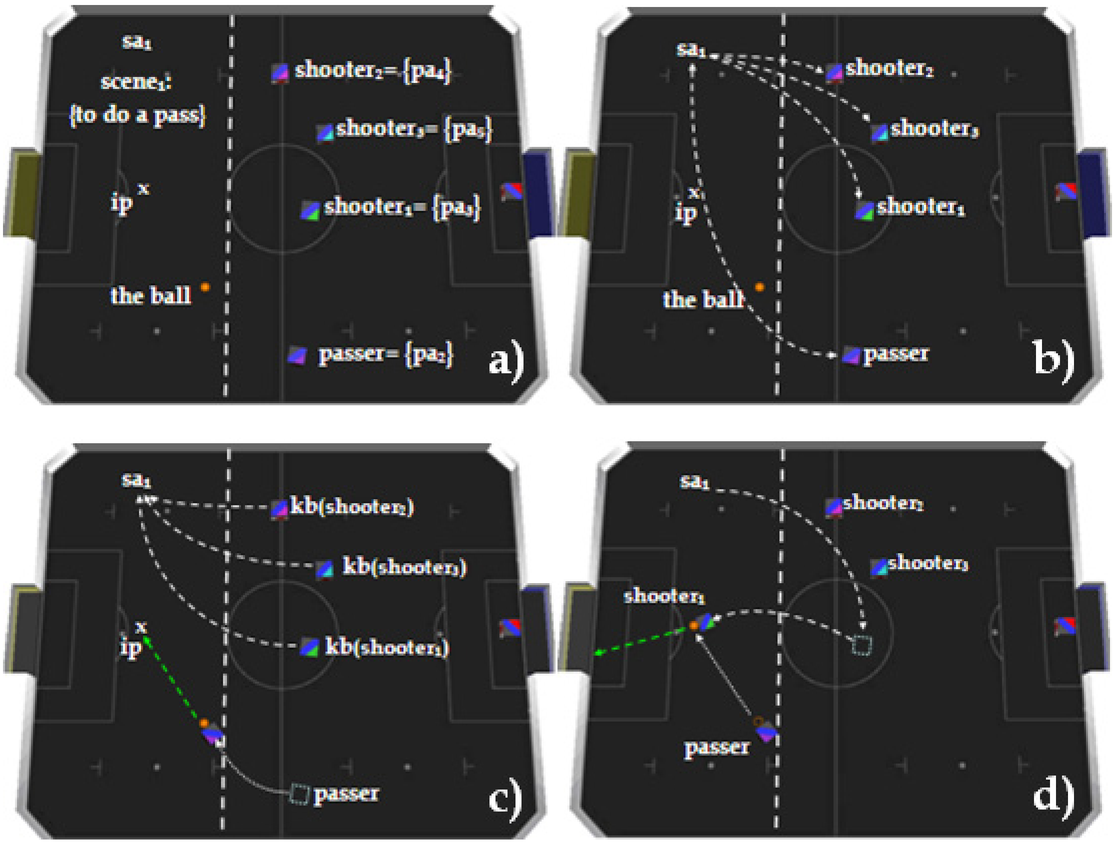

Fig. 5.9. General scheme of the passing a ball implementation as a Task Allocation.

5.2.4 Robot Soccer System

Robot soccer is a high-tech scientific sport. Following this philosophy, the *miroSOT*[5] arises as a multi-purpose testing ground for learning and application of high-tech technology field such as image analysis, artificial intelligence, sensors, communication, electronic precision control, dive motors as well as software and hardware. Since then and until now it has grown steadily as more and more young scientists participate. Basically, robots, a vision system, a host computer and a communication system are needed for a robot soccer game. A vision-based soccer robot system has been used as operating method implemented as a remote-brainless soccer robot system [Kim and Vadakkepat, 00]. Each robot has its own driving mechanism, communication board

[5] http://www.fira.net/soccer/mirosot/overview.html

and CPU board in the remote-brainless soccer robot system. The computacional part controls the robot's velocity according to the command data received from a host computer. All calculations on vision data processing, decision-making, strategies, position control of robots, are done in a host computer which controls the robots via radio communication. In robot soccer different kinds of system configurations exist.

Here, the *miroSOT* has been used to apply the main ideas of the formalization for cooperating multi-agent systems proposed in this dissertation. Such test bed facilitates the testing and implementation of the main ideas to execute cooperative actions aiming to improve the expected performance of multi-agent systems. So, in this experimental test bed (i.e., the middle league *miroSOT*) each team consists of five (5) robots, which they shall be limited to (*7.5cm*, *7.5cm and 7.5cm*). The playing field has the size of a table-tennis table which is about (*220cm*) in width and (*180cm*) in length. An orange golf ball shall be used as the ball, with (*42.7mm*) in diameter and (*46g*) in weight. A separate computer, which receives a global view of the field from an overhead camera, controls the different robots. Research areas which are important for this test bed include those of the *Middle Size League*, but because of the global control the focus is more on strategy development. Fig. 5.10 shows the team of real *MiroSOT* robots used in the experiments.

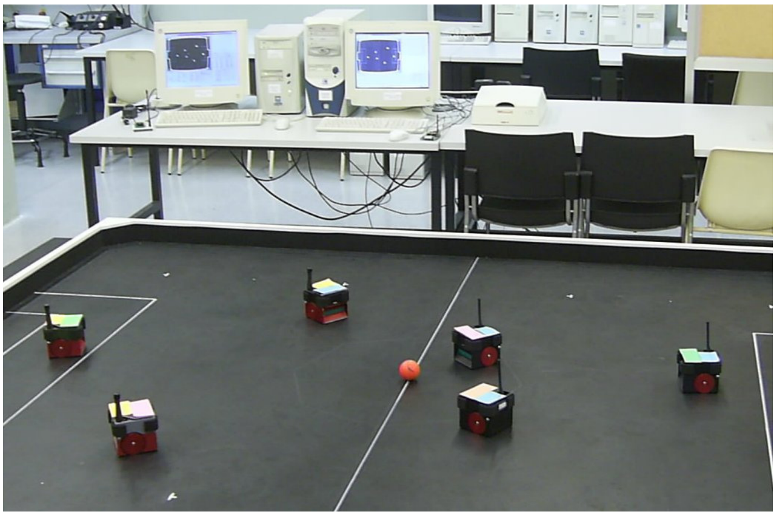

Fig. 5.10. Team of real MiroSOT robots.

5.2.4.1 Robot Modeling

The state *S(t)* of the MiroSOT robots can be established by any set of the following representations: (see Fig. 5.11).

$$S(t) = \{x, y, \theta, v_l, v_r\} \quad \text{or} \quad S(t) = \{x, y, \theta, v, w\} \quad \text{or} \quad S(t) = (x, y, \theta, v_x, v_y\}$$

The relation among the different representations is established from the following kinematics relations:

$$v_l = R\omega_l\,; \quad v_r = Rw_r$$

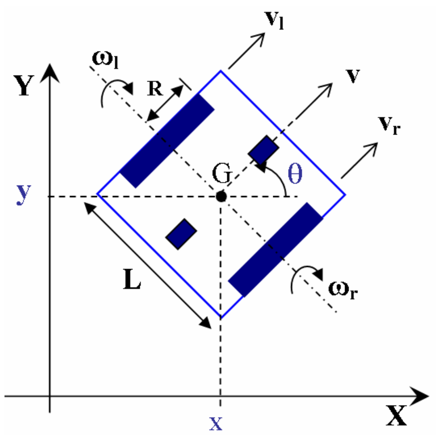

Fig. 5.11. Variables that describe the robots' state, L=7.5 cm, R=2.25 cm, G: geometric center.

Where v_l and v_r are the linear velocities of the wheels left and right respectively, ω_l and ω_r are the angular velocities of the wheels left and right respectively and *R* is the radius of the wheels. Also, it can be shown that:

$$v = \frac{v_l + v_r}{2} \quad \text{and} \quad \omega = \frac{v_l - v_r}{L}$$

Where v is the linear velocity of the mobile robot; ω is the robot's angular velocity and *L* is the distance between the wheels. The projections of the linear velocity on the *X* and *Y* axes are given by:

$$v_x = v\cos(\theta) \quad \text{and} \quad v_y = v\sin(\theta)$$

From the above relations is observed the need of controlling the linear velocities of each wheel (v_l , v_r) to be able of controlling the movement of the geometrical center of the robot (G) represented by means of the coordinates (x, y, θ).

A mobile robot is then a MIMO (Multi-Input Multi-Output) system and its control is typically too complex to be developed and operated when it must include the specifications of the system's response. These specifications must take into account the dynamical limitations and the non-holonomic features of the mobile robot and the geometric and kinematics properties of the movement path. In this sense, Equation (5.1) provides the robot model used.

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{2.3}{0.2833s+1} & 0 \\ 0 & \frac{2.07}{0.0687s+1} \end{bmatrix} \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{L} & -\frac{1}{L} \end{bmatrix} \begin{bmatrix} v_r \\ v_l \end{bmatrix} \quad (5.1)$$

Other higher order transfer functions, non-linearities and other variables will be analysed in future work.

5.2.4.2 Real Features

The real case study has several similarities with the above simulated features, such that: there is a group of three supervisor agents, such that, $Gsa = \{sa_1, sa_2, sa_3\}$ and a group of three physical agents, such that, $Gpa = \{pa_1, pa_2, pa_3\}$ to play a game against other team robot. Each supervisor agent is in charge to manage a zone (scene) on the field. In this sense, there are three (3) pre-defined scenes, such that, S = {s_1=attack; s_2=midfield; s_3=defense} that represent the zones in such environment as it shows in Fig. 5.12. In addition, each physical agent has an obstacle-free movement trajectory controller to move in the environment. For sake of simplicity, the main action for each physical agent in each scene is to kick the ball with the overall intention of scoring in the opposite goal to win the match. The remaining actions are related to other specific aims (e.g., move the ball towards the opposite goal; defend their own goal, etc) that form part of the game strategy. In addition, the information between the physical agents (i.e., the robots) is broadcast by using a frequency of *133 MHz* or *433 MHz* to communicate with the central host. In this sense, the supervisor agents must agree between them to establish how they will manage the overall intentions in order to provide physical agents with the information about the requirements involved in the scene under their supervision.

Besides, physical agents must coordinate between them by using several coordination parameters in their decision-making to select the most suitable agent for the main action according with the established strategy. The other reaming agents follow the same process to select their actions according with the conditions established for the current scene. Fig. 5.13 shows an example of this experimented case study for the achievement of the "*kick the ball*" action. Finally, the coordinated task and task allocation cases studies in the real robot soccer are using the same features introduced by the simulated robot soccer as is described in Sections 5.2.2.1 and 5.2.2.2 respectively.

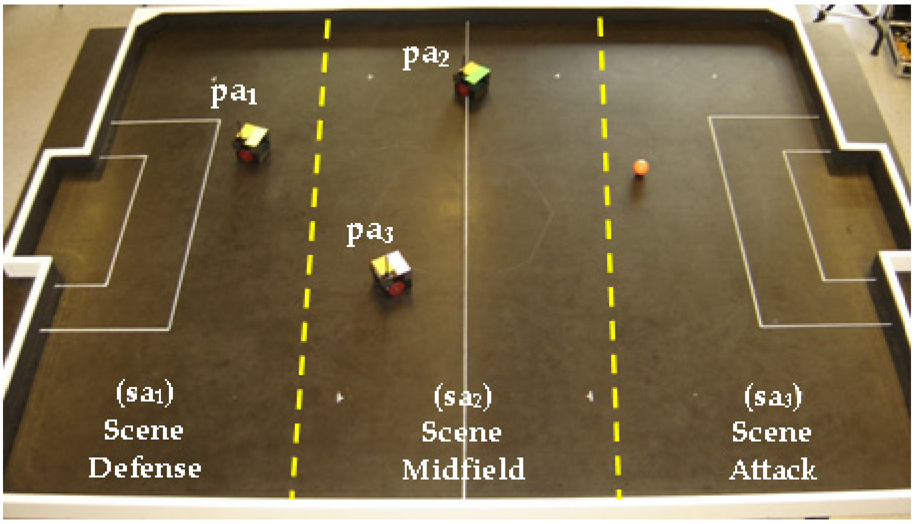

Fig. 5.12. Supervisor agents, physical agents and scenes in the real robot soccer scenario.

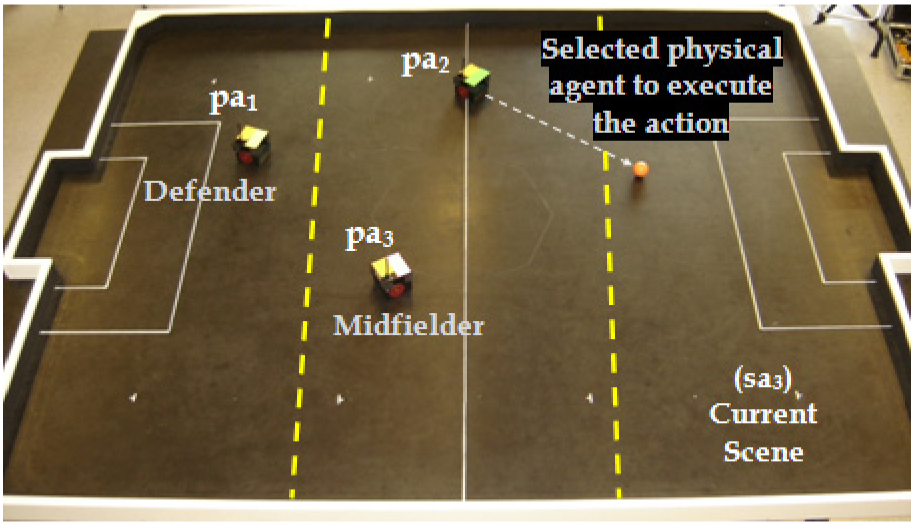

Fig. 5.13. Example of the execution of a cooperative action in the real robot soccer.

5.3 Implementations in Robot Soccer

In all the implementations, each physical agent has a movement controller to execute a proposed action. Thus, four different *PID* controllers (each one represents each physical agent' movement controller) have been designed using a set of suitable control laws to put into a practice the team of physical agents used in the experimental phases. In this light, each physical agent can be denoted by its behavior showed when they try to perform a trajectory, such that: pa_2 is "precise"; pa_3 is "disturbed"; pa_4 is "fast" and pa_5 is "fast and disturbed". Table 5.1 shows the dependence of each designed physical agent according to the four selected control design criteria. Thus,

speediness *refers to the velocity response of the physical agents to reach any desired target. Such criteria represent an indicator of the controlled system's response when it reaches the set point.*

precision *refers to the capability of the agents to achieve their goals with a minimal error. This represents the skills of the controlled systems to follow the changes of the set point.*

persistence *refers to the capability of the agents to follow the set point when there are external signals affecting the aims' value of the agents. The persistence is related to the capability of the controlled system to reject disturbances and maintain their performance at a suitable value.*

control effort *represents the energy consumes present in each physical agent when tries to achieve its goals.*

Table 5.1. Physical agents' criteria design dependence

(↑: great dependence; ↓: minor dependence)

	speediness	**precision**	**persistence**	**control effort**
pa_2	↓	↑	↑	↓
pa_3	↓	↓	↓	↑
pa_4	↑	↓	↑	↑
pa_5	↑	↓	↓	↑

Fig. 5.14 shows how in dependence of consider each criteria; it produces different dynamics in the free movements of the physical agent in the execution of the any proposed trajectory. The result of the actions' executions will be different; due to the physical agents have different control laws under the same environmental condition and actions requirements. Thus, it is possible to obtain a capability associated with the controller assigned for each physical agent. In fact, these capabilities describe the dynamic features of the system during the execution of the actions. For instance, Fig. 5.15 shows the spatial evolution of each physical agent under some specific movement constraints, such that: (initial position *ip* = (*10cm*, *10cm*, *0°*); set point *sp* = (*180cm*, *90cm*, *180°*).

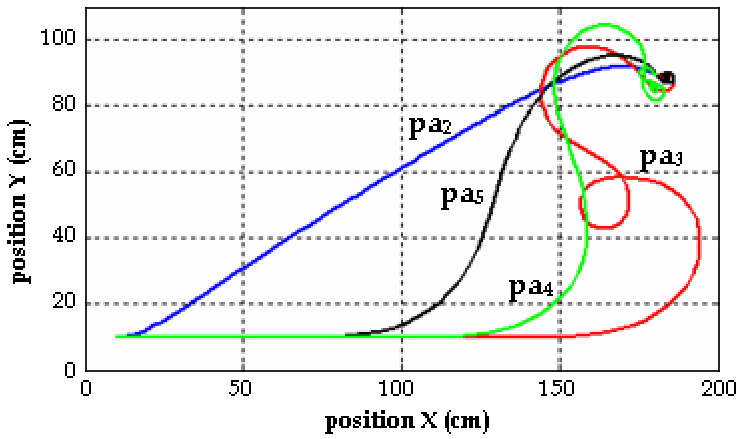

Fig. 5.14. Spatial evolution of the physical agents.

Such physical agents' movement behavior was intentionally designed with idea to generate diversity (i.e., heterogeneity) in the dynamic of the controlled system. Thus, it should be noted that the correct management of such diversity is quite relevant for physical agents to avoid undesirable situations and to fulfil correctly the proposed actions.

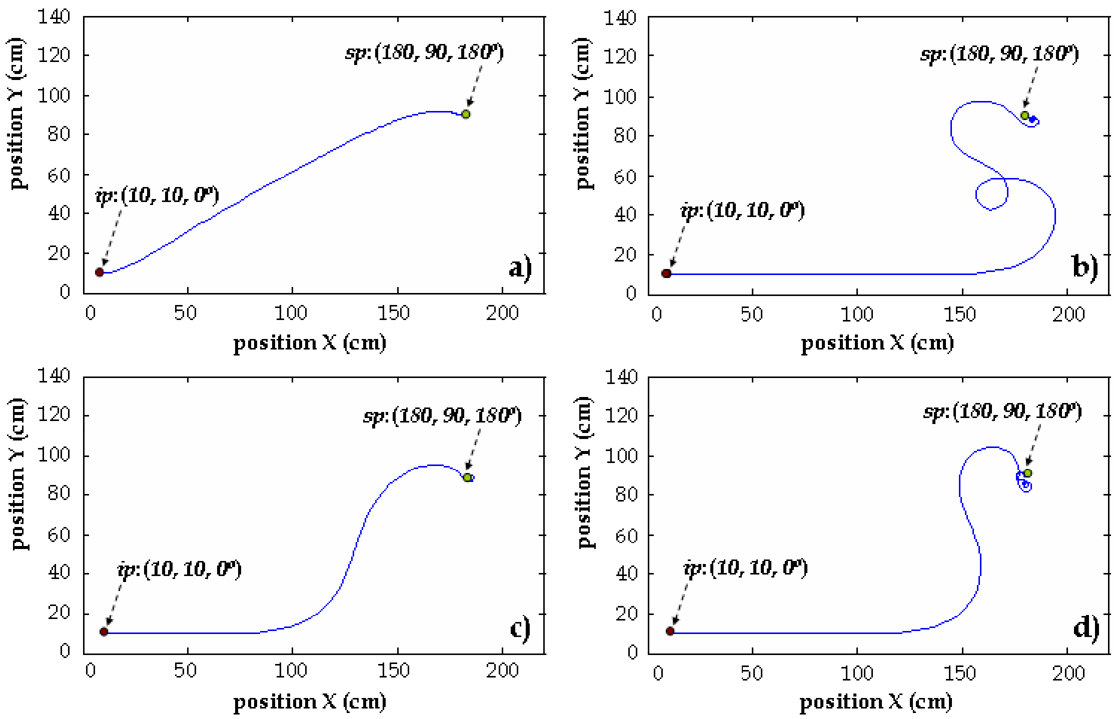

Fig. 5.15. Spatial evolution of the physical agents under geographic requirements; from initial point (10cm, 10cm, 0º) to the set point (180cm, 90cm, 180º).

As the Fig. 5.12 and 5.13 show, in real robot soccer those only three physical agents have been implemented. In this case, such physical agents are denoted by its behavior such that, pa_1 is "*precise*", pa_2 is "*disturbed*" and pa_3 is "*fast*".

5.3.1 The Game Strategy

In a soccer game, a strategy refers to the statement of a determined set of actions that must be executed in a particular area of the field. In this sense, the strategy aims to provide supervisor agents with the adequate knowledge about which are the expected issues (i.e., goals, tasks or roles) in each scene according with the features of the game. In addition, Table 5.2 shows the game strategy that has been defined to be implemented in the experiment that will performed in this dissertation. In particular, such strategy defines the selected set of goals, tasks and roles to define the specific expected actions in each scene. In addition, some roles can be recurrent in the execution of some tasks, such that in (*task*$_4$). It is due to the importance of covering a great area of the defense zone, and to give to the goalkeeper of the team.

Table 5.2. General classification of the goals, tasks and roles for each scene.

Supervisor agent	Scene	Goals	Tasks	Roles
sa_1	s_1	g_1 : score a goal	t_1 : To do a pass	r_1 : Kick the ball r_2 : Take a position
			t_2 : Shooting towards the goal	r_1 : Kick the ball r_2 : Take a position
sa_2	s_2	g_2 : to carry the ball	t_3 : To mark a player	r_3 : Go towards the player r_4 : Cover an area r_2 : Take a position
			t_2 : Shooting towards the goal	r_1 : Kick the ball r_2 : Take a position
sa_3	s_3	g_3 : to defend	t_4 : Goal-kick	r_1 : Kick the ball r_{2_1} : Take a position r_{2_2} : Take a position
			t_5 : to protect the goal	r_1 : kick the ball r_4 : Cover an area r_2 : Take a position

To the end, the Fig. 5.16, 5.17 and 5.18 show a simulated representation of the strategy proposed for the experiments. Here, the current ball position (*cbp*) indicates the priority index ω of the actions involved in each scene. It means, if the ball is inside an established area indicates the goal or task that must be executed, where the shaded zone determines the spatial region not consider in each case.

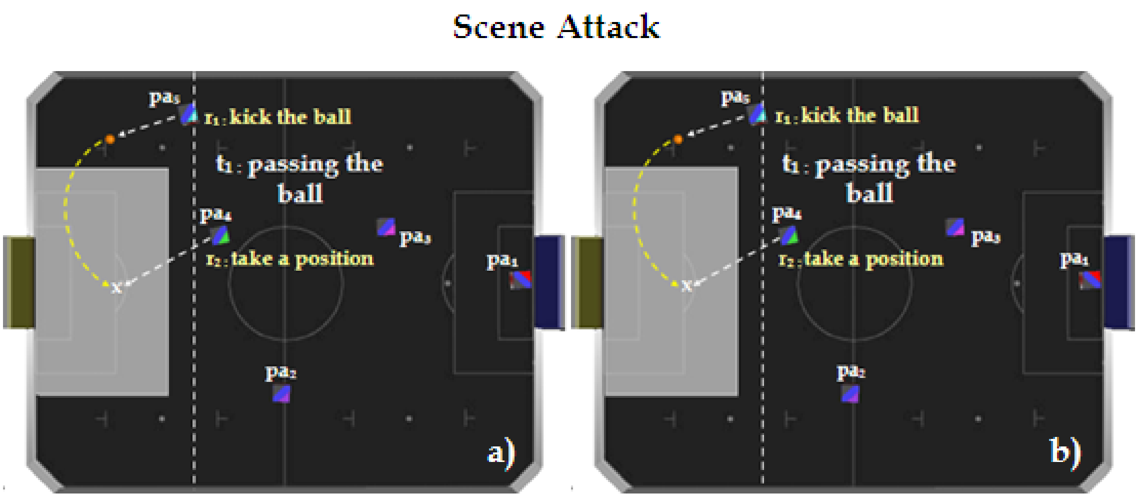

Fig. 5.16. Simulated representation of the Strategy in the scene attack. a) General scheme of the t_1; b) General scheme of the t_2.

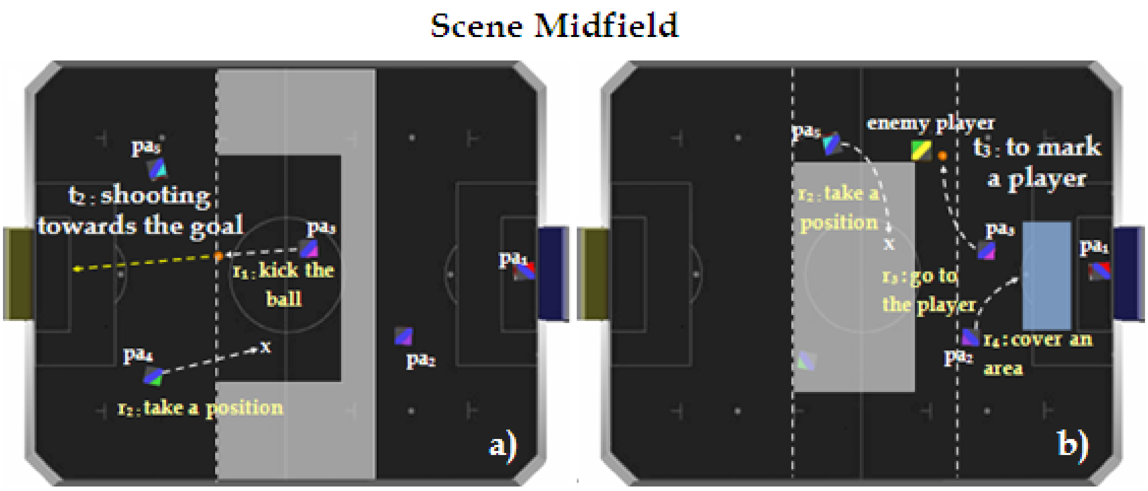

Fig. 5.17. Simulated representation of the Strategy in the scene midfield. General scheme of the t_2; b) General scheme of the t_3.

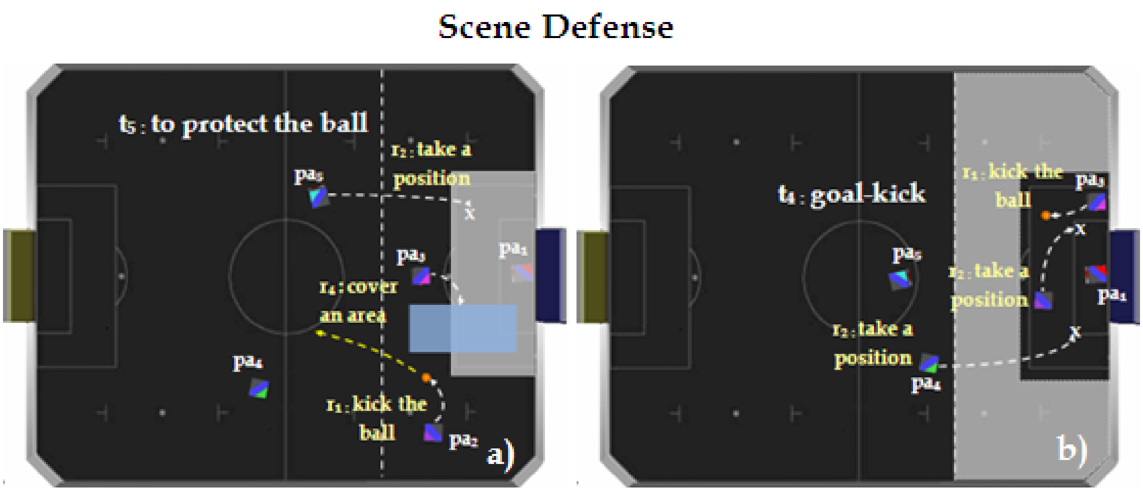

Fig. 5.18. Simulated representation of the Strategy in the scene defense. a) General scheme of the t_4; b) General scheme of t_5.

5.3.2 Decision Axes in the Robot Soccer Environment

In the literature, there are several coordination parameters to take into account in the decision-making process for multi-agent coordination. However, this implementation introduces a proper calculation for the three decision axes proposed in Section 4.3.

5.3.2.1 Axis 1 – Environmental Conditions Calculation

Environment condition refers to the physical situation of each agent within an environment and, here is related to the distance between the current location of a physical agent and the current location of the proposed actions in a scene in a determined time. Such situation is called ***proximity.*** The proximity parameter *P* is related to the distance between the current location of the physical agent pa_i and the proposed position for the role r_j involved in the scene s_k at the time t as is described in (5.2)

$$P(pa_i, r_j)_{t_{s_k}} = \left(1 - \frac{d(pa_i, r_j)}{d\max_{s_k}}\right)_{t_{s_k}} \quad (5.2)$$

$$i = \{1,2,3,4\} \; j = \{1,2,3,\ldots, r_q\} \; k = \{1,2,3\} \quad P(pa_i, r_\varphi)_{t_{s_k}} \in [0,1]$$

Where $d(pa_i, r_j)_{t_{s_k}}$ is the distance between the physical agent pa_i and the role r_j in a determine time t in the scene s_k and $d\max_{s_k}$ establishes the distance between all the physical agents and the actions proposed by the current supervisor agent, such that:

$$d\max_{s_k} = \max(d(pa_1, r_j)_{t_{s_k}}, \ldots, d(pa_i, r_j)_{t_{s_k}}) \quad (5.3)$$

Fig. 5.19 depicts a scheme of the physical agents' state for the proximity calculation.

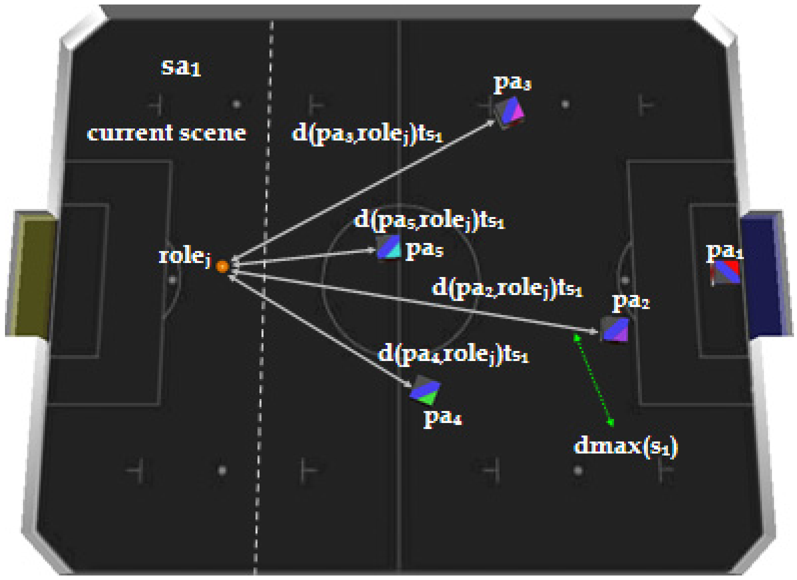

Fig. 5.19. General scheme of the robot soccer environment for the proximity calculation.

5.3.2.2 Axis 2 - Physical Knowledge Calculation

Physical knowledge refers to the cognitive ability of each physical agent to estimate the knowledge related to the capabilities of its body involved in the execution of a proposed action in a scene in determined time. Such ability is called ***introspection***. The introspection parameter I is calculated implementing feed-forward back-propagation neural networks. Such networks give the capabilities of a physical agent pa_i to execute a proposed role r_j in determined scene s_k in the time t. In particular, each physical agent calculates its introspection value to the execution of all the proposed actions as is described in (5.4).

$$I(pa_i, r_j)_{t_{s_k}} = (\max(I(pa_i, r_j)))_{t_{s_k}} \qquad (5.4)$$

$$i = \{1,2,3,4\} \quad j = \{1,2,3,\ldots, r_q\} \quad k = \{1,2,3\} \quad I(pa_i, r_\varphi)_{t_{s_k}} \in [0,1]$$

A higher introspection value $I(pa_i, r_j)_{t_{s_k}}$ represents that the physical agent pa_i is the most suitable agent for the execution of the proposed role r_j in a time t of the scene s_k. Likewise, a low introspection value indicates that the agent cannot perform the action in a reliable way. So, Fig. 5.20 shows the general scheme of the physical agents' introspection reasoning in the execution of a particular action (e.g., kick the ball).

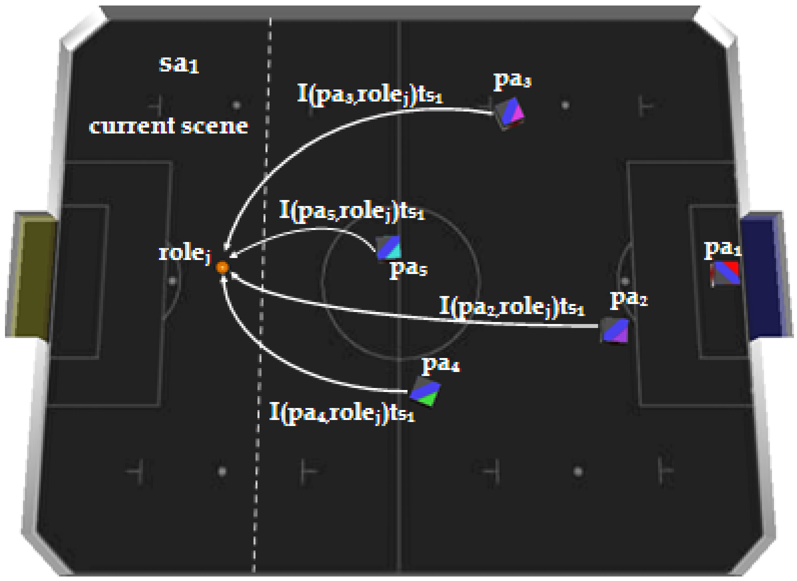

Fig. 5.20. General scheme of the robot soccer environment for the introspection calculation.

5.3.2.3 Axis 3 – Trust Value Calculation

Trust value refers to the social relationship among agents taking into account the result of previous interactions in a scene in determined time. Such relationship is here called ***trust***. The *Trust* parameter *T* is estimated by the outcome of the previous interaction between physical agents. Such parameter rules the interaction and behavior expected for each physical agent. The execution of the proposed action r_j in the scene s_k in a time t is then evaluated based on this parameter, such that: equation (5.5) shows the reinforcement calculus when actions are correctly reached by the physical agent. Otherwise, the equation (5.6) shows the calculus when the actions are not reached in a correct way.

$$T(pa_i, r_j)_{t_{s_k}} = (T(pa_i, r_j) + \Delta(pa_i)a_{s_k})_{t_{s_k}} \quad (5.5)$$

$$T(pa_i, r_j)_{t_{s_k}} = (T(pa_i, r_j) - \Delta(pa_i)p_{s_k})_{t_{s_k}} \quad (5.6)$$

$$i = \{1,2,3,4\} \quad j = \{1,2,3,\ldots,r_q\} \quad k = \{1,2,3\} \quad T(pa_i, r_\varphi)_{t_{s_k}} \in [0,1]$$

Where $\Delta(pa_i, r_j)a_{s_k}$ and $\Delta(pa_i, r_j)a_{s_k}$ are the awards and punishments given to pa_i in the roles r_j in a time t within the scene s_k respectively. For sake of simplicity, an action is correctly performed by a physical agent when it kicks the ball towards the opposite goal or it arrives to the fixed set point of the strategy. The physical agents are then awarded. Else, the physical agent is punished due to a possible failure in the execution of the actions. In addition, when a physical agent has a higher $T(pa_i, r_j)_{t_{s_k}}$ value, it represents a more trusted physical agent in the action. Specifically, different trust values have been established for each physical agent depending on the scene as is depicted in Fig. 5.21.

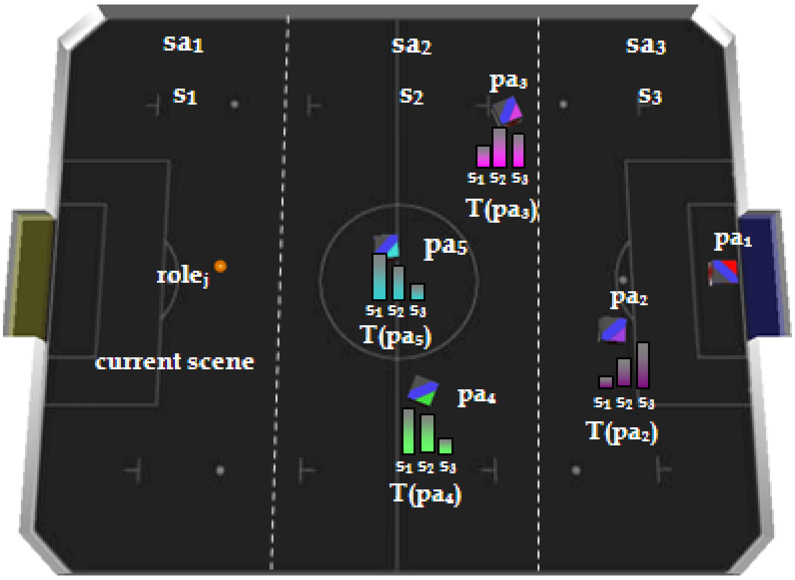

Fig. 5.21. General scheme of the robot soccer environment for the trust calculation.

Asides, appropriate values for the awards and punishments have been empirically selected for each scene. In particular, Table 5.3 shows such values. It means that all the experiments both coordinated tasks and task allocation use the same values in their *Trust* calculation, such that:

Table 5.3. Empirical values for the awards and punishments within the scenes.

Scene	Award	Punishment
s_1	$\Delta(pa_i)a_{s_1} = 0.1$	$\Delta(pa_i)p_{s_1} = 0.05$
s_2	$\Delta(pa_i)a_{s_2} = 0.04$	$\Delta(pa_i)p_{s_2} = 0.08$
s_3	$\Delta(pa_i)a_{s_3} = 0.05$	$\Delta(pa_i)p_{s_3} = 0.1$

- **Norms' Statement**

Two norms are introduced for the experimental soccer games. In this light, the table 5.4 depicts the mentioned rules. Therefore, the first norm N_1 is useful by the *supervisors* to define which goal must be solved. On the other hand, the norm N_2 helps *supervisors* to schedule the execution of the tasks involved in its supervised scene. In particular, both norms are related to the current ball position (*cbp*) at each moment of each simulation. Here, the priority of such issues (i.e., goals or tasks) operate as an activation flag which is (*1*) when the ball is in the assigned area for such issue and (*0*) when the position of the ball is in other region, such as follow:

$$\omega(g_\gamma) \begin{cases} 1 & \text{if cpb is in the range of the } g_\gamma \\ 0 & \text{if cpb is not in the range of } g_\gamma \end{cases} \qquad \omega(t_\delta) \begin{cases} 1 & \text{if cpb is in the range of the } t_\delta \\ 0 & \text{if cpb is not in the range of } t_\delta \end{cases}$$

Table 5.4. Rules' Statement for the experimental phases.

N_1:	if current ball position (cbp) is into the spatial region assigned to particular goal, the supervisor in-charge must activate it.
N_2:	if current ball position (cbp) is into the spatial region assigned to a particular task, such task must be performed, therefore, its roles must be executed.

For illustrative reasons, using the task allocation problem-solving algorithm, let us suppose a group of three supervisor agents, such that, $Gsa = \{sa_1, sa_2, sa_3\}$ supervising three scenes, such that, $S = \{s_1, s_2, s_3\}$ respectively. For sake of simplicity, each scene only has one goal, such that, $s_1 \rightarrow g_1$, $s_2 \rightarrow g_2$, $s_3 \rightarrow g_3$. So, *supervisors* must agree among them to select which supervisor begins to interact with the physical agents. Such *supervisors*' interaction is here, ruled by the norm N_1. In this sense, in the developed experiments in the robot soccer test bed the *supervisors* are, in all moment, look for the current position of the ball. In this case, when a *supervisor* knows that the position of the ball is into its area, inform this to the other *supervisors* as follow:

$$\text{inf orm}(sa_1, \{sa_2, sa_3\}, \{\omega(g_1) = [1]\}, s_1)$$

Then, the other *supervisors* (sa_2, sa_3) must evaluate if this information is correct (they know that the ball is not in its area, therefore, $\omega(g_2)=[0]$ and $\omega(g_3)=[0]$) and response that they are agree in that sa_1 solves the goal involved in its scene, as follow:

$$\text{request}(\{sa_2, sa_3\}, sa_1, \omega(g_1) \rightarrow \text{ok}, s_1)$$

Once *supervisors* are agree in the execution of the goals, the agreed *supervisor* must self-analyze and define the execution sequence of the tasks involved in its defined goals. Using the priority order (ω) established for the proposed tasks, the supervisor must follow the norm $norm_2$ such that,

$$\text{if } (\omega(t_\delta) = \{[0\text{or}1]) \text{ do } \{\text{execute task}_\delta\}$$

In this sense, the current *supervisor* looks for and evaluates the priority (ω) of the roles involved in the active task. In fact, this process allows *supervisor* to schedule the order of the role allocation. So, supervisor sa_1 requests information from the physical agents to search for the most suitable physical for the execution of every role.

5.3.3 The Influence Degrees

The influence degrees for the experiments developed in this dissertation are summarized in Table 5.5. In this sense, the binary combination of the three parameters defined in the decision axes enhances the relevance that each parameter represents in each case study. In this light, such classification defines how the relevance of each one of the decision axes can be reflected in the selection/allocation of the actions within determine scene. In this sense, eight combinations (cases studies) have been obtained. For sake of simplicity, the relevance of the parameters are related to is consideration or not in each case. Moreover, in all the experiments, the three scenes are using the same combination of elements at same time in each simulation. In particular, each case study determines the relevance of the axes in each one of the agents-team used in the developed experiments.

Table 5.5. Combination of the Decision Axes

(0 → it is not taken into account; 1 → it is taken into account)

Case Study	Proximity	Introspection	Trust
0	0	0	0
1	0	0	1
2	0	1	0
3	0	1	1
4	1	0	0
5	1	0	1
6	1	1	0
7	1	1	1

To the end, for illustrative reasons, let us to show how a group of four physical agents, such that, $Gpa = \{pa_2, pa_3, pa_4, pa_5\}$, uses the proposed calculation for the three decision axes (see Section 5.3.2) introduced in this dissertation. So, in Fig. 5.22 is depicted a real possible situation in the robot soccer environment, where the supervisor agent sa_1 must manage the scene s_1 to the execution of three actions, such that:

$$r_1 : \mathrm{kicktheball}(\mathrm{cbp\_x}; \mathrm{cbp\_y}) \quad \mathrm{cbp} = \mathrm{currentballposition}$$

r_{2_1} : takeaposs(27cm,66cm) r_{2_2} : takeaposs(67cm,112cm)

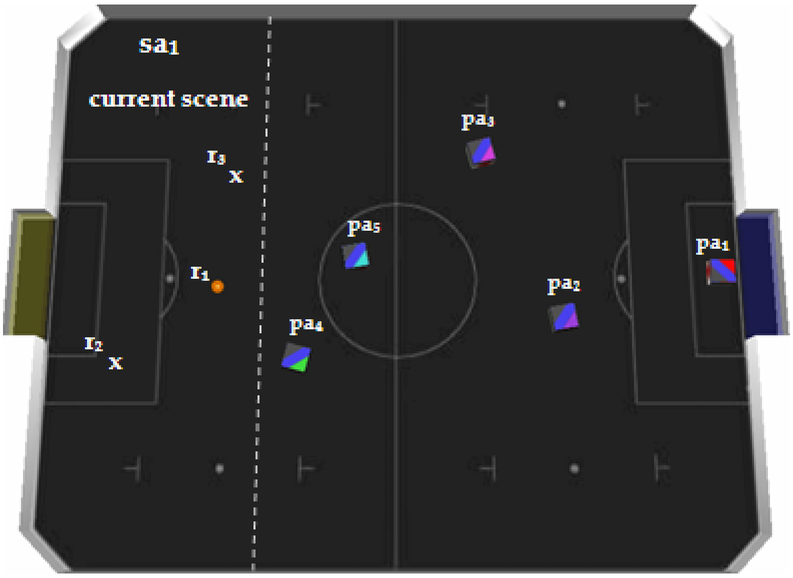

Fig. 5.22. Possible situation of the robot soccer environment.

In this sense, according with the coordinated task solving-problem algorithms, the supervisor sa_1 informs to the group of physical agent the roles involved in its scene s_1. So, each physical agent looks for and evaluates its *situation* related to the three proposed roles in the current scene. So, the Table 5.6 shows the values of the distance between the physical agents and the target for the proximity calculation. In addition, the tables 5.7, 5.8 and 5.9 show the values of the proximity, introspection and trust respectively for each agent for each action, highlighting and selecting the nearest role that each physical agent can execute taking into account an empirical threshold fixed in π=0.65. Likewise, one physical agent could be able to execute more than one role but it will execute the role for which it has a higher suitability rate.

Table 5.6. Distances between physical agents and the proposed target.

Physical agent	$role_1$	$role_2$	$role_3$
pa2	92.1954	128.1913	96.2549
pa3	76.4853	144.6342	65.00
pa4	21.9545	55.0364	46.4866
pa5	37.7359	75.5844	30.8707

Table 5.7. Values of the Proximity parameter (Case Study 4)

Physical agent	$role_1$	$role_2$	$role_3$	Selected role
pa2	0	0	0	pa_2 cannot perform any role
pa3	0.1704	0.1058	0.3247	pa_3 cannot perform any role
pa4	0.7619	0.5707	0.4104	{ $role_1$ }
pa5	0.5907	0.4104	0.6793	{ $role_3$ }

Table 5.8. Values of the Introspection Parameter (Case Study 2)

Physical agent	$role_1$	$role_2$	$role_3$	Selected role
pa2	0.4163	0.0347	0.4954	pa_2 cannot perform any role
pa3	0.3698	0.5103	0.1085	pa_3 cannot perform any role
pa4	0.8517	0.6921	0.6035	{ $role_1$, $role_2$ }
pa5	0.7944	0.6537	0.784	{ $role_1$, $role_3$, $role_2$}

Table 5.9. Values of the Trust Parameter (Case Study 1)

Physical agent	$role_1$	$role_2$	$role_3$	Selected role
pa2	0.35	0.15	0.4	pa_2 cannot perform any role
pa3	0.25	0.3	0.5	pa_3 cannot perform any role
pa4	0.65	0.6	0.85	{ $role_3$, $role_1$ }
pa5	0.75	0.6	0.65	{ $role_1$, $role_3$ }

On the other hand, Tables 5.10, 5.11, 5.12 and 5.13 show the data for the others cases study presented in this dissertation. Following the above idea, in these tables, the selected roles for each physical agent are also highlighting. In this case, to obtain such value, the physical agents perform a combination of the three parameters of the decision axes by using the equation (4.12) introduced in the Section 4.7.1. Such equation allows physical agents to perform a match between its capabilities to perform the action and the influence degree ψ used in each case to calculate its suitability rates for the proposed set of roles.

Table 5.10. Physical Agents' selection for the Case Study 3 (Introspection + Trust)

Physical agent	$role_1$	$role_2$	$role_3$	Selected role
pa2	0.3832	0.0924	0.4477	pa_2 cannot perform any role
pa3	0.3099	0.4052	0.3043	pa_3 cannot perform any role
pa4	0.7509	0.6461	0.7268	{ $role_1$, $role_3$ }
pa5	0.7722	0.6269	0.7170	{ $role_1$, $role_3$ }

Table 5.11. Physical Agents' selection for the Case Study 5 (Proximity + Trust)

Physical agent	$role_1$	$role_2$	$role_3$	Selected role
pa2	0.1750	0.0750	0.2000	pa_2 cannot perform any role
pa3	0.2102	0.2029	0.4124	pa_3 cannot perform any role
pa4	0.7060	0.5854	0.6302	{ $role_1$ }
pa5	0.6704	0.5052	0.6647	{ $role_1$, $role_3$ }

Table 5.12. Physical Agents' selection for the Case Study 6 (Proximity + Introspection)

Physical agent	$role_1$	$role_2$	$role_3$	Selected role
pa2	0.2082	0.0174	0.2477	pa_2 cannot perform any role
pa3	0.2701	0.3081	0.2166	pa_3 cannot perform any role
pa4	0.8068	0.6314	0.5070	{ $role_1$ }
pa5	0.6926	0.5321	0.7317	{ $role_3$, $role_1$}

Table 5.13. Physical Agents' selection for the Case Study 7 (Proximity + Introspection + Trust)

Physical agent	$role_1$	$role_2$	$role_3$	Selected role
pa2	0.2554	0.0616	0.2985	pa_2 cannot perform any role
pa3	0.2634	0.3054	0.3111	pa_3 cannot perform any role
pa4	0.7545	0.6209	0.6213	{ $role_1$ }
pa5	0.7117	0.5547	0.7044	{ $role_1$, $role_3$ }

These tables show that each physical agent sorts the actions that it can perform in an increasing order based on the match performed to compare critically their action capability against the actions' requirements by considering the threshold implicated in the current scene. Therefore, each physical agent performs the action for which it is the most suitable. However, if there is more than one physical agent able to perform the same action, the selected agent is the one with the highest suitability rate while the other agents go to perform the next action in their ranking, deleting the action selected by other agent with a highest suitability rate. Besides, if there are physical agents with no one action in their scheduling rank, then these agents look for and evaluate actions involved in other scene. It means that these physical agents should calculate their suitability rates for the actions proposed by other supervisor agent. So, this approach guarantees that physical agents try to execute at least one action in any scene. This fact aims to increase the cooperative multi-agent performance in cooperative and dynamics environments due to the physical agents are aware of their capabilities which reflect in a more reliable decision-making. Agents can discriminate between the tasks in which they have no chance of correct performing and those in which they have no chance.

5.4 Simulated Experimental Results

Empirical experiments featuring simulated cooperative scenarios have been established in order to put into practice the formalization of the framework to decision support for situated agents described in this dissertation. In addition, two experimental implementations have been selected: *soccer games* and *the passing a ball*. Moreover, such implementations are tested in two different scenarios, such that, coordinated task and task allocation. Both scenarios have been individually tested in each implementation. In particular, the soccer games implementation is tested in two different tournaments. The first tournament is related to a set of soccer games between agents-teams against a blind opponent. Meanwhile, the second tournament is devoted to perform a set of games where the above agent-teams compete among themselves. In addition, each agent-team is personified by means of its consideration (or not) of the each parameter of the influence degree (see Section 5.3.3). So, there are eight agent-teams as well as case studies. For illustrative reasons, in all the experiments developed in this implementation, the game strategy (see Section 5.3.1); the decision axes' calculation (see Section 5.3.2) and the stated norms (see Section 5.3.2) have been used. Likewise, the relevance of the actions is based on each one of the cases study defined by the influence degrees presented (see Section 5.3.3). In particular, for successful reasons in the agents' collective decision an empirical decision threshold (*th=0.65)* is established. In addition, the results are analyzed by showing the average (*AVE*) of each case study (*CS*) calculated by (5.7) taking into account the total number of successful points (or trials) Π compared with the total of the possible points (or trials) Γ in each experiment.

$$\mathrm{AVE}(\%) = \left(\frac{\Pi * 100}{\Gamma}\right) \quad 5.7$$

To the end, the improvement rate (*IR*) is calculated taking as benchmark the worst case (*A*) and comparing it critically with the other cases (*B*). So, the *IR* is obtained by (5.8).

$$\mathrm{IR}(\%) = 100 - \left(\frac{\%\mathrm{A} * 100}{\%\mathrm{B}}\right) \quad 5.8$$

5.4.1 Implementation 1: Soccer Tournaments

The first tournament is constituted by a predefined number of championships (10), each one with a predefined number of thirty (30) games, where each agents-team plays versus a default opponent robotic team provided by the simulator where the initial state of each physical agent in the playground was randomly set at ever game. Moreover, the performance is measured as a ratio between the total points (*won game: 3 points; tied game: 1 points*) achieved by the proposed teams in each championship. In addition, in all the experiments the initial state of the physical agents was randomly changed after each kick-off (due to a goal scored by any team). Aside, the second tournament was predefined with (10) championships, each one with a predefined number of twenty-eight (28) games, where each agent-team plays against the other agents-teams. In total, each agent-team plays (280) match and its performance is calculates in a radius of (*won game: 3 point; tied game: 1 point*). In fact, in all the experiments the initial state of the physical agents was randomly changed after each kick-off (due to a goal scored by any team).

5.4.1.1 Simulated Tournament 1

This section is devoted to present the obtained results in the first simulated tournament both for its implementation in the coordinated task scenario as in task allocation scenario. In fact, the teams are ranked by considering the total number of point obtained along the championships. Such rank is sorted in a decreasing order taking into account the number of obtained points to highlight the case with higher performance. In light of stressing the relevance of the agents' situation in the agents' decision making, the analysis has been focused on the influence of consider each one of the decision axes or their possible combination at the moment to decide (in the coordinated task scenario) or to allocate (in the task allocation scenario) which is the most suitable physical agent for any proposed action. So, a comparison used the obtained results has been performed in order to note how the system performance improves when agents take into account their situation regard the proposed actions.

Scenario 1 - Coordinated Task

The table 5.14 shows the results obtained in the performed experiments (for more information sees Appendix A, Table A1 → A14).

Table 5.14. Ranking of the Tournament – Coordinated Task.

Rank	Case Study	JJ	WG	TG	LG	G+	G-	PTS	AVE (%)	IR (%)
1	**P+I+T**	**100**	**58**	**5**	**37**	**346**	**184**	**179**	**59.67**	**+51.40**
2	P+I	100	52	8	40	366	182	164	54.67	+46.95
3	I	100	49	4	47	346	189	151	50.33	+42.38
4	P	100	42	8	50	268	195	134	44.67	+36.07
5	I+T	100	41	7	52	261	201	130	43.33	+33.07
6	P+T	100	39	6	55	248	201	123	41	+29.27
7	T	100	38	6	56	316	231	120	40	+27.5
8	R	100	26	9	65	143	273	87	29	

In addition, the Fig. 5.23 and 5.24 illustrate the systems' performance of each case study taking into account the successful number of the obtained points based on the won and tied games along the championships. In fact, the Fig. 5.23 shows a comparison between the worst case ($case_0$: random) the simple cases ($case_1$: trust, $case_2$: introspection and $case_4$: proximity) and the best case ($case_7$: P+I+T).

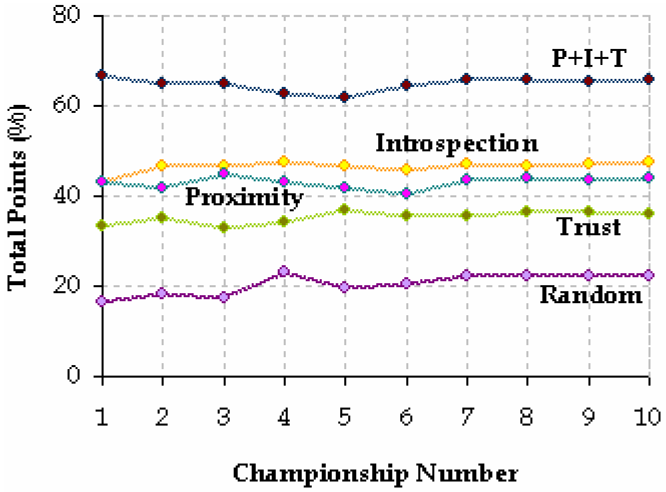

Fig. 5.23. Performance comparison between the cases 0,1,2,4 and 7.

On the other hand, the Fig. 5.24 shows a comparison between the worst case ($case_0$: random) the composed cases ($case_3$: I+T, $case_5$: P+T and $case_6$: P+I) and the best case ($case_7$: P+I+T).

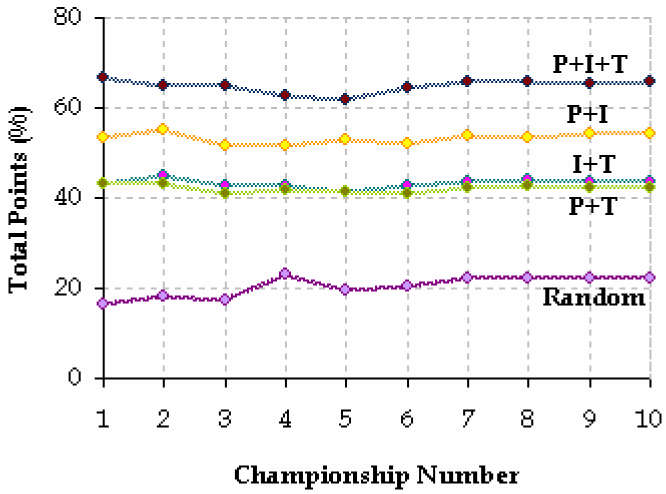

Fig. 5.24. Performance comparison between the cases 0,3,5,6 and 7.

Scenario 2 – Task Allocation

The table 5.15 shows the results obtained in the performed experiments (for more information sees Appendix A, Table A15 → A28).

Table 5.15. Ranking of the Tournament - Task Allocation.

Rank	Case Study	JJ	WG	TG	LG	G+	G-	PTS	AVE (%)	IR (%)
1	**P+I+T**	**100**	**61**	**29**	**10**	**363**	**174**	**212**	**70.67**	**+55.18**
2	P+I	100	55	12	33	379	218	177	59	+46.32
3	I	100	52	8	40	355	193	164	54.67	+42.07
4	P	100	47	11	42	276	202	152	50.67	+37.50
5	T+I	100	43	15	42	283	214	144	48	+34.02
6	T+P	100	41	12	47	239	176	135	45	+29.63
7	T	100	39	10	51	275	206	127	43.33	+25.19
8	R	100	27	14	59	193	294	95	31.67	

In addition, the Fig. 5.25 and 5.26 illustrate the systems' performance of each case study taking into account the successful number of points obtained based on the won and tied games along the championships. In fact, the Fig. 5.25 shows a comparison between the worst case ($case_0$: random) the simple cases ($case_1$: trust, $case_2$: introspection and $case_4$: proximity) and the best case ($case_7$: P+I+T).

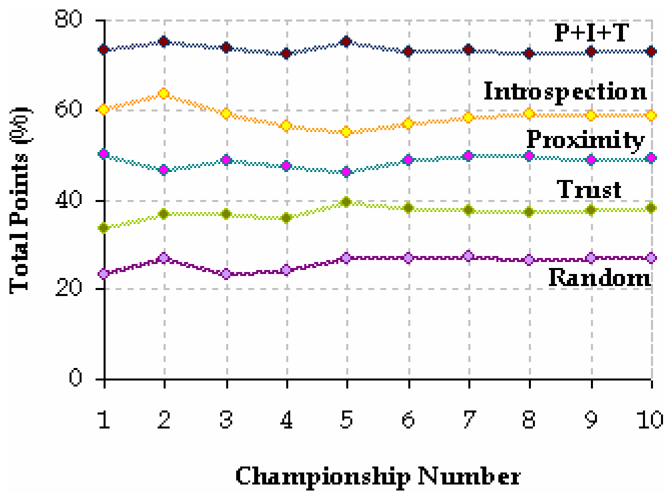

Fig. 5.25. Performance comparison between the cases 0,1,2,4 and 7.

On the other hand, the Fig. 5.26 shows a comparison between the worst case ($case_0$: random) the composed cases ($case_3$: I+T, $case_5$: P+T and $case_6$: P+I) and the best case ($case_7$: P+I+T).

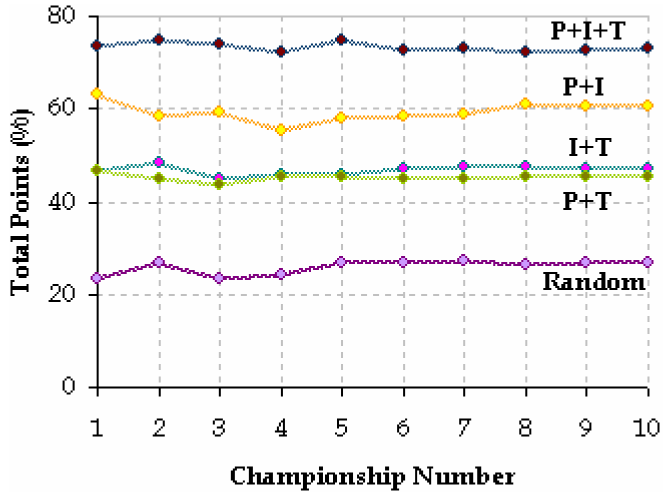

Fig. 5.26. Performance comparison between the cases 0,3,5,6 and 7.

The above statistical results demonstrate clearly how agents (both supervisor as physical) can make sure decisions that carry a better performance when they use knowledge related to their *situation* to perform the proposed action. The performance does not improve significantly beyond about the 6 championship to both examples. The number of trials (championships) to initially confirm the systems performance will be fixed in 10 championships. In particular, there is an improvement rate of around a **51%** in the coordinated task scenario and an improvement rate of around a **55%** in the task allocation scenario. A preliminary conclusion of these results is how the system performance improves when the agents become more "conscious" about which kind of information must be included in their knowledge bases when they must define their *situation* to execute a proposed action. Reasonable decision performance is achieved when agents includes such knowledge in their reasoning process when they must work jointly. But more importantly, the system performance (successful performance) is significantly better when the agents increase the information (i.e., when the agents use grater amount of knowledge) involved in their decision-making to perform any action. Concluding, the Fig. 5.27 illustrates a comparison between the higher performances of the two tested scenarios. Such analysis discloses how task allocation reaches a higher performance than the reached by the agents using the coordinated task solving-problem algorithm. In such case, both performances are the best one in their stages.

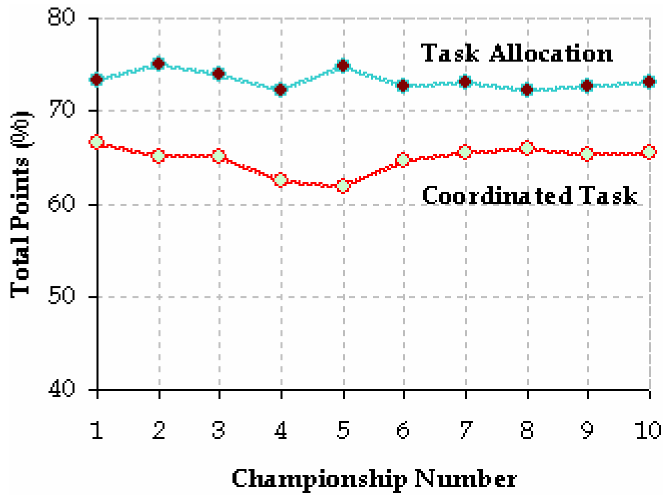

Fig. 5.27. Comparison between the case 7 in the Coordinated Task and Task Allocation scenarios.

5.4.1.2 Simulated Tournament 2

This section is devoted to present the obtained results in the second simulated tournament both for its implementation in the coordinated task scenario as in task allocation scenario. In fact, the teams are ranked by considering the total number of point obtained along the championships. Such rank is sorted in a decreasing order taking into account the number of obtained points to highlight the case with higher performance. In light of stressing the relevance of the agents' situation in the agents' decision making, the analysis has been focused on the influence of consider each one of the decision axes or their possible combination at the moment to decide (in the coordinated task scenario) or to allocate (in the task allocation scenario) which is the most suitable physical agent for any proposed action. So, a comparison using the obtained results has been performed in order to note how the system performance improves when agents take into account their *situation* regard the proposed actions.

Scenario 1 – Coordinated Task

The table 5.16 shows the results obtained in the performed experiments.

Table 5.16. Ranking of the Tournament – Coordinated Task

Rank	Case Study	280 Games			G+	G-	PTS (840)	AVE (%)	IR (%)
		WG	TG	LG					
1	**P+I+T**	**241**	**2**	**37**	**308**	**176**	**725**	**86.31**	**89.93**
2	P+I	219	3	58	269	164	660	78.57	88.94
3	I	170	3	107	196	177	513	61.07	85.77
4	P	156	3	121	251	193	471	56.07	84.50
5	P+T	121	3	156	215	208	366	43.57	80.06
6	I+T	95	3	182	192	288	288	34.29	74.66
7	T	71	4	205	193	223	217	25.83	66.36
8	R	23	4	253	121	316	73	8.69	

In particular, the Fig. 5.28 and 5.29 illustrate the systems' performance of each case study taking into account the successful number of points obtained based on the won and tied games along the championships. In fact, the Fig. 5.28 shows a comparison between the worst case ($case_0$: random) the simple cases ($case_1$: trust, $case_2$: introspection and $case_4$: proximity) and the best case ($case_7$: P+I+T).

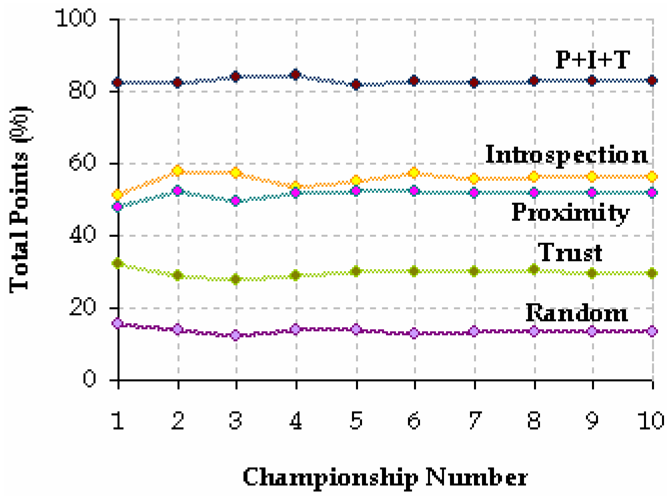

Fig. 5.28. Performance comparison between the cases 0,1,2,4 and 7.

On the other hand, the Fig. 5.29 shows a comparison between the worst case ($case_0$: random) the composed cases ($case_3$: I+T, $case_5$: P+T and $case_6$: P+I) and the best case ($case_7$: P+I+T).

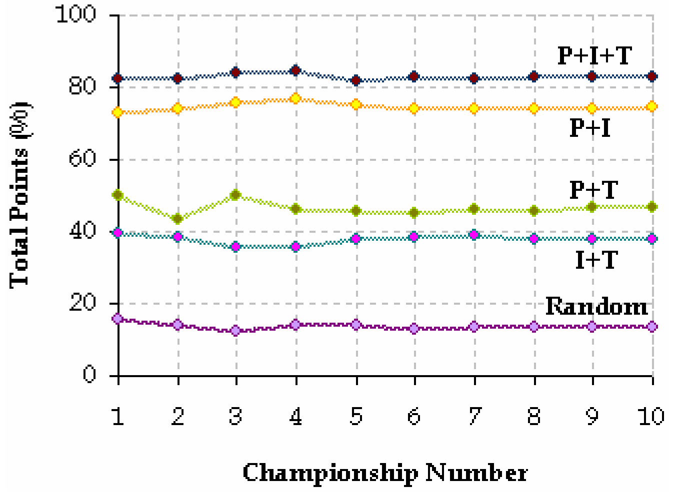

Fig. 5.29. Performance comparison between the cases 0,3,5,6 and 7.

Scenario 2 – Task Allocation

The table 5.17 shows the results obtained in the performed experiments.

Table 5.17. Ranking of the Tournament – Task Allocation.

Rank	Case Study	280 Games			G+	G-	PTS (840)	AVE (%)	IR (%)
		WG	TG	LG					
1	**P+I+T**	**230**	**1**	**49**	**308**	**176**	**691**	**82.26**	**86.25**
2	P+I	208	2	70	269	164	626	74.52	84.82
3	I	165	4	111	196	177	499	59.40	80.96
4	P	156	2	122	251	193	470	55.95	79.79
5	P+T	121	2	157	215	208	365	43.45	73.97
6	I+T	106	3	171	192	288	321	38.21	70.40
7	T	82	3	195	193	223	249	29.64	61.84
8	R	30	5	245	121	316	95	11.31	

The Fig. 5.30 and 5.31 illustrate the systems' performance of each case study taking into account the successful number of points obtained based on the won and tied games along the championships. In fact, the Fig. 5.30 shows a comparison between the worst case (case$_0$: random) the simple cases (case$_1$: trust, case$_2$: introspection and case$_4$: proximity) and the best case (case$_7$: P+I+T).

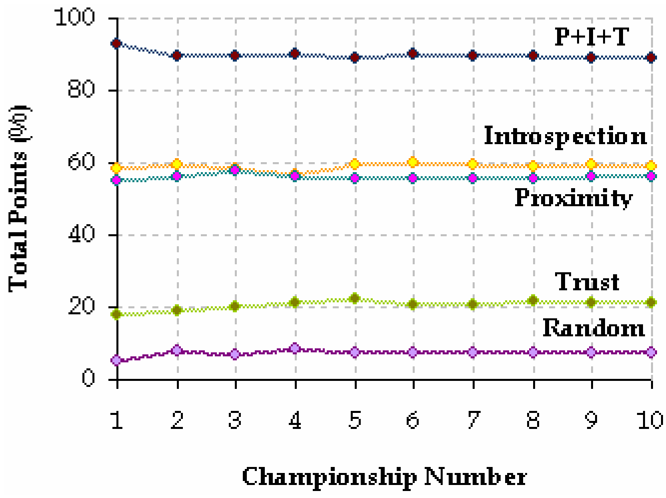

Fig. 5.30. Performance comparison between the cases 0,1,2,4 and 7.

On the other hand, the Fig. 5.31 shows a comparison between the worst case (case 0: random) the composed cases ($case_3$: I+T, $case_5$: P+T and $case_6$: P+I) and the best case ($case_7$: P+I+T).

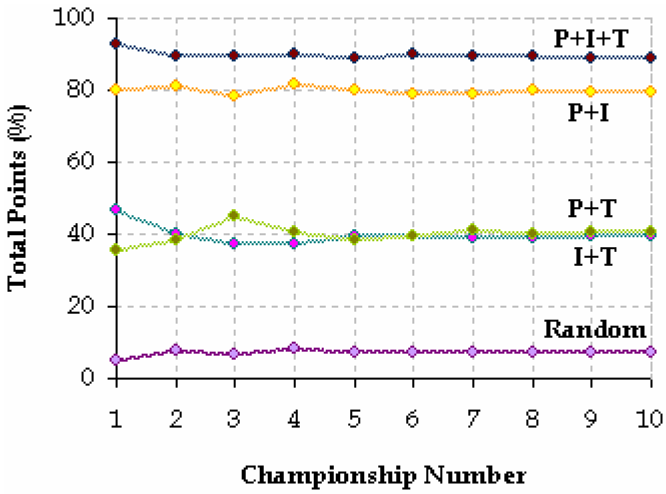

Fig. 5.31. Performance comparison between the cases 0,3,5,6 and 7.

The above statistical results show clearly how agents (both supervisor as physical) can make sure decisions that carry a better performance when they use knowledge related to their *situation* to perform the proposed action. The performance does not improve significantly beyond about the 6 championship to both examples. The number of trials (championships) to initially confirm the systems performance will be fixed in 10 championships. In particular, there is an improvement rate of around a **90%** in the coordinated task scenario and an improvement rate of around an **86%** in the task allocation scenario. Summarizing, this preliminary deduction argues how the system performance improves when the agents become more "conscious" about which kind of information must be included in their knowledge bases when they must define their capabilities to execute a proposed action. Reasonable decision performance is achieved when agents includes such knowledge in their reasoning process when they must work jointly. But more importantly, the system performance (successful performance) is significantly better when the agents increase the information (i.e., when the agents use the greater amount of knowledge) involved in their decision-making to perform any action. In addition, the Fig. 5.32 illustrates a comparison between the higher performances of the two tested scenarios. Such analysis discloses how task allocation reaches a higher performance than the reached by the agents using the coordinated task solving-problem algorithm. In such case, both performances are the best one in their stages.

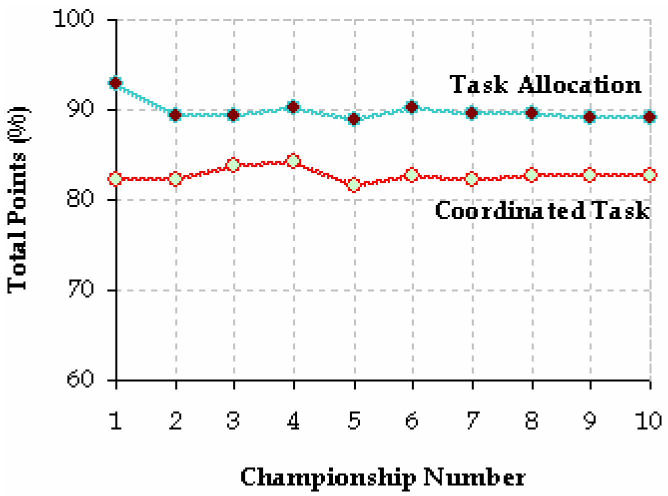

Fig. 5.32. Comparison between the case 7 in the Coordinated Task and Task Allocation scenarios.

5.4.2 Implementation 2: Passing a ball

In the experiments performed in the passing a ball implementation, the game the decision axes calculation (see Section 5.3.2) has been used. Likewise, the relevance of the actions is based on each one of the case study defined by the influence degrees presented (see Section 5.3.3). To the end, for successful reasons in the agents' collective decision an empirical decision threshold (*π=0.65)* is established. Only one rule has been defined for the *passing a ball* implementation, such that, the *$role_2$* can be performed only if the shooter chosen *shooter* fulfils with the proposed threshold for the *$role_2$*.

For sake of simplicity, the *$role_1$→pass_the_ball* is, in all the cases, assigned to the physical agent *pa_2*. In such case, the remaining physical agents compete to play the remaining role r_2 forming the *shooters* group $G_{shooters}$ = {*$shooter_1$*, *$shooter_2$*, *$shooter_3$*} *kick_the_ball*. Besides, the shooter performance has been tested with a large number of examples (500 for each case study).

Likewise, this is devoted to present the obtained results in the implementation 2 both for its implementation in the coordinated task scenario as in task allocation scenario. In fact, the teams are ranked by considering the total number of successful scores obtained along the trials (500). Such rank is sorted in a decreasing order taking into account the number of obtained points to highlight the case with higher performance. In light of stressing the relevance of the agents' situation in the agents' decision making, the analysis has been focused on the influence of consider each one of the decision axes or their possible combination at the moment to decide (in the coordinated task scenario) or to allocate (in the task allocation scenario) which is the most suitable *shooter*. So, a comparison using the obtained results has been performed in order to note how the system performance improves when agents take into account their *situation* regard the proposed actions.

5.4.2.1 Scenario 1: Coordinated Task

The table 5.18 shows the results obtained in the performed experiments.

Table 5.18. Results in the Passing a ball experiment – Coordinated Task.

Rank	Case Study	Trial	Score	AVE (%)	IR (%)
1	**P+I+T**	**500**	**324**	**64.8**	**+75.31**
2	P+I	500	257	51.4	+68.87
3	I	500	226	45.1	+64.52
4	P	500	189	37.8	+57.67
5	P+T	500	132	26.40	+39.39
6	I+T	500	129	25.8	+37.98
7	T	500	100	20.0	+20.0
8	Random	500	80	16.0	

The Fig. 5.33 and 5.34 depict the results of the cases where in each curve is computed the algorithm mean of success (scores) of the most recent trails using a sliding window up to the current trial. In fact, the Fig. 5.33 shows a comparison between the worst case ($case_0$: random) the simple cases ($case_1$: trust, $case_2$: introspection and $case_4$: proximity) and the best case ($case_7$: P+I+T).

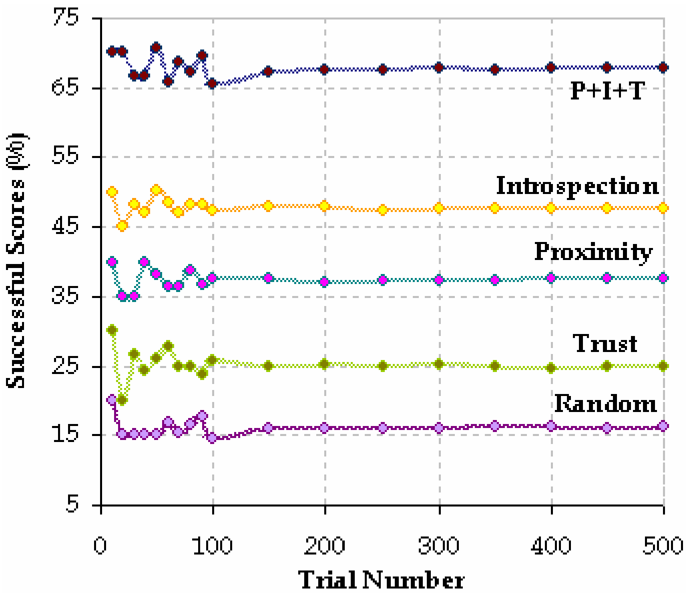

Fig. 5.33. Performance comparison between the cases 0,1,2,4 and 7.

On the other hand, the Fig. 5.34 shows a comparison between the worst case ($case_0$: random) the composed cases ($case_3$: I+T, $case_5$: P+T and $case_6$: P+I) and the best case ($case_7$: P+I+T).

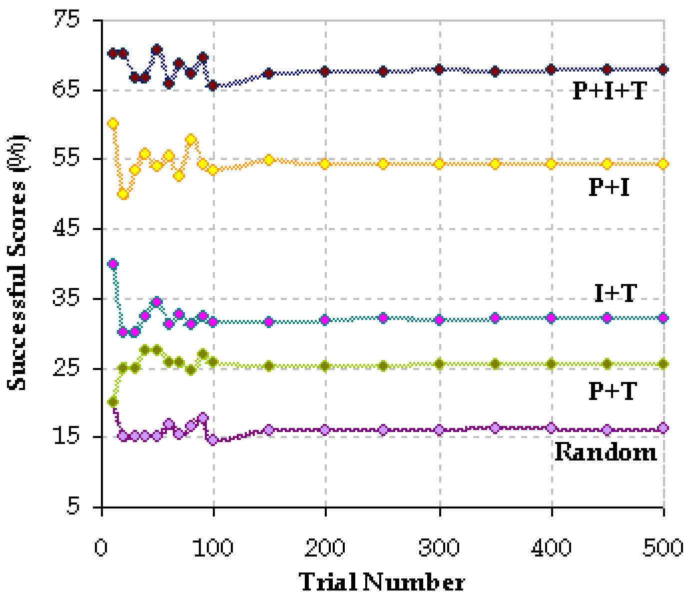

Fig. 5.34. Performance comparison between the cases 0,3,5,6 and 7.

5.4.2.2 Scenario 2: Task Allocation

The table 5.19 shows the results obtained in the performed experiments.

Table 5.19. Results in the Passing a ball experiment – Task Allocation.

Rank	Case Study	Trial	Score	AVE (%)	IR (%)
1	**P+I+T**	**500**	**316**	**65.0**	**+70.15**
2	P+I	500	305	61.4	+68.40
3	I	500	276	60.6	+67.99
4	P	500	259	57.8	+66.44
5	T+I	500	173	38.0	+48.95
6	T+P	500	153	32.0	+39.38
7	T	500	121	21.4	+9.35
8	Random	500	100	19.4	

The Fig. 5.35 and 5.36 depict the results of the cases where in each curve is computed the algorithm mean of success (scores) of the most recent trails using a sliding window up to the current trial. In fact, the Fig. 5.35 shows a comparison between the worst case ($case_0$: random) the simple cases ($case_1$: trust, $case_2$: introspection and $case_4$: proximity) and the best case ($case_7$: P+I+T).

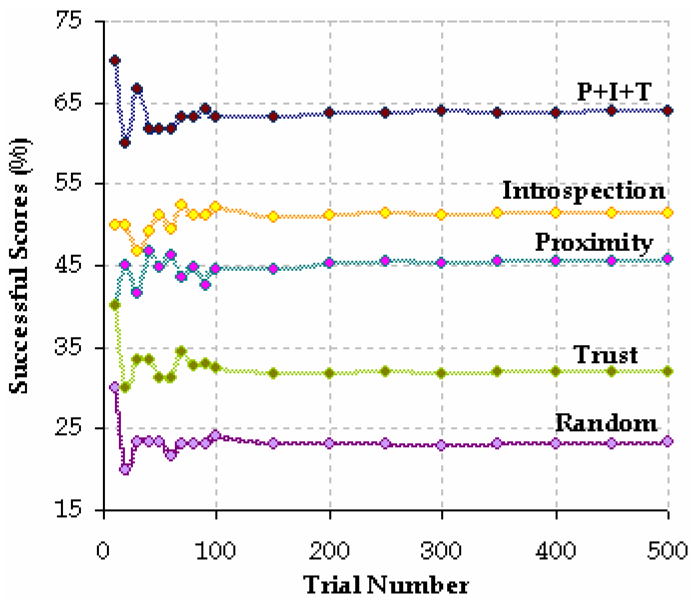

Fig. 5.35. Performance comparison between the cases 0,1,2,4 and 7.

On the other hand, the Fig. 5.36 shows a comparison between the worst case ($case_0$: random) the composed cases ($case_3$: I+T, $case_5$: P+T and $case_6$: P+I) and the best case ($case_7$: P+I+T).

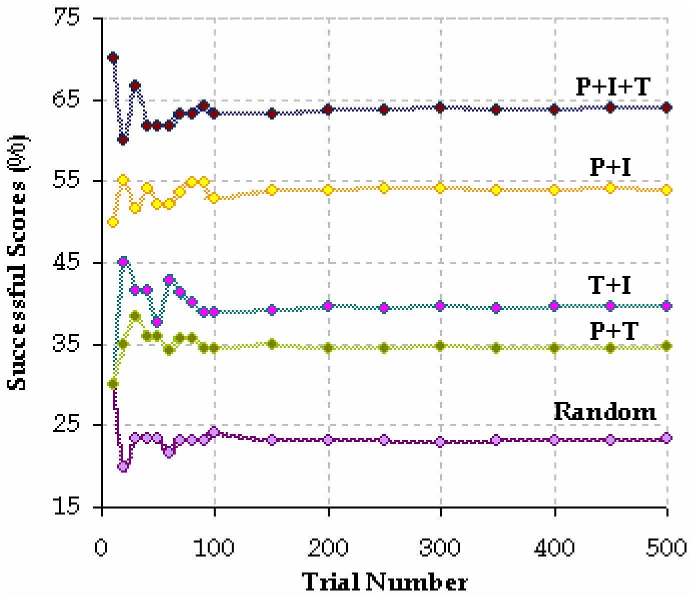

Fig. 5.36. Performance comparison between the cases 0,3,5,6 and 7.

The above results show clearly how agents (both supervisor as physical) can make sure decisions that carry a better performance when they use knowledge related to their *situation* to perform the proposed action. The performance does not improve significantly beyond about the 150 trials to both examples. This number of trials is therefore used initially to confirm the task performance. In particular, there is an improvement rate of around a **75%** in the coordinated task scenario and an improvement rate of around a **70%** in the task allocation scenario. In addition, the Fig. 5.37 illustrates a comparison between the higher performances of the two tested scenarios. Such analysis discloses how coordinated task reaches a higher performance than the reached by the agents using the task allocation solving problem algorithm.

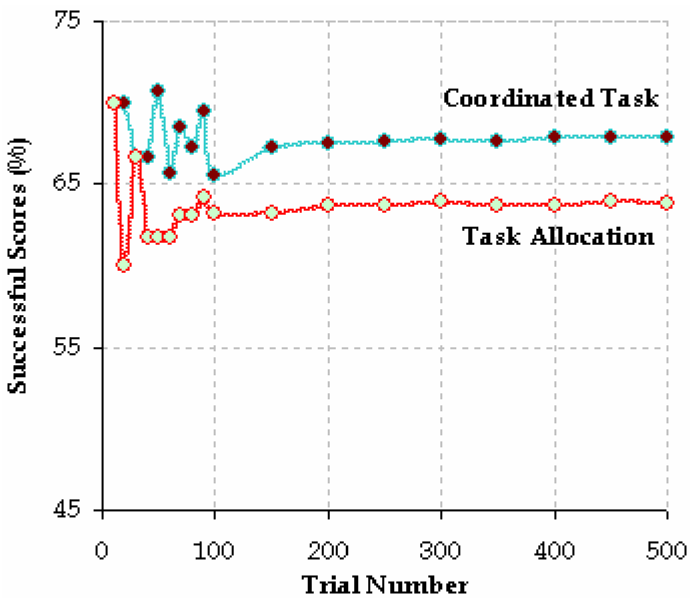

Fig. 5.37. Comparison between the case 7 in the Coordinated Task and Task Allocation scenarios.

5.5 Real Experimental Results

Empirical experiments featuring real robot soccer matches have been established in order to emulate and corroborate the usefulness of the approach before tested in the simulated robot soccer test bed. In particular, two experimental features are presented. In this sense, the main goal of this real experimental phase is to test whether the successful results obtained through simulation are also obtained with the real robot soccer environment. In theory, this would be the case, so only some modifications as the consideration of the system's vision and the radio-frequency communication are needed to perform such experiments. However, carrying from the simulated to the real robot soccer test bed is not so easy at all, as many problems arise when working with physical robots which were not present on the simulated world, in spite of that the simulator is very close to the reality. Moreover, undesirable situation related to the variation of the lights due to changes in illumination or interference, radio-frequency failures, details of design in the field, physical damages in the team-robot (e.g., an unscrewed wheel), battery discharge, are between other, the most concurrent situations that there does of the experiments with real robots an extremely difficult, complicated and laborious task of carrying out. In spite of this, both real experimental phases was developed to solve cooperative task and task allocation situation using the framework for situated agents presented in this dissertation. To the end, the game strategy (see Section 5.3.1); the decision axes' calculation (see Section 5.3.2) and the stated norms (see Section 5.3.2) have been used. In addition, the agents' teams use the influence degree introduced in Section 5.3.3. Besides, for successful reasons in the agents' decisions an empirical decision threshold (*th*=0.65) is established.

5.5.1 Experimental Results in the Implicit Opponent Benchmark

In the first experiment, agents-teams (using the influence degree showed in the Section 5.3.3) play a predefined number of (10) episodes, each one with a predefine period of 5 minutes, where the robots (see Appendix B) face to a fictitious (implicit) opponent [Muñoz, 02], [Johnson et al., 98]. Such opponent is modelled by a pre-meditated inclination (*0.3cm*) of the field (see Fig. 5.38). In such case, the expected teams' performance is related to achieve the greater number of scores in the opposite goal along the (10) episodes.

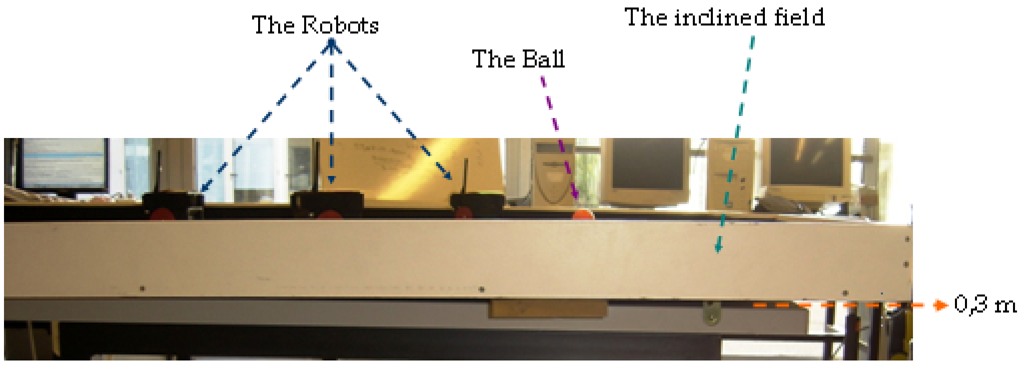

Fig. 5.38. Proposed benchmark set-up.

5.5.1.1 Scenario 1: Coordinated Task

In particular, the Table 5.20 shows the successful number of goals achieved by each case study along the test-time for the coordinated task problem-solving approach.

Table 5.20. Successful scores for the first experimental phase.

Rank	Case	Goals
1	**P + I + T**	**45**
2	P + I	38
3	I	34
4	P	32
5	P + T	27
5	P + I	27
7	T	22
8	R	5

In addition, the Fig. 5.39 depicts a statistical analysis of the achieved results where compare critically between the worst case ($case_0$: random), the simple cases ($case_1$: trust; $case_2$: introspection and $case_4$: proximity) and the best case ($case_7$: P+I+T).

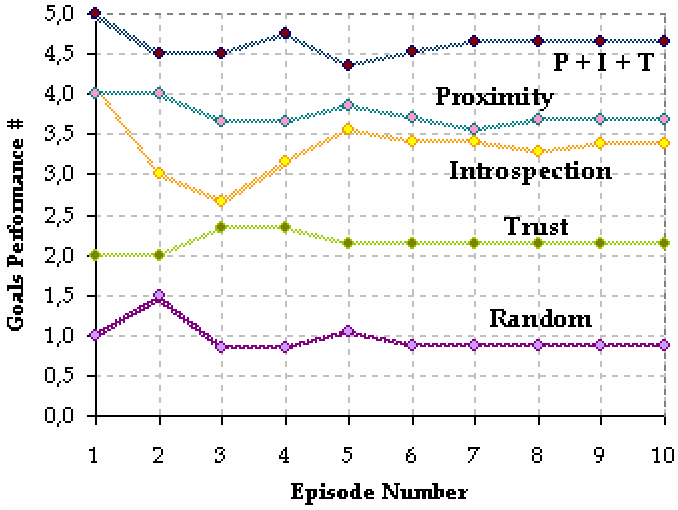

Fig. 5.39. Performance comparison between the cases 0,1,2,4 and 7.

Besides, in Fig. 5.40 the worst case ($case_0$: random), the coupled cases (c $case_3$: I+T, $case_5$: P+T and $case_6$: P+I) and the best case ($case_7$: P+I+T) have been also compared.

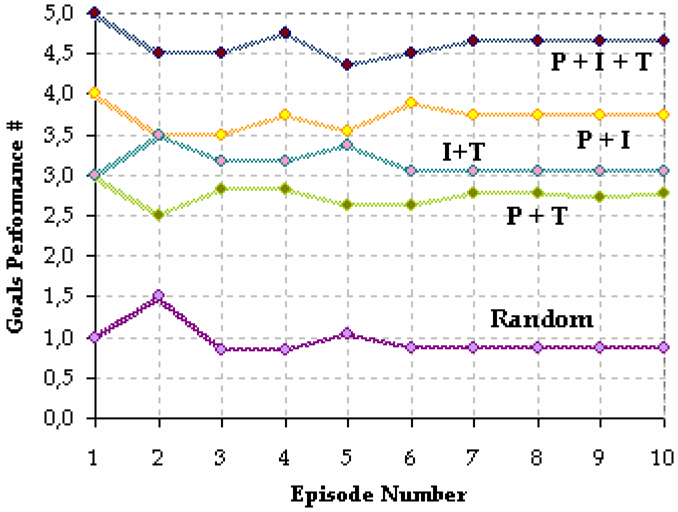

Fig. 5.40. Performance comparison between the cases 0,3,5,6 and 7.

5.5.1.2 Scenario 2: Task Allocation

The Table 5.21 shows the successful number of scores achieved by each case along the test-time, for the task allocation problem-solving approach.

Table 5.21. Successful scores for the second experimental phase.

Rank	Case	Goals
1	**P + I + T**	**48**
2	P + I	36
3	P	32
4	I	30
5	P + I	27
6	P + T	26
7	T	23
8	R	4

In addition, the Fig. 5.41 depicts a statistical analysis of the achieved results where compare critically between the worst case ($case_0$: random), the simple cases ($case_1$: trust; $case_2$: introspection and $case_4$: proximity) and the best case ($case_7$: P+I+T).

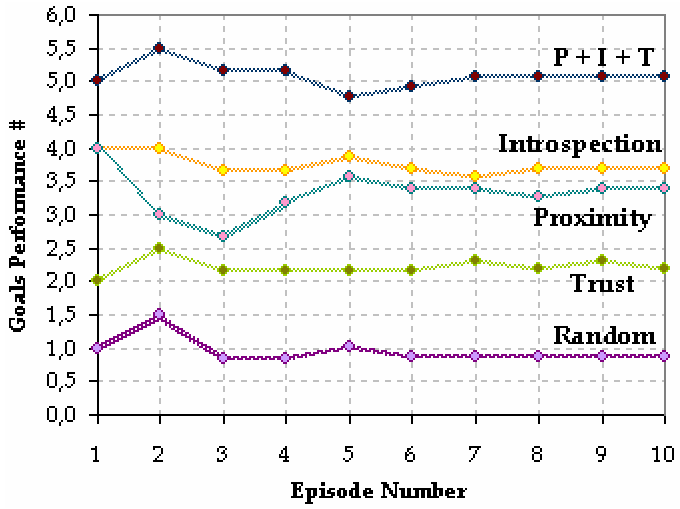

Fig. 5.41. Performance comparison between the cases 0,1,2,4 and 7.

In addition, in Fig. 5.42 the worst case ($case_0$: random), the coupled cases (c $case_3$: I+T, $case_5$: P+T and $case_6$: P+I) and the best case ($case_7$: P+I+T) have been also compared.

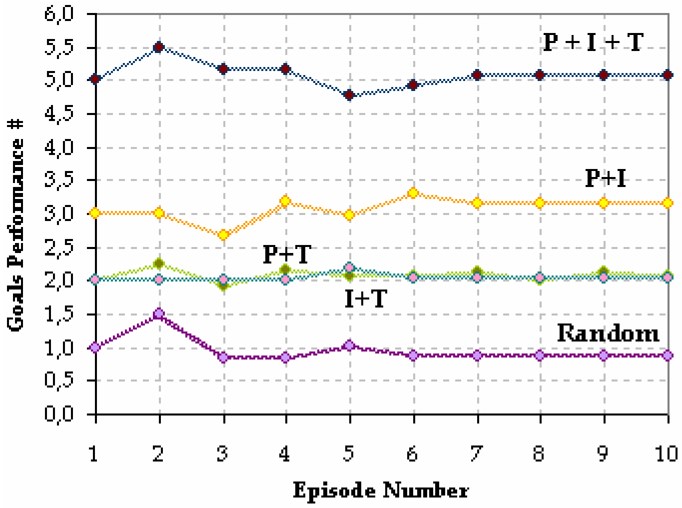

Fig. 5.42. Performance comparison between the cases 0,3,5,6 and 7.

The real obtained results show how agents (both supervisor as physical) can make sure decisions that carry a better performance when they use knowledge related to their *situation* to perform the proposed action. The performance does not improve significantly beyond about the 6 episode to both examples. This number of episodes is therefore used initially to confirm the task performance. In particular, there is an improvement rate of around an **88%** in the coordinated task scenario and an improvement rate of around a **91.6%** in the task allocation scenario. The above results confirm clearly the results obtained in the simulated experiments where the task allocation scenario obtains a higher performance than the obtained in the coordinated task scenario. In this light, the Fig. 5.43 illustrates a comparison between the higher performances of the two tested scenarios. Such analysis discloses the above affirmation. In such case, both performances are the best one in their stages.

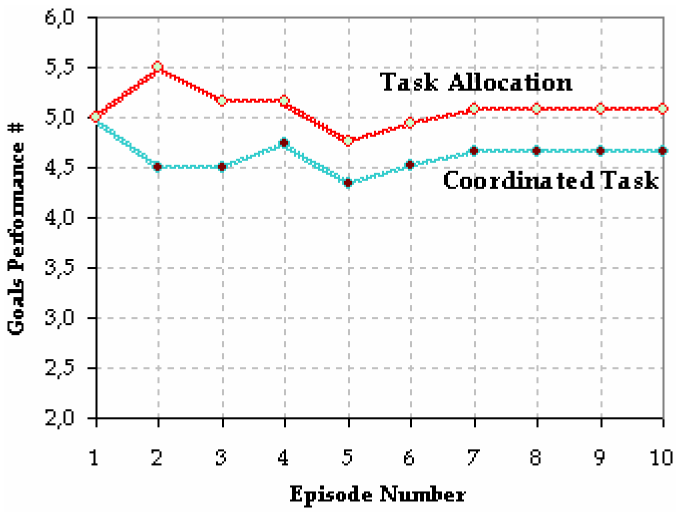

Fig. 5.43. Comparison between the case 7 in the Coordinated Task and Task Allocation scenarios.

5.5.2 Experimental Results in the Robot Soccer League

In the second experiment, agents-teams using the influence degree introduced in Section 5.3.3 compete among themselves in only one game with a predefined period of (5) minutes. In particular, the overall expected team's performance is related to do the greater number of goals. So, the next sections present the obtained results of this experiment facing both cooperative actions as task allocation situations. Here, the overall expected performance is measured by the goal average (G_{AVE}) obtained by each team robot. In particular, the goal average is calculated by the difference between the obtained goals (*G*+) and the received goals (*G-)*.In addition, the agents-teams

5.5.2.1 Scenario 1: Coordinated Task

In Table 5.22 shows the scores resulting of the experiment at each match performed. In this sense, the Table 5.23 exposes the rank obtained for this experimental stage.

Table 5.22. Information about the performance in the performed matches.

	R	**T**	**I**	**IT**	**P**	**PT**	**PI**	**PIT**
R		7-7	3-6	7-7	3-9	7-10	5-9	2-9
T	7-7		4-7	3-7	5-7	8-8	3-7	6-8
I	6-3	7-4		9-5	4-4	9-6	6-6	7-7
IT	7-7	7-3	5-9		6-6	6-6	5-7	2-5
P	9-3	7-2	4-4	6-6		7-2	8-8	5-9
PT	10-7	8-8	6-9	6-6	3-7		5-6	4-7
PI	9-5	7-5	6-6	7-5	8-8	6-5		5-5
PIT	9-2	8-6	7-7	5-2	9-5	7-4	5-5	

Table 5.23. Ranking of the results achieved in the real games.

Rank	**Case**	**Points**	**G+**	**G-**	**G_{AVE}**
1	**P+I+T**	**17**	**50**	**31**	**+19**
2	I	15	48	39	+9
3	P + I	15	48	37	+11
4	P	12	46	34	+12
5	I+T	6	38	43	-5
6	P+T	5	42	50	-8
7	T	2	36	51	-15
8	R	2	35	57	-22

5.5.2.2 Scenario 2: Task Allocation

In Table 5.24 shows the scores resulting of the experiment at each match performed. In this sense, the Table 5.25 exposes the rank obtained for this experimental stage.

Table 5.24. Information about the performance in the performed matches.

	R	T	I	IT	P	PT	PI	PIT
R		4-4	4-9	3-7	3-6	5-5	2-5	0-4
T	4-4		4-9	4-9	3-8	5-4	1-7	1-6
I	9-4	9-4		4--4	4-1	6-6	5-5	6-7
IT	7-3	9-4	4-4		7-8	7-4	5-6	2-5
P	6-3	8-3	1-4	8-7		5-6	4-4	4-6
PT	5-5	4-5	6-6	4-7	6-5		4-7	1-7
PI	5-2	7-1	5-5	6-5	5-2	7-4		3-3
PIT	4-0	6-1	7-6	5-2	6-4	7-1	3-3	

Table 5.25. Ranking of the results achieved in the real games.

Rank	Case	Points	G+	G-	G_{AVE}
1	**P+I+T**	**19**	**38**	**17**	**+21**
2	P+I	15	37	24	+13
3	I	12	43	31	+12
4	P	10	36	33	+3
5	I+T	7	41	34	+7
6	P+T	5	30	42	-12
7	T	4	22	48	-26
8	R	2	21	40	-19

Concluding, these results confirm the idea that agents (both supervisor as physical) can make sure decisions that carry a better performance when they use knowledge related to their *situation* to perform the proposed action. Due to difficult of the development of these experiments, the number of games is smaller but not less important for the aims of this dissertation. So, the exposed results confirm clearly the difference between the system performances where it uses task allocation or coordinated task problem-solving algorithm. In particular, there is an improvement rate of around an **88%** in the coordinated task scenario and an improvement rate of around an **89%** in the task allocation scenario. The Table 5.26 shows a comparison emphasizing such difference.

Table 5.26. Comparison between the case 7 in the Coordinated Task and Task Allocation scenarios.

Scenario	Case	Points	G+	G-	G_{AVE}
TA	P+I+T	19	38	17	+21
CT	P+I+T	17	50	31	+19

5.6 Final Remarks

The decision performance (successful decisions) of each agent (both supervisor as physical) is better when they are able to estimate their *situation* (i.e., their knowledge base) related to the execution of any proposed actions than when the agents does not use it. Successful decisions in all the experimental phases are related to the radio between the number of successful tasks performed by the agent and the total number of decided actions by the same agent. According to this, the agents (both supervisor as physical) increase the number of successful decision if they are embodies their *situation* based on the decision axes considered over the environment. The data from the experiments discloses that the implementation of the three parameters of the decision axes combined in the agents' decision-making produces best performance in all the experiments. However, the remaining cases show interesting results but not an optimal strategy for the present domains at all. Such fact illustrates that the choice of a strategy for include knowledge in the agents' decision-making is far from trivial. In this case, the obtained results are significant, and show the need for further investigation about the agents' situation and its effect in the performance of complex problems in dynamic and cooperative environments. To the end, the system performance is better using task allocation than using coordinated task solving-problem when *agents* must face dynamic and competitive environments. This fact is in response to the high level of interaction present in the above environments. In this sense, *MAS* using task allocation decision-making can reach a more suitable way to solve complex problems in competitive and dynamic scenarios. Against, to perform a steady and more complex action (e.g., the passing a ball task), *MAS* using coordinated task solving-problem present a feasible and successfully way to achieve higher levels of interaction. This fact is reinforced by the obtained results in the real test bed. In this sense, in real as well as in simulated test bed task allocation presents better performance than coordinated task in the developed soccer games. As was stated previously, the goal of this thesis is not to compare the results obtained in the two scenarios, but rather insight into to confirm that the proposed formalization of decision support in the framework for situated agents can face different kinds of coordinated and collaborative scenarios in a suitable way by reaching reliable and successful system performance.

Chapter 6

Conclusions and Future Work

This chapter summarizes the main contributions arisen of the analysis and discussion of the results reported in this work. The chapter also reviews the dissertation's scientific contributions and then discusses promising directions for future research and application in certain topics in which the work of this thesis can continue. Finally, some concluding remarks are drawn.

6.1 Revisiting Objectives

The work and results presented in Chapters 4 and 5, show that a good framework for situated agent based on the knowledge of the introduced decision axes can increase the autonomy and self-control of agent in cooperative actions and allows obtaining reliable capabilities/requirements function in the agent cooperative resolution for coordinated task and task allocation problems. Such ***decision axes*** aid agents increasing their organizational control by improving their individual efficiency. It utilizes information, provides an easy-to-use method, and allows for the decision maker's own insights.

Collaboration enables different entities to work more efficiently and to complete activities that they are not able to accomplish individually. However, in order to work jointly agents should coordinate their actions to benefit their temporal group achieving the common goal. Such coordination must be based on a regulation which defines how agents must interact and with whom must they do it. In this light, *e-Institutions* features facilitate an appropriate coordination and provide good levels of interaction among agents. In addition, the developed *e-Institutions* adaption has given the answer to solve complex situation involved in a robot soccer environment where agents, both supervisor and physicals, must form temporal groups in determined regions of the field. To the end, the main goal of this thesis was to develop and formalize a multi-agent decision support system for supporting the distributed planning of collective tasks performance in dynamic and cooperative environments.

This is a complicated process because the number of action grows exponentially and an increase of the number of agents could be a new situation, and each agent takes individual decisions of which the outcome can be influenced by the actions performed by the other agents. For thus, each agent is capable of perceive and interpret the information involved in the proposed actions and include such information in its knowledge base. This fact, allow agents to be only focused in those particular actions that it can execute taking into account its calculated estimation (suitability rate) regards such actions. ***Redundancy in the tasks performance is then avoided.***

This new and effective approach contributes to improve multi-agent efficiency and performance in dynamic and cooperative environments because the agents can know if they can perform any proposed action. If agents cannot perform any action, the agents can make another decision depending on the general interest of the multi-agent system. Thus, the agents' situation is based on the elements of the three decision axes and is useful in the agent's decision-making aiming to increase the general system performance.

This thesis has reported the research carried out in order to accomplish the main goal argued. For achieving it, a study about multi-agent coordination, a formal framework, an implementation stage and experimental results both simulated and real robot soccer test bed have been development. In light of this, ***the objective of this thesis was to have a formal multi-agent decision support as the framework for situated agents in dynamic and cooperative environments.***

6.2 Conclusion and Contributions

This thesis presents the outline of a multi-agent decision support system that contributes with a powerful method, independent of particular implementation technologies, for building intelligent agents with strong and useful capability to perceive and include knowledge mainly related to their situation on the environment, aiming at a correct performance of collective tasks in cooperative environments. In particular, this thesis presents an appropriate alternative to get more reliable knowledge about the agents' situation which is influencing the agent's individual reasoning process reflecting in the collective decision-making.

Much work still remains to be done on the decision support for situated agents. The thesis has identified some limitations of the current coordination methods/techniques, but these suggest in turn some natural extensions which will let the proposed framework to cover a wide range of intelligent knowledge that, it believe, will prove difficult to achieve in a traditional architectural background. It is also interesting to compare this approach with other techniques, in order to evaluate the usefulness and advantages of the proposal here.

The main contributions of this thesis are summarized as follow:

An study and definition of decision axes based on world representation (proximity), awareness (introspection) and interaction (trust), to be considered in the embodiment of the agents' situation.

The thesis reported a suitable way to embody agents by means of the knowledge involved in the agents' actions rates. Such knowledge is then represented in the agents' knowledge base meaning all the information that agents have available at moment to decide if they are able or not to execute the action required.

A formal design framework for coordination of multi-agent systems within cooperative environments using the claimed decision axes.

The thesis reported a good and feasible way to taking advantages of the combination of three kinds of knowledge related to the agents' actions rates and outlined the way of including such knowledge in the agents' decision-making. For thus, a formal multi-agent decision support based on the information of the three decision axes aforementioned was proposed. Such axes are seen a proper alternative used by the physical agents to include the knowledge of their ***situation*** related to any proposed actions. More specifically, these axes consist in parameters that embody the agent capability to perform any proposed action.

A decision-maker tool as a bridge to the gap between the actions' requirements and the agents' capabilities to perform such actions.

In this sense, the thesis argues the need to define that agent will be able (or not) to accomplish a certain action according to its individual capabilities. Indeed, the overall system performance increases if agents can perform individual actions in a better and more reliable way. It utility and feasibility of this approach on several coordinated cases and task allocation examples have been demonstrated.

A taxonomy for classification of approaches related to coordinated activities both in physical multi-agent systems as in multi-robot systems.

Finally, a classification by considering the three decision axes in the agents' decision-making is introduced. Such consideration determines the information selected to the agents. These elements therefore, have been ranked aiming to enhance future trends on the research on multi-agent and multi-robot systems.

6.3 Related Publications

The work developed for this thesis has lead to several contributions presented and discussed in different conference and congress. The most relevant works are listed and briefly commented below.

Ibarra M., Salvador, Quintero, C.G., Ramon, J., De la Rosa, J. Ll. and Castán, J.A., "Confianza entre Agentes. Un Estudio para Asignación de Tareas en Robot Soccer", In Proc. of the **7ma Conferencia Iberoamericana en Sistemas, Cibernética e Informática CISCI 2008**, to appear.

A proposal for task allocation in physical multi-agent systems by means of trust parameters in the task capabilities/requirements function is presented. The consideration of the agents' ability to reach cooperative agreements increases the performance of temporal groups of physical agents. Empirical results are presented in the successful performing of tasks by cooperative mobile robots in a simulated robot soccer environment.

De la Rosa J. Ll., Figueras A., Quintero C. G., Ramon J. A., **Ibarra M**. **Salvador**, and Esteva S. "Outline of Modofication Systems", **Studies in Computational Intelligence**, vol. 57, pp. 55-69 Spring-Verlag, ISSN: 1860-949X, 2007.

New hints for engineers to design control systems are presented. This work proposes that control engineers may keep KISS design in the control dimension, by explicitly introducing awareness (introspection) and interaction (trust) that let improve the performance of a machine while keeping the design simplicity.

Ibarra M. Salvador, Quintero C. G., Ramon J. A., De la Rosa J. Ll. and Castán J. A. "PAULA: Multi-agent Architecture for Coordination of Intelligent Agent Systems", In Proceeding of the **European Control Conference 2007**, vol. 1, pp. 2185-2192, ISBN: 978-960-89028-5-5, Kos - Grecee, July 2, 2007.

An architecture for coordination of multi-agent systems by means of knowledge based on the agents' situation within dynamic environments is presented. Agents are classified into two categories: Supervisor agents and Physical agents. Such classification allows agent to differentiate between them aiming to improve the cooperative task allocation in dynamic and competitive environment. Indeed, preliminary results in the simulated robot soocer test bet are presented.

Ibarra M. Salvador, Quintero C. G., De la Rosa J. Ll. "Physical Multi-agent Systems: A new Taxonomy aimed on Coordination", In Proceedings of the **2nd Spanish Congress on Computer Science CEDI 2007**, vol. 1, pp. 97 – 104, Thomson-Paraninfo Press, ISBN: 978-84-9732-597-4. Zaragoza – Spain, September 11, 2007.

A survey of the work most early in cooperative physical multi-agent systems is presented by examining several ways of cooperation and coordination performed on such systems. In particular, the work proposes a new taxonomy based on three parameters related to awareness (introspection), interaction (trust) and world representation (proximity) for the classification of approaches on coordination in physical multi-agent and multi-robot systems and describes some systems, which it considers representative in the taxonomy.

Quintero C. G., **Ibarra M. Salvador**, De la Rosa J. Ll., Vehí J. "Introspection on Control-grounded Capabilities. A Task Allocation Study Case in Robot Soccer", In Proceedings of the **4th International Conference on Informatics in Control, Automation and Robotics 2007**, vol. 2, pp. 461– 467, ISBN: 978-972-8865-87-0, Angers – France, May 9, 2007.

A proposal for task allocation in physical multi-agent systems by means of novel coordination parameters in the task utility/cost functions is presented. The composition of any parameters with introspection increases the performance as the result of most suitable task allocation. This proposal is demonstrated in the successful performing of tasks by cooperative mobile robots in a simulated robot soccer environment.

Quintero C. G., **Ibarra M. Salvador**, De la Rosa J. Ll. "A Coordination Approach for Task Allocation. Case Study in Robot Soccer", In Proceedings of the **2nd Spanish Congress on Computer Science CEDI 2007**, vol. 1, pp. 35 – 42, Thomson-Paraninfo Press, ISBN: 978-84-9732-597-4. Zaragoza – Spain, September 11, 2007.

An illustrative example in robot soccer of new coordination parameters to improve the coordination among physical agents in task allocation problems is shown. The approach proposes introspection, proximity and trust as key in the utility/cost functions to achieve the above aim. These parameters were managed in a holistic manner to select the most suitable agent to perform the proposed task.

Ibarra Salvador, Quintero C. G., Ramón J. A., De la Rosa J. Ll. and Castán J. A. "Studies About Multi-agent Team work Coordination in the Robot Soccer Environment", In Proceeding of the **11th Fira Robot Worl Congress 2006,** vol. 1, pp. 63 - 67, ISBN: 3-00-019061-9, Dortmund – Germany, Jun. 30 – Jul. 1, 2006.

A mechanism based on a characteristic of physical agent named "degrees of situation" that aids to improve the coordination among heterogeneous agents is suggested. These systems can be represented by means of the "physical agent" paradigm. This work has studied how the team work can be improved by the "degree of situation" management in robot soccer environment.

Ibarra Salvador, Quintero C. G., Busquets D., Ramón J. A., De la Rosa J. Ll. and Castán J. A. "Improving the Team-work in Heterogeneous Multi-agent Systems: Situation Matching Approach", **Frontiers in Artificial Intelligence and Applications – AI Research & Development**, vol. 146, pp. 275 – 282, IOS Press ISSN: 0922-6389, Amsterdam – Netherlands, October, 2006.

A "situation matching" method that aims at improving cooperative tasks in heterogeneous multi-agent systems is proposed. The situation matching represents a match between the systems requirements and the agents' capabilities. This work has studied how the heterogeneous agents' performance improves by means of such "situation matching" in the robot soccer test bed.

Ibarra M. Salvador, Quintero C. G., De la Rosa J. Ll. and Castán J. A. "An Approach based on New Coordination Mechanisms to Improve the Teamwork of Cooperative Intelligent Agents", In Proceedings of the **IEEE Seventh Mexican International Conference on Computer Science ENC 2006**, vol. 1, pp. 164 -172, IOS Press ISSN: 1550-4069, San Luis Potosí – Mexico, Sept. 2006.

The impact of the agents' situation study to include knowledge involved directly in the agents' task requirements in the decision-making of physical heterogeneous agents is highlighted. This approach allows to each agent a reliable self-knowledge which concludes in achieving sure commitments and intelligent task acceptance in dynamic and cooperative scenarios.

Quintero C. G., **Ibarra M. Salvador**, De la Rosa J. Ll. and Vehí Josep, "Dynamics Features on Robots Decisions. A Perspective based on Control-grounded Capabilities", In Proceedings of the 5th **IEEE International Symposium on Robotics and Automation ISRA 2006**, vol. 1, pp. 199 – 206, ISBN: 970-769-070-4, Hidalgo – Mexico, Ago. 25, 2006.

Theoretical and practical groundwork based on control-grounded capabilities to include dynamics features on the decision-making of cooperative mobile robots from a control-oriented viewpoint is presented. This work stresses the advantages of the proposed approach in coordinated tasks of robot soccer.

Quintero C. G., **Ibarra M. Salvador**, De la Rosa J. Ll. and Vehí J. "Exploring the Physical Agents' Behaviors to Improve Collective Decisions in Multi-Agent Environments", In Proceedings of the **1st Spanish Congress on Computer Science CEDI 2005**, vol. 1, pp. 9 – 15, Thomson-Paraninfo Press, ISBN: 84-9732-435-8. Granada– Spain, September 16, 2005.

This paper presents a machine learning perspective to include environment-oriented knowledge in the decisions making structure of physical agents. This approach solves the opposite team's behaviors problem, improving our team decisions based on the CBR methodology in a robotic soccer test bed. It is provided the outline of the research applied to strategy decisions in robotic soccer. Examples and conclusions are presented, emphasising the advantages of our proposal in the improvement of the multi-agent performance in cooperative systems.

Ibarra M. Salvador, Christian G. Quintero M., Josep A. Ramon., Josep Ll. De La Rosa, A. Figueras., "Generación y Gestión de Diversidad Dinámica En Agentes Físicos", **26th Spanish Congress on Automation JA 2005**, vol. 1, pp. 157 – 163, ISBN: 84-689-0730-8, Alicante – Spain, Septiembre 7, 2005.

An approach to show how artificial intelligence techniques improve the coordination of dynamic systems (physical agents) is presented. In particular, the physical agent uses introspection about their physical bodies to get a better self-knowledge increase the agent performance in cooperative scenarios. Some preliminary results emphasizing the advantages of this approach by improving the performance of cooperative systems are shown.

6.4 Future Trends

Agent technology is studied by several research groups and is commonly useful to solve complex problems of the real world in a wide range of industrial and commercial applications that are beyond human systems. Specially, in applications that require autonomy and cooperation as key properties for the proper development of the system's goals. Many interesting fields for the application of the multi-agent systems are vaguely mentioned in [Luck et al., 05] where the most predominant area is related to industrial applications (e.g., manufacturing process, telecommunications, aircraft and transport systems). While the industrial applications tend to be highly complex, there are indications about agent systems working in areas less complex oriented to commercial application (e.g., information management, e-commerce, etc) as well as leisure implementations (e.g., games). However, an increasing area in the artificial intelligence is the application of agents in medical procedures. Such area aims to being one of the most relevant applications of the agent technology [Luck et al., 05].

Because there are many approaches to decision-making and because of the wide range of domains in which decisions are made, the idea of multi-agent decision support is very broad. Along the research developed in this thesis; the ***agents' situation*** on multi-agent cooperation has been extensively studied in the robot soccer domain. The obtained results present some features that could be extended to other domains and applications that may also benefit from the explicit knowledge on the ***decision axes*** mentioned in this work. In this sense, a novel application of the proposed approach could be applied in other simulated test beds where teams of autonomous mobile agents must take cooperative decision in real time within dynamics and hazardous environments such as rescue scenarios [Quintero et al., 07b], [Murphy, 04]. Agents can reflect their situation regarding to each possible danger condition in their knowledge bases. Such information lets agents to be aware about the set of actions that they can do and to establish a certainty index about their success in the task that they will perform. While agents can identify and include more and more useful information in their situation, they can increase the task performance impacting positively in the overall system.

The current efforts and results showed in this thesis emphasising that the decision axes notion is very useful for cooperative multi-agent systems. However, it is still difficult to choose the needed information to be included in the decision axes as well as the most suitable particular implementation technologies for imitating awareness in physical agents. In this direction, the thesis has reported some preliminary steps, showing some results obtained by using different machine learning and soft-computing techniques for building the world representation (*proximity*), the awareness (*introspection*), and the interaction (*trust*). In this light, more extensive studies on these topics should be carried out to guarantee a better agent-oriented representation of the agents' situation regarded to the environment and other relevant details that can increase and benefit the cooperative multi-agent performance.

Multi-agent decision support has been studied in this thesis mainly in the context of the agents' situation resulting from the knowledge of the three decision axes. The relevance of this new approach has been shown especially in cooperative mobile robots, but the agents' situation concept in other interesting types of application should be explored more in depth to enrich the agents' decision-making with information directly related to the agents' embodiment and other aspects of cooperation. In addition, the contribution presented in this thesis reveals the possible emergence of a new line of research mainly related to the ***quantity*** and ***quality*** of the information that agents can conceive in their knowledge bases in order to be ***situated*** once they are placed in a cooperative environment.

De la Rosa et al., [De la Rosa et al., 07] introduces a new paradigm in the research field of the agents called *Modification Systems* which are designed as a generalization of control systems and situated agents, where anybody does not control a system but modifies a system by some multidimensional change of its original behavior toward a desired target behavior. In this sense, modification systems refer to the property of one machine to have three modifiers of its behavior (Fig. 6.1) and it can modify its behavior by increasing or decreasing its consideration in each dimension.

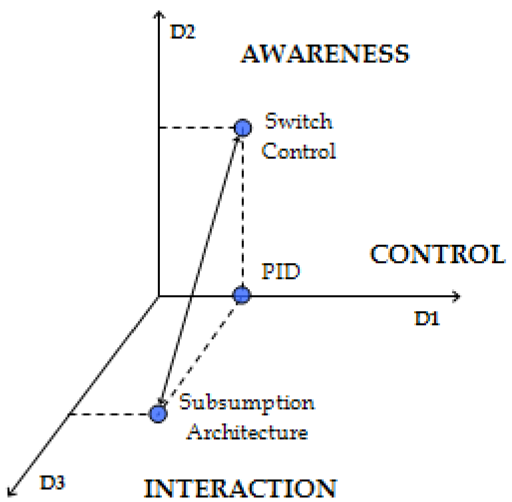

Fig. 6.1. General scheme of modifiers in the Modification System approach.

The thesis argues that a promising line of research could be the Modification Degrees approach (see Fig. 6.2). It can adopt the principle of the modification systems to generate a new perspective to increase the agents' situation. Such modification degrees can influence the amount of information that agents include in their knowledge bases aiming to improve the cooperative performance of this systems due to the agents can added more o less information in any dimension. In this sense, it new application aims to improve the cooperative global performance in systems where the information proposed for the agents will more representative in one specific dimension. Decision axes can change as for complexity, interest or usefulness, however a deeper study on how deciding the relevance of information for the agents' situation, would be very interesting in order to strengthen and to stimulate the agents' decision-making in dynamic and cooperative environments.

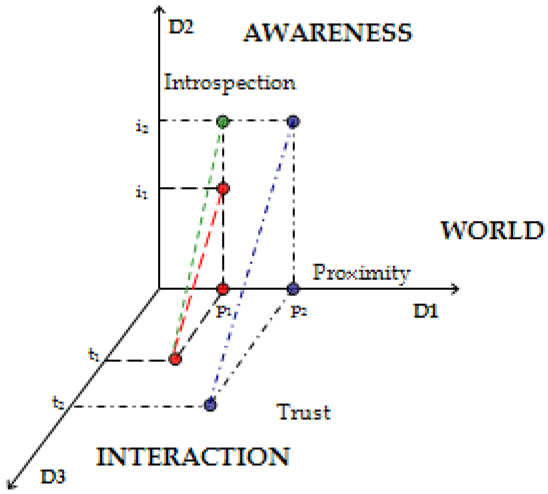

Fig. 6.2. General scheme of the Situation Degree proposed for future research work.

6.5 Final Remarks

This thesis was intended to bring the agents research community one step closer to an understanding how information involved in the execution of the action can embody the agents' situation. Such embodiment allows agents to be sure about what action can perform in a more reliable way. In addition, the thesis argues the need for a formalization of decision axes for physically situated agents to improve the agents' decision-making performance in both individual and cooperative decisions and close the gap between the requirements involved in the execution of any action and the agents' capabilities to perform such actions.

Decision axes in the framework of the decision support for situated agents allows agents to achieve sure and trustworthy individual decisions in cooperative systems, improving the performance of agents in coordinated task and task allocation scenarios. The thesis has shown how the decision support for situated agents helps to prevent undesirable situation, to make safer decisions, to increase the coordinated organizational control, to facilitate interpersonal communication, to expedite a proper problem solving path and to obtain enhanced levels of performance and autonomy in any group of cooperating agents.

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Appendix A

Other Interesting Results

In order to strength the results showed in the chapter 5, this appendix includes information related to the experimental results.

A.1 Simulated Results - Implementation 1

In order to provide the reader with more information related to the simulated experimental results obtained in the implementation 1; this section presents a study of the successful action for each case study. In this light, the tables depict the goals and tasks trials and their successful performance; as well as the relation between the physical agent and the roles, analyzing the occasions in which each physical agent decide to play a role, and its effectiveness to perform such selected role, respectively.

A.1.1 Scenario 1: Coordinated Task

Case 1: Trust [0, 0, 1]

The table A1 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A2 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A1. Successful decisions using the Trust parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	441298	42.05	$task_1$	183403	41.56	40.53
				$task_2$	257895	58.44	46.88
$scene_2$	$goal_2$	739105	66.83	$task_2$	382386	51.73	39.41
				$task_3$	356809	48.27	42.52
$scene_3$	$goal_3$	565239	41.67	$task_4$	305681	54.08	33.57
				$task_5$	259558	45,92	43.70

Table A2. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		Trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1388923	421260	50.23	455112	42.56	116570	52.84	211969	36.18	45.11
pa_3	174572	224589	48.56	460000	48.52	96909	46.78	161735	48.56	48.36
pa_4	356809	335841	51.86	458080	39,55	71754	55,34	139176	42.39	45.20
pa_5	616367	407232	52.24	372539	40.67	71576	48.56	103488	24.75	44.47

Case 2: Introspection [0, 1, 0]

The table A3 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A4 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A3. Successful decisions using the Introspection parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	510375	49.05	$task_1$	187104	36.66	60.02
				$task_2$	323272	63.34	48.93
$scene_2$	$goal_2$	758204	69.37	$task_2$	463869	61.18	43.29
				$task_3$	294335	38.82	54.21
$scene_3$	$goal_3$	548349	50.32	$task_4$	327748	59.77	54.56
				$task_5$	220601	40.23	58.66

Table A4. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		Trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1107495	392220	60.66	468586	61.32	95865	58.94	150825	45.43	58.72
pa_3	1021546	366488	51.35	449871	56.29	74290	50.21	130897	50.77	53.37
pa_4	1055561	382323	61.94	484393	54.78	61398	58.47	127447	53.22	57.40
pa_5	964189	381562	54.11	414078	58.43	62782	56.78	105768	49.56	55.64

Case 3: Introspection + Trust [0, 1, 1]

The table A5 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A6 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A5. Successful decisions using the Trust and Introspection parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	438423	32.61	$task_1$	238151	54.32	29.43
				$task_2$	200272	45.68	27.32
$scene_2$	$goal_2$	759440	29.44	$task_2$	407515	53.66	30.45
				$task_3$	351924	46.34	32.66
$scene_3$	$goal_3$	605604	28.13	$task_4$	317518	52.43	29.87
				$task_5$	288086	47.57	31.98

Table A6. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1451543	108912	33.2	427061	34.65	89741	31.99	156803	40.12	34.79
pa_3	1803467	358096	36.54	444915	31.22	90445	33.75	170883	30.55	33.12
pa_4	351924	366660	34.12	469803	34.9	92556	31.5	162563	30.44	33.69
pa_5	640010	398739	38.5	461688	33.64	79183	29.76	149762	29.43	34.56

Case 4: Proximity [1, 0, 0]

The table A7 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A8 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A7. Successful decisions using the Trust parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	428900	54,33	$task_1$	198581	46.30	37.38
				$task_2$	230319	53.70	58.34
$scene_2$	$goal_2$	804738	75.65	$task_2$	465782	57.88	27.46
				$task_3$	338956	42.12	48.03
$scene_3$	$goal_3$	529205	63.58	$task_4$	319852	60.44	51.37
				$task_5$	209353	39.56	40.34

Table A8. Physical Agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1133908	308747	50.23	498995	42.56	103619	52.84	161587	36.18	45.17
pa_3	1022998	300298	48.56	475439	48.52	96806	46.78	150456	48.56	48.37
pa_4	986264	362664	51.86	416560	39,55	72265	55,34	134774	42.39	45.64
pa_5	930825	380178	52.24	382889	40.67	66266	48.56	101492	24.75	44.22

Case 5: Proximity + Trust [1, 0, 1]

The table A9 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A10 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A9. Successful decisions using the Trust and Proximity parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	452230	40.31	$task_1$	259218	57.32	41.13
				$task_2$	193012	42.68	47.22
$scene_2$	$goal_2$	739531	49.12	$task_2$	377678	51.07	41.07
				$task_3$	361852	48.93	43.76
$scene_3$	$goal_3$	574072	39.68	$task_4$	317864	55.37	35.44
				$task_5$	256208	44.63	45.01

Table A10. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	978559	300733	33.2	418149	34.65	95891	31.99	163786	40.12	34.86
pa_3	1042360	357453	36.54	435631	31.22	96615	33.75	152661	30.55	33.18
pa_4	1072651	371353	34.12	459999	34.9	84312	31.5	156987	30.44	33.71
pa_5	1056156	374442	38.5	452053	33.64	85035	29.76	144626	29.43	34.47

Case 6: Proximity + Introspection [1, 1, 0]

The table A11 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A12 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A11. Successful decisions using the Introspection and Proximity parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	489920	59.66	$task_1$	284252	58.02	69.88
				$task_2$	205669	41.98	56.47
$scene_2$	$goal_2$	704877	64.75	$task_2$	382959	54.33	59.32
				$task_3$	321917	45.67	61.76
$scene_3$	$goal_3$	534537	66.72	$task_4$	310994	58.18	60.43
				$task_5$	223543	41.82	66.32

Table A12. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1027196	313010	61.22	443401	62.43	94547	60.35	176238	47.11	59.24
pa_3	988672	329758	53.44	421957	57.37	88592	53.44	148365	51.23	54.79
pa_4	997991	375217	60.23	436484	58.02	67925	59.43	118365	54.66	58.55
pa_5	990270	389432	56.22	427491	59.55	70854	57.13	102492	51.08	57.19

Case 7: Proximity + Introspection + Trust [1, 1, 1]

The table A13 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A14 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A13. Successful decisions using the Trust and Introspection and Proximity parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	557374	63.71	$task_1$	317870	57.03	70.59
				$task_2$	239504	42.97	64.6
$scene_2$	$goal_2$	679556	64.59	$task_2$	385784	56.77	66.55
				$task_3$	293772	43.23	61.27
$scene_3$	$goal_3$	628445	68.44	$task_4$	368583	58.65	60.13
				$task_5$	259862	41.35	58.92

Table A14. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1078824	390857	61.39	453472	58.67	72944	60.33	161550	64.36	60.62
pa_3	1066961	403116	68.35	438923	60.24	77380	59.66	147543	62.41	63.56
pa_4	1075692	389600	71.33	490966	72.45	74765	66.8	120360	63.45	70.64
pa_5	1062905	388029	77.39	482013	71.33	68684	65.4	124180	68.04	72.77

A.1.2 Scenario 2: Task Allocation

Case 1: Trust [0, 0, 1]

The table A15 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A16 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A15. Successful decisions using the Trust parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	493389	41.94	$task_1$	269736	54,67	41.2
				$task_2$	223653	45,33	45.72
$scene_2$	$goal_2$	758830	66.59	$task_2$	445206	58,67	40.1
				$task_3$	313624	41,33	41.87
$scene_3$	$goal_3$	613145	41.08	$task_4$	369972	60,34	33.76
				$task_5$	243173	39,66	42.45

Table A16. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1215548	443177	33.56	512042	30.49	98133	31.04	162195	30.76	31.69
pa_3	1083427	380797	29.46	466901	31.24	89069	30.08	146661	28.49	30.15
pa_4	1039706	374435	31.34	469512	29.3	66582	28.95	129177	29.57	30.05
pa_5	948844	353331	31.28	416909	33.84	59840	25.79	118765	24.05	31.15

Case 2: Introspection [0, 1, 0]

The table A17 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A18 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A17. Successful decisions using the Introspection parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	588784	48.69	$task_1$	325715	55,32	58.67
				$task_2$	263069	44,68	49.72
$scene_2$	$goal_2$	816049	69.55	$task_2$	479510	58,76	45.03
				$task_3$	336538	41,24	53.55
$scene_3$	$goal_3$	617091	51.73	$task_4$	422399	68,45	52.65
				$task_5$	194692	31,55	59.34

Table A18. Physical Agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1281522	464661	61.76	534799	60.35	109678	65.98	172384	59.76	61.26
pa_3	1182534	417976	67.54	521859	69.09	92043	64.95	150657	61.44	67.25
pa_4	1097957	410223	63.13	495978	70.24	69361	60.51	122396	55.09	66.4
pa_5	1013065	392526	71.3	469289	67.08	65457	62.43	85794	69,64	68.63

Case 3: Introspection +Trust [0, 1, 1]

The table A19 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A20 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A19. Successful decisions using the Trust and Introspection parameters.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	477475	30.28	$task_1$	255401	53,49	28.74
				$task_2$	222074	46,51	29.11
$scene_2$	$goal_2$	851657	27.45	$task_2$	499156	58,61	31.44
				$task_3$	352501	41,39	33.48
$scene_3$	$goal_3$	545525	29.4	$task_4$	319896	58,64	31.02
				$task_5$	225629	41,36	29.33

Table A20. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1233518	416005	33.05	527528	33.79	112730	31.88	177255	41.35	34.45
pa_3	1096199	403219	36.38	444481	30.69	103388	34.04	145111	30.76	33.11
pa_4	1055473	370188	34.5	489473	33.67	66658	32	129154	29.8	33.38
pa_5	942253	332743	39.44	413174	34.11	69725	28.49	126610	30.02	35.03

Case 4: Proximity [1, 0, 0]

The table A21 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A22 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A21. Successful decisions using the Proximity parameter.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	515849	52.84	$task_1$	279642	54.21	36.85
				$task_2$	236207	45.79	57.77
$scene_2$	$goal_2$	812063	69.43	$task_2$	488212	60.12	31.6
				$task_3$	323851	39.88	50.43
$scene_3$	$goal_3$	615753	65.23	$task_4$	353996	57.49	52.09
				$task_5$	261757	42.51	38.76

Table A22. Physical Agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1098657	371099	36.54	454818	36.84	97058	37.44	175682	36.21	36.69
pa_3	1142926	397340	38.61	491747	30.87	89869	32.45	163970	38.9	34.84
pa_4	1129997	414025	29.78	499522	32.44	70049	27.12	146402	38.88	31.97
pa_5	1101357	437350	33.55	497578	36.09	66875	33.19	99553	32.75	34.60

Case 5: Proximity + Trust [1, 0, 1]

The table A23 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A24 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A23. Successful decisions using the Trust and Proximity parameters.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	537356	38.56	$task_1$	273299	50,86	42.34
				$task_2$	264057	49,14	46.55
$scene_2$	$goal_2$	841904	43.76	$task_2$	516255	61,32	39.54
				$task_3$	325648	38,68	40.97
$scene_3$	$goal_3$	575474	41.4	$task_4$	342062	59,44	39.75
				$task_5$	233412	40,56	45.21

Table A24. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1189087	401570	32.45	519177	34.87	109288	32.09	159053	41.48	34.68
pa_3	1147106	436106	35.94	488293	31.77	90042	34.04	132665	29.68	33.29
pa_4	1136570	413951	35.11	522109	35.75	65553	32.14	134957	29.66	34.59
pa_5	995765	377459	37.65	425155	32.4	60766	30.43	132386	31.01	34.09

Case 6: Proximity + Introspection + [1, 1, 0]

The table A25 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A26 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A25. Successful decisions using the Introspection and Proximity parameters.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	548349	61.04	$task_1$	291776	53,21	68.56
				$task_2$	256572	46,79	61.33
$scene_2$	$goal_2$	785854	61.43	$task_2$	474184	60,34	60.21
				$task_3$	311670	39,66	59.87
$scene_3$	$goal_3$	653288	64.49	$task_4$	379365	58,07	68.56
				$task_5$	273924	41,93	60.43

Table A26. Physical Agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1228650	463532	64.56	480774	70.13	102165	69.54	182178	61.3	66.67
pa_3	1243287	453980	61.45	529468	66.9	88670	68.76	171169	66.04	64.92
pa_4	1044662	373708	70.34	486140	70.01	63830	66.78	120984	65.71	69.43
pa_5	1043977	384601	71.1	491109	66.02	57004	68.4	111263	61.33	67.52

Case 7: Proximity + Introspection + Trust [1, 1, 1]

The table A27 summarizes the goals and tasks performance rates. Such information is studied taking into account the average of the achieved successful actions at the simulated championships. In addition, the Table A28 shows the successful performance of each physical agent in the execution of the roles. In particular, the overall individual performance of each physical agent is obtained by estimating the successful rates of all its executed actions.

Table A27. Successful decisions using the Trust and Introspection and Proximity parameters.

Scene	Goals	Trials	Successful Performance (%)	Tasks	Trials	Trials (%)	Successful Performance (%)
$scene_1$	$goal_1$	575700	64.33	$task_1$	330624	57,43	69.32
				$task_2$	245075	42,57	66.47
$scene_2$	$goal_2$	770988	66.18	$task_2$	423118	54,88	70.32
				$task_3$	347870	45,12	65.42
$scene_3$	$goal_3$	608150	67.85	$task_4$	318184	52,32	59.65
				$task_5$	289966	47,68	59.18

Table A28. Physical agents' successful roles' performance.

Physical Agent	Trials	Roles								Overall Successful Rate (%)
		$role_1$		$role_2$		$role_3$		$role_4$		
		trial	(%)	trial	(%)	trial	(%)	trial	(%)	
pa_2	1269178	438702	61.32	527806	60.33	111318	66.95	191351	60.4	61.26
pa_3	1166499	424240	66.24	469161	64.23	100882	60.01	172216	55.67	63.33
pa_4	1090658	385672	69.45	488710	70.33	69574	72.4	146702	53.76	67.92
pa_5	1021177	358354	79.68	469161	74.32	66095	62.04	127567	58.43	73.42

Appendix B

The Robots

This appendix is devoted to show the more transcendent aspects of the robots used in the real experiments developed in this dissertation.

B.1. Team Robots' Description

The robots used in the experimentation are the *Yujin Robot Soccer*[6] official robots. In this sense, two models of robot have been used along the real experimental phases: the YSR-A and the VICTO robots. The physical description of each model of robot and vision systems are here, described as follow.

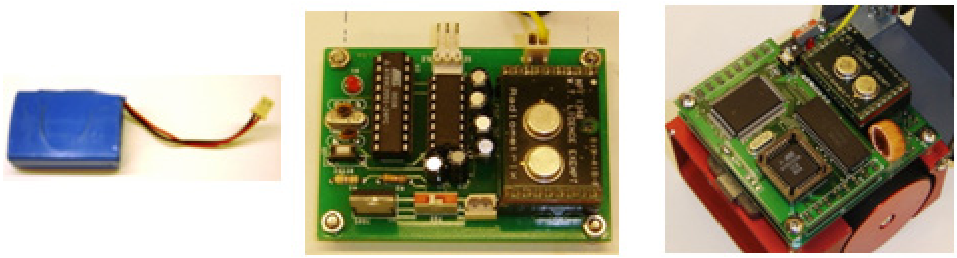
B.1.1 YSR-A Robot

The *team-robot*$_1$ is constituted by three (3) *YSR-A* robots (some pictures of the robots are shown in Fig. B1). They are a 2-wheel robots, equipped with a radio frequency module RADIOMATIX BIM 418 or 433 *MHz*. The dimensions of the robots are 7.5 x 7.5 x 7.5 (in cm, *length* × *width* × *height*) and 600 gr. in weight. They body was entirely done of duralumin to prevent the internal shock and maintain stability. Each robot has a cover (on the top of its body) makes out of a steel to protect the board form powerful exterior impact in the robot soccer.

[6] http://www.yujinrobot.com/

In this sense, each robot has a CPU board micro-controller Intel 80C296SA with ROM (29C010) using a L298 drive board to control two with one chip. The motors are SWISS MINIMOTS with and integral encoder IE2- 512 and its resolution is 512 pulses / revolution. Besides, the wheels are of silicon tired mounted with gear on, material of aluminium. Finally, the robots' power is provided by a re-chargeable lithium-ion battery of 7.4v, 1200mA.

Fig. B1. YSR-A robot.



a) b) c)

Fig. B2. Part of the YSR-A robot; a) the battery; b) RF antenna; c) CPU board

6.5.1.1 B.1.1.1 Vision System

A frame grabber card is required for the vision program. The, a METEOR-II/4 from MATROX have been used. And the computer system runs over Windows 98. In the vision system, a CCD camera with zoom lens should be used for the playground to fit into the view area of screen. SAMSUNG Digital Color CCD Camera may be used as the CCD camera (see Fig. B3). The model number is SDC-410ND. The camera stand is 2 m or higher in height, and to display the whole area of the playground on the screen at this height, a lens with a zoom function has to be used. The length of the focus of the zoom lens must be between 3.5mm and 8.0mm and it must have a manually controllable iris. By controlling the iris, the brightness of the image on the screen can be set to a proper level of brightness even though the brightness of the surrounding environment around the game field is changed.

Fig. B3. Camera

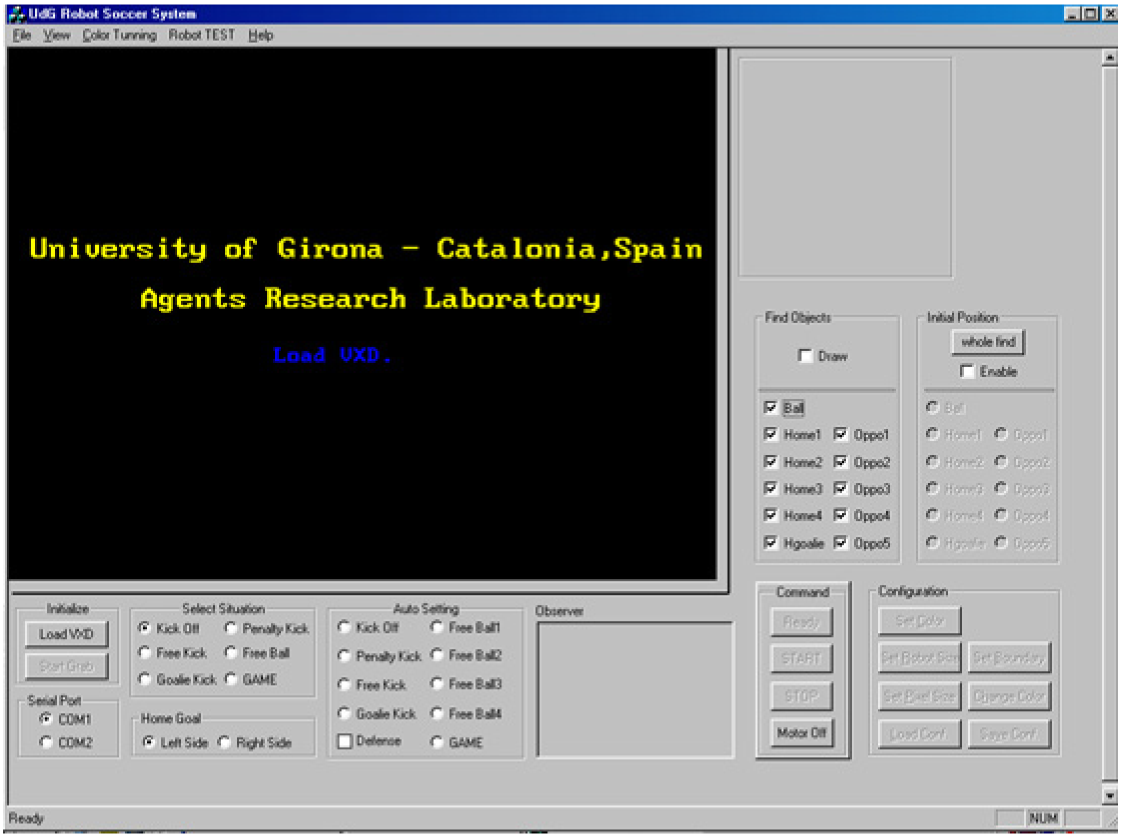


Fig. B4. YSR-A Vision System – General Scheme.

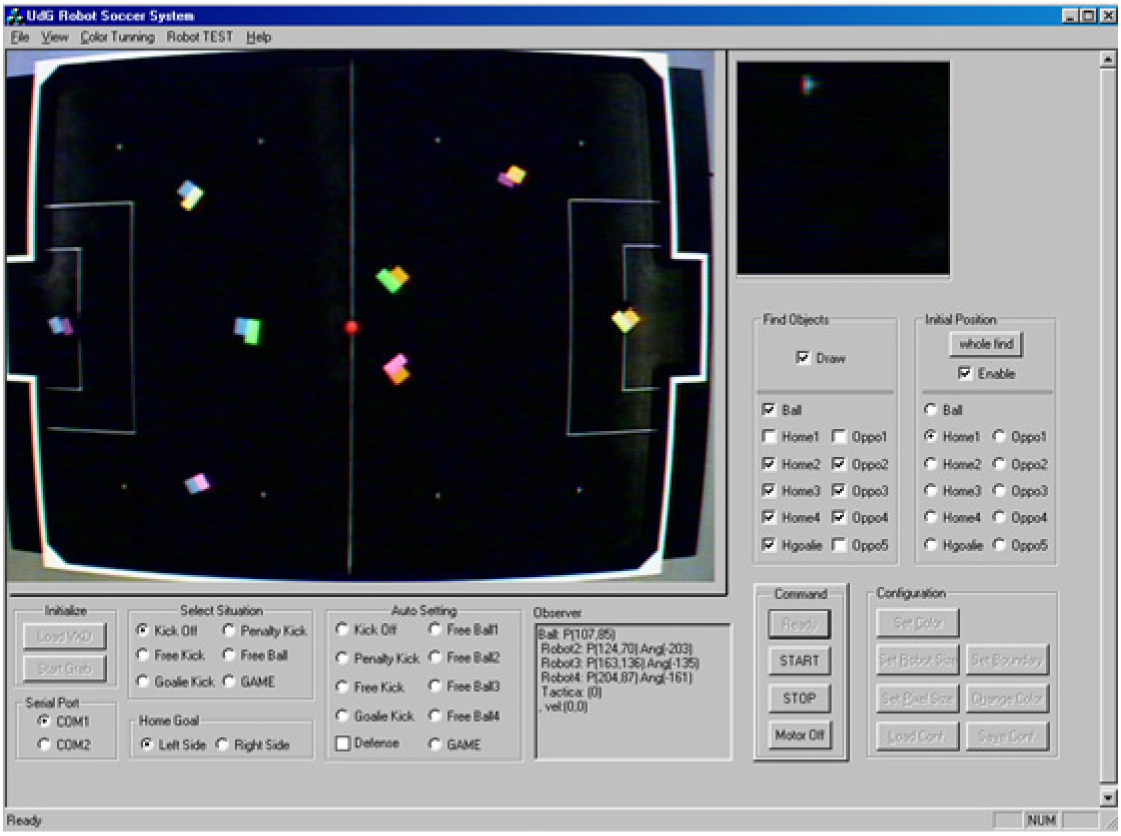


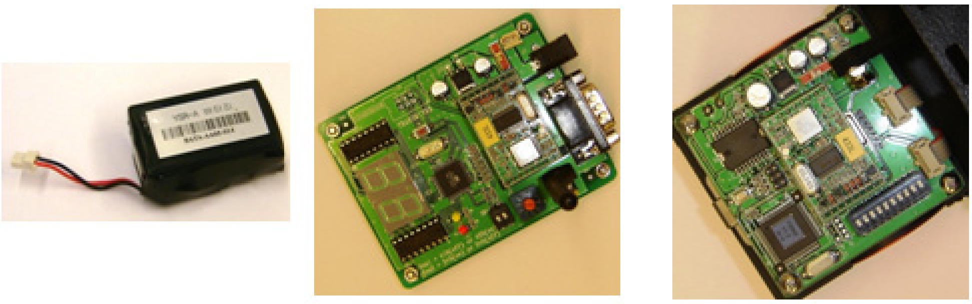
Fig. B5. YSR-A Vision System – The Game.

B.2 VICTO Robot

The *team-robot*$_2$ is constituted by three (3) *VICTO* robots (some pictures of the robots are shown in Fig. B6). They are 2-wheel robots, equipped with a radio frequency module SRF-418 or 433 *MHz* multi-channel developed by *Yujin Robotics Co*. The dimensions of the robots are 7.5 x 7.5 x 7.5 (in cm, *length* × *width* × *height*) and 450 gr. in weight. They body was entirely done of die casting to prevent the inner shock and keep solid shape. Each robot has a cover (on the top of its body) made of a plastic to prevent outer shock and inside noise.

Moreover, each robot has a CPU board micro-controller ATMEGA 163 from ATMEL, and a Flash ROM (inside). Each robot also has two motors of 6v-DC motor of 7400 *rpm* endowed with encoders of 144 pulses per revolution. Besides, the wheels are of silicon tired mounted with gear on, material of aluminium. Finally, the robots' power is provided by a re-chargeable lithium-ion battery of 7.4v, 1000*mA*.

Fig. B6. The VICTO robot.



a) b) c)

Fig. B7. Part of the VICTO robot; a) the battery; b) RF antenna; c) CPU board

6.5.1.2 B.2.1 Vision System

A frame grabber card is required for the vision program. The, a METEOR-II/4 from MATROX have been used. And the computer system runs over Windows 2000. For the camera, a CCD camera with zoom lens should be used for the playground to fit into the view area of screen. SAMSUNG Digital Color CCD Camera may be used as the CCD camera. The model number is SDC-410ND. The camera stand is 2 m or higher in height, and to display the whole area of the playground on the screen at this height, a lens with a zoom function has to be used. The length of the focus of the zoom lens must be between 3.5mm and 8.0mm and it must have a manually controllable iris. By controlling the iris, the brightness of the image on the screen can be set to a proper level of brightness even though the brightness of the surrounding environment around the game field is changed.

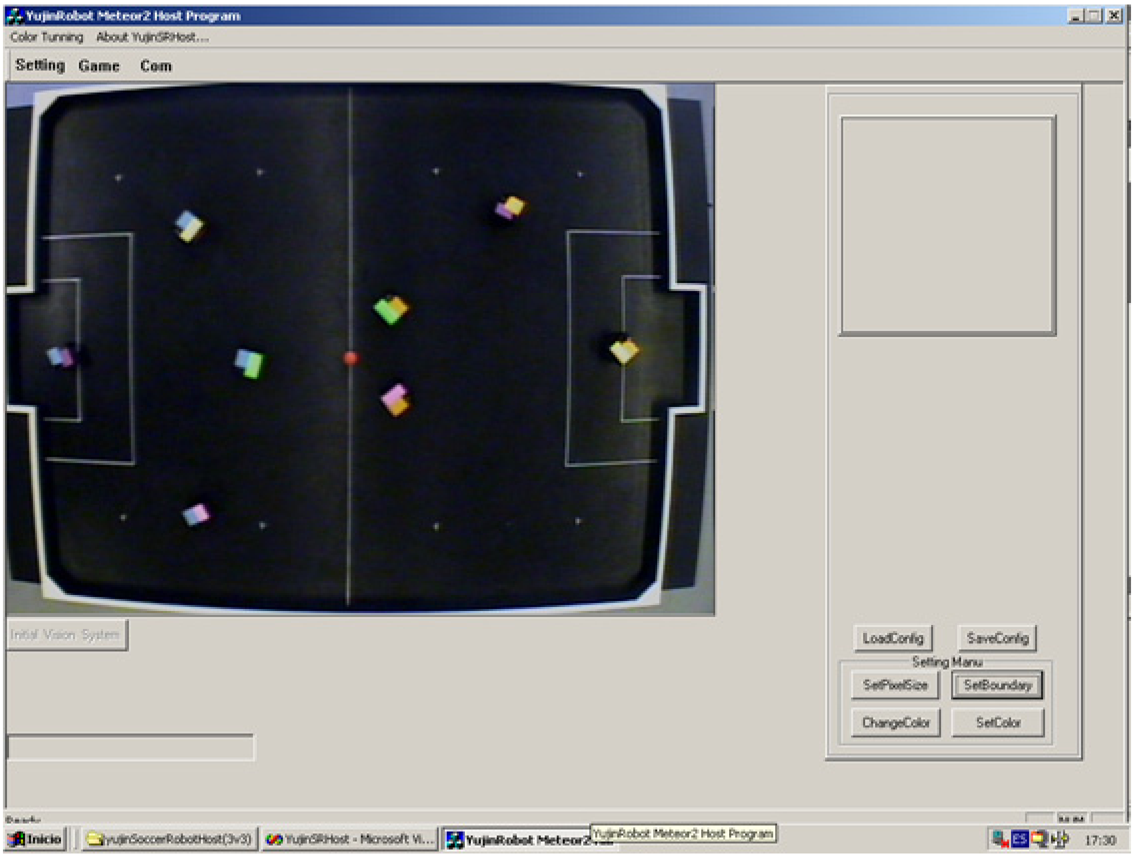


Fig. B8. Robot Soccer Vision System – General Scheme

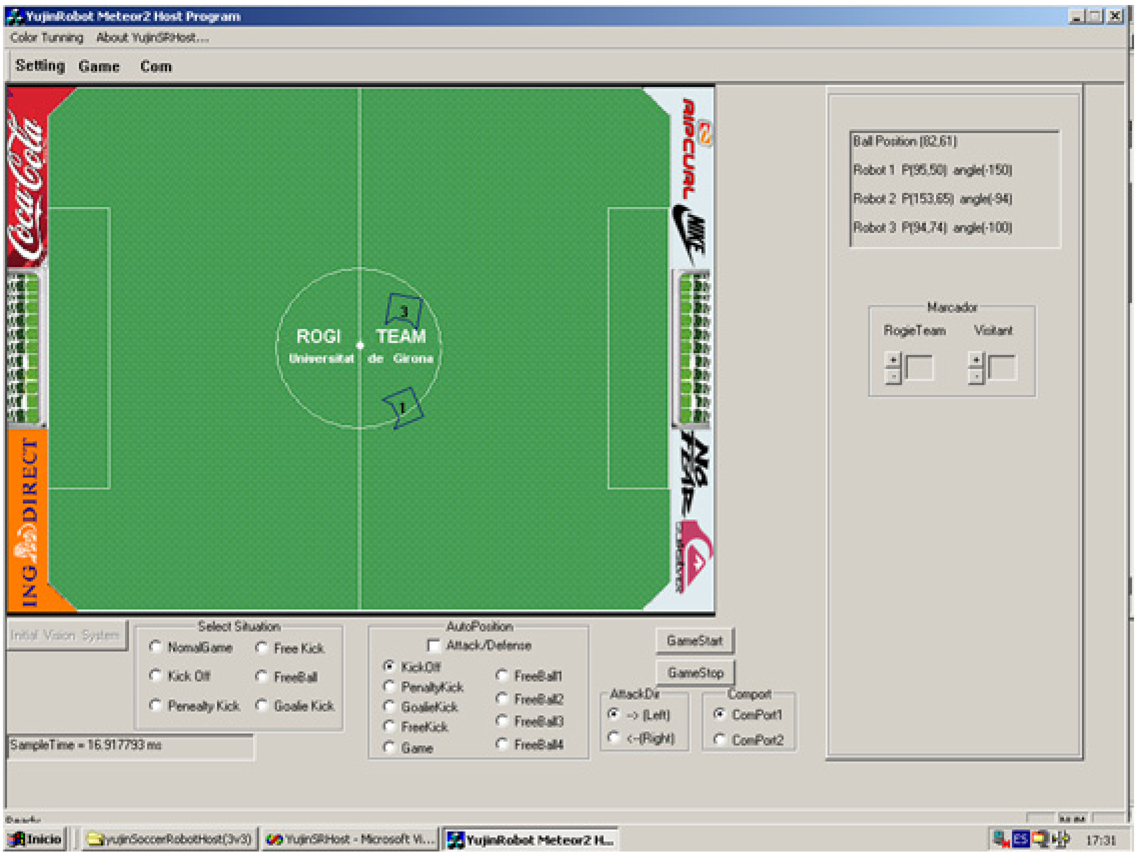


Fig. B9. VICTO Vision System – The Game.

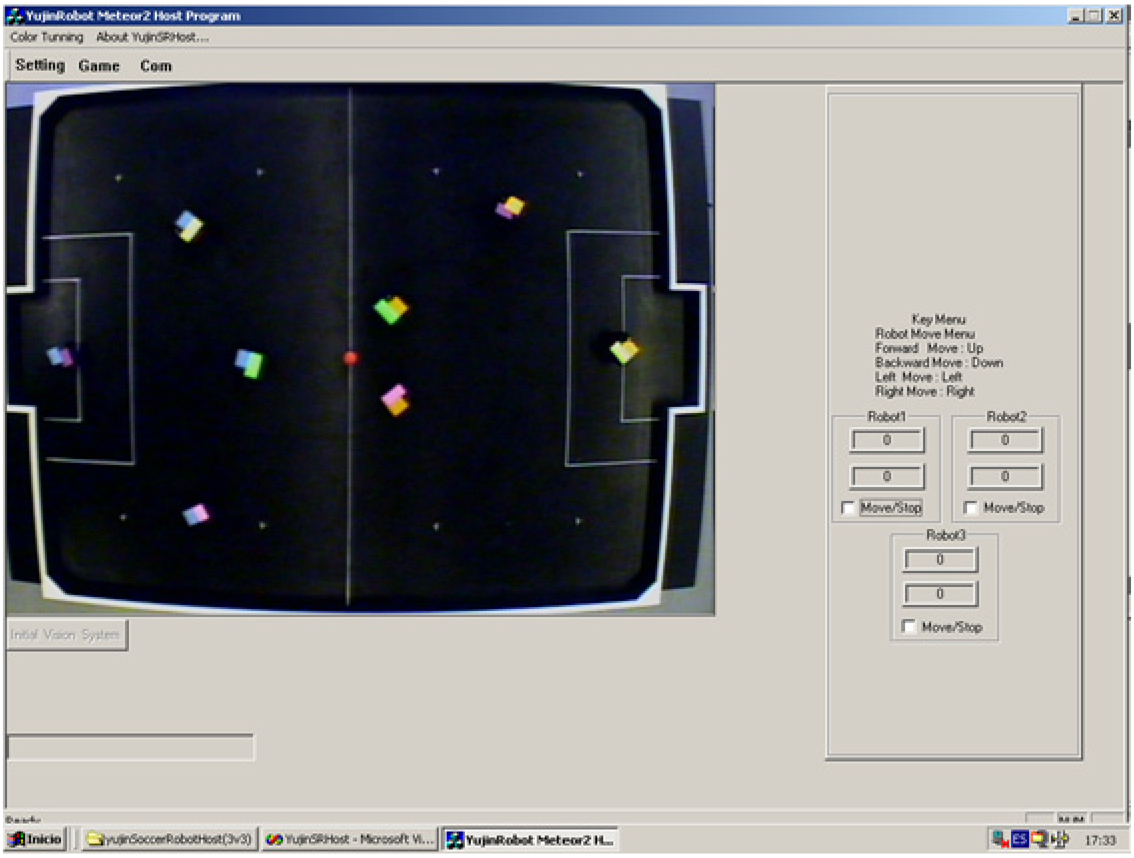


Fig. B10. VICTO Vision System – RoboTest.