Situated Agents Solving Coordinated Tasks in Dynamical Scenarios

Salvador Ibarra M., José A. Castán R., Julio Laria M., Mayra G. Treviño B., Julissa Pérez C., Emilio Castán R.

ABSTRACT - Cognitive systems aim to endow physical agents with higher levels of cognitive functions which enable them to reason, act and perceive in changing, incompletely known and unpredictable environments. Agents are typical implementations of cognitive entities. In fact, this paper introduces a framework suitable for supporting the distributed performing of cooperative actions in dynamical and complex multi-agent environments based on the knowledge involved in the agents' situation. The framework allows agents to self-calculate their suitability rates to execute any proposed action. In this light, experimental results are obtained using the robot soccer simulator test bed. Such experiments show that the selected information to generate the knowledge used by agents is useful when such agents must perform actions in a suitable way or they must achieve trustworthy commitments. Conclusions emphasizing the advantages and usefulness of the introduced framework improving the multi-agent performance in coordinated task situations are presented.

Key Words: Situated Agents, Cooperation, Environmental Conditions, Physical Knowledge, Trust Value.

1. INTRODUCTION

Most of the research into cooperative systems to date has concentrated on how to obtain desired dynamics interaction between autonomous agents [1]. In this sense, to solve complex problems, multi-agent systems require knowledge about each agent and their skills to perform individual actions in distributed and cooperative environments where entities share goals and their actions are beneficial to their teammates [2]. In this light, cognitive systems aim to endow physical agents with higher levels of cognitive functions which allow them to reason, act and perceive in changing, incompletely known and unpredictable environments. Such agents, for example, must be able to reason about goals and actions, the cognitive state of other agents, times, resources, collaborative task execution, etc. In short, cognitive robotics is concerned with integrating reasoning, perception, and action within a uniform theoretical and implementation framework (using methods drawn from logic, probability and decision support theory, reinforcement learning, etc). Methods for cooperative multi-agent decisions are therefore, in extensive cases, intensive software applications and highly sophisticated algorithms that use advanced design technologies to support collective decisions. Besides, these systems have generally requirements that go beyond single disciplines (*form control engineering to computer sciences*). Over the past decade, there are some works towards combining artificial intelligence (*AI*) approaches with traditional control theories to obtain intelligent systems. Despite several researches in multi-agent systems, important theoretical aspects of cooperation have been untreatable [3]. 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 [4]. One typical implementation of the agent technology is the physical agent paradigm. A physical agent is an intelligent entity which is embodied in some environment (i.e., has a physical representation) and which must take its decisions based on the capabilities of the physical body its must manages. 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 [5]. In this sense, the control and coordination of multiple autonomous mobile agents (i.e., physical agents) is a challenging task; particularly in environments with multiple, rapidly changing conditions and agents [6]. 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 [7]. 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 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 [8]. 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 [9]. Coherence refers to 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). Generally speaking, one the most transcendent topic in the literature is the **coordinated task** problem-solving algorithm. **Agents can improve cooperation by planning the execution of complex**

J. A. Castán, S. Ibarra, J. Laria, M. G. Treviño, J. Guzmán and L. J. González are members of the Computer Technology Group at the Engineering School at the Autonomous University of Tamaulipas, Mexico. (sibarram@uat.edu.mx).

E. Castán is professor at the Electric and Electronic Department at the Madero Institute of Technology.

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problems. Planning for a single agent is a process of constructing a sequence of actions considering only goals, suitability rates, capabilities, and environmental constraints. However, planning the execution of a coordinated task in a 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 [10]. 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 [10].

1.1 Related Approaches to Coordinated Tasks

Most early work in distributed artificial intelligence *(DAI)* has dealt with groups of agents pursuing common goals (e.g., Jung [11]; Simmons [12]). In this sense, **agents' interaction is 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 modeling team-work explicitly. Explicit modeling of team-work is particularly helpful in dynamic environments where team-members might fail or be presented with new opportunities, such in [13]. 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 a temporal agent group. For instance, reference [14] 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 [15] [16] 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 Sub-sumption architecture [17], 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 [12] 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. For instance, reference [11] 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 [18] 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: [19], [20], and [21] show similar alternatives to perform the coordination process of their systems. Moreover, in [22] 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 [23] 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 [24] 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 [25], [26] 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 [27] 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 [28] where agents' interaction and physical agents' capabilities are

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the information that the agents have used to express a certain level of awareness to perform cooperative behavior.

Architecture that allows teams of heterogeneous robots that dynamically adapt their actions over time is present in [29]. 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 [30], [31], [32] 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 decisions.
- 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 section.

2. IMPLEMENTING THE COORDINATED PROBLEM-SOLVING ALGORITHM

The execution of any coordinated task performed by a group of multiple autonomous and situated agents[2] will be inexact for a number of reasons, including interaction faults, general uncertainty and environmental changes. These unavoidable characteristics of the multi-agent scenarios will necessarily limit the efficiency with which coordination can be achieved. In this sense, scientific research and practice in cooperative multi-agent systems, which in the past has been called *distributed artificial intelligence*, 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 [33]. In this sense, distributed intelligence on computer science is, currently, focused on 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 [34].

2.1 Coordination Aspects

Let us suppose that a supervisor agent **SA** is an omnipresent and omniscient agent which is in-charge both to *supervise* the development and execution of the actions and to validate the final performance of such actions. In this sense, the *supervisor* knows the goals of the system. Let us define that a goal $\mathbf{G}_\gamma$ means the general target of a specific region of the environment. In particular, tasks are assigned to a specific region of the environment, here called scenes[3]. Thus,

$$\exists\, G_i, G_j \in G(S_\alpha) \mid G_i \neq G_j \wedge G(S_\alpha) \subseteq GG$$

Such goal generally must involve more than one task for its achievement. Hence, a task $\mathbf{T}_\beta$ is part of a set of cooperative activities that must be performed to efficiently solve the expected goal. Such fact limits the range of operatively of the tasks to its assigned scene $\mathbf{S}_\alpha$. Thus,

$$\exists\, T_i, T_j \in T(S_\alpha) \mid T_i \neq T_j \wedge T(S_\alpha) \subseteq TT$$
$$\text{where,}\quad T(S_\alpha) = \{T_1, T_2, T_3, \ldots, T_p\}$$

In fact, let us define that a role $\mathbf{R}_\varphi$ is part of a set of actions that must be fulfillment to achieve a specific task $\mathbf{T}_\beta$ in any determined region of the environment. Thus,

$$\exists\, R_i, R_j \in R(T_\beta) \mid R_i \neq R_j \wedge R(T_\beta) \subseteq R(S_\alpha) \subseteq RR$$
$$\text{where,}\quad R(T_\beta) = \{R_1, R_2, R_3, \ldots, R_q\}$$

Particularly, roles are physical and executable actions that must be performed to change the settings on the environment. Such actions only can be executed by situated agents which are physical and cognitive entities capable to work in a real scenario. Let us define a situated agent $\mathbf{PA_j}$ as an intelligent entity with a physical representation on the environment and through which the multi-agent system can realize physical actions in the environment. Such situated agents are embodied by considering the knowledge involved in their capability to execute an action within their knowledge base. Let us suppose that a $\mathbf{PA_j}$ is part of a cooperative group of physical agents $\mathbf{G_{PA}}$. A group of physical agents must generally involve more than one physical agent for the fulfillment of a task.

$$\exists\, PA_i, PA_j \in G_{PA} \mid PA_i \neq PA_j \wedge G_{PA} \subseteq Q$$
$$\text{where,}\quad G_{PA} = \{PA_1, PA_2, PA_3, \ldots, PA_m\}$$

In this sense, to situate an agent is used the knowledge provided by three dimensions, here called **decision axes**, where each axis provides situated agents with knowledge related to its capability to execute any determined action in particular kind of knowledge. The agents' environmental conditions **EC** (axis 1) are composed by information related to the state of the environment, directly involved in the performance of a cooperative action. The agents' physical knowledge **PK** (axis 2) meaning the specification, the structure and other relevant details related to the agents' physical skills and characteristics. Finally, the agents' trust value **TV** (axis 3) related to the capability of an agent to communicate, to interact and other relevant details to entrust in other agents. In this light, the situated agent's knowledge base **KB** is therefore founded on the combination of the three above parameters (EC, PK and TV) directly implicated in the execution of any action, such as is described by (1)

$$KB(PA_j, R_\varphi) = [EC(PA_j) \cup PK(PA_j) \cup TV(PA_j)] \quad (1)$$

In particular the situated agent's knowledge base for the execution of a specific role R_φ in a given time **t** in any determined scene $\mathbf{S}_\alpha$ is given by (2).

[2] A situated agent refers to a cognitive agent which has a physical body and is placed on a real environment. In fact, such agent must base its decisions on reasoning and including all knowledge involved in the execution of any action [10].

[3] A **scene** refers to a spatial region where agents must interact and cooperate to perform some set of action in order to satisfy the whole system's goal.

$$\forall PA_j \in G_{PA}\ \exists\, KB(PA_j, R_\varphi)_{t_{S_\alpha}} =$$
$$[EC(PA_j, R_\varphi)_{t_{S_\alpha}}\ PK(PA_j, R_\varphi)_{t_{S_\alpha}}\ TV(PA_j, R_\varphi)_{t_{S_\alpha}}] \quad (2)$$

In particular, this paper assumes that each situated agent is capable to evaluate its aptitude to execute of any action. Such estimation is performed by a match which include two aspects to calculate the suitability rate of each physical agent to execute any proposed action, such as,

- the capabilities of the physical agents (i.e., their situation) taking into account the information provided by the decision axes, to perform any proposed action.
- the influence degree that each axes has over the execution of any determined action.

In particular, the influence degree **Ψ** refers to the relevance that decision axes have in the execution of a determined action in a particular scene. Such influence aims to calculate critically the suitability of a physical agent to execute any action in a successful and reliable way. In this sense, such influence degree **Ψ** is represented as is described by the duple (3).

$$\Psi R(T_\beta) = [\Psi EC\ \Psi PK\ \Psi TV] \quad (3)$$
$$\text{where,}\quad \Psi EC, \Psi PK, \Psi TV \in [0,1]$$

Where ΨEC is the relevance of the environmental conditions, ΨPK is the relevance of the physical knowledge and ΨTV is the relevance of the trust value. In particular the influence degree for the development of any specific role in any determined scene is given by (4).

$$\forall R_i \in R(T_\beta)\ \exists\, \psi R_i, S_\alpha \in \Psi R(T_\beta) \quad (4)$$
$$\psi R_i, S_\alpha = [\psi EC_{R_i,S_\alpha}\ \psi PK_{R_i,S_\alpha}\ \psi TV_{R_i,S_\alpha}]$$

In such case, the suitability rate ξ of any physical agents is obtained by a match function which works as a requirements/capabilities function. Let us to suppose that a physical agent $\mathbf{PA_j}$ is capable of executing a role **Ri** with a suitability rate ξ in a time **t** of a scene $\mathbf{S_\alpha}$ as is described in (5).

$$\xi_{(PA_j,R_i)_{t_{S_\alpha}}} = \left(\frac{\sum_{b=1}^{3} kb(PA_j)_{(b)} * \psi(R_j, S_\alpha)_{(b)}}{\sum_{b=1}^{3} \psi(R_i, S_\alpha)_{(b)}} \right)_{t_{S_\alpha}} \quad (5)$$

2.2 Problem Solving Algorithm

For illustrative reasons, let us to consider a supervisor agent **SA** in-charge of supervise two scenes such that, $S = \{s_1, s_2\}$. Such SA must lead the execution of a set of actions performed by a cooperative group of three physical agents, such that, $\mathbf{G_{PA}} = \{PA_1, PA_2, PA_3\}$, to solve a complex problem as is depicted in (Fig. 1). To follow, the scheme of the coordinated task algorithm is concisely explained.

Definition – The **SA** must analyze the regions that must *supervise*. **SA** knows which actions must be performed in each region; it should evaluate the priority of the tasks to schedule the sequence of their execution. Once the **SA** knows the sequence of the tasks, it must identify which roles are needed to achieve each task. In this sense, each task involves several roles for its fulfillment. Therefore, **SA** uses the priority of the roles to schedule the execution of them.

Proposition –Once, **SA** defines the roles that must be executed, informs this items (i.e., the roles) in order of relevance, to the group of physical agents. **SA** also sends the influence degree of the implicated roles. Finally, the **SA** informs to each of the invited physical agents the result of their previous actions.

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 base, 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** which role will execute. In addition, the *physical* that cannot execute any role in the current scene must also inform such event to the *supervisor*. Thus, the **SA** knows that there are some physical available to execute the actions of the remaining scenes. So, the **SA** must begin the process to inform the involved roles for its other supervised scenes.

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.

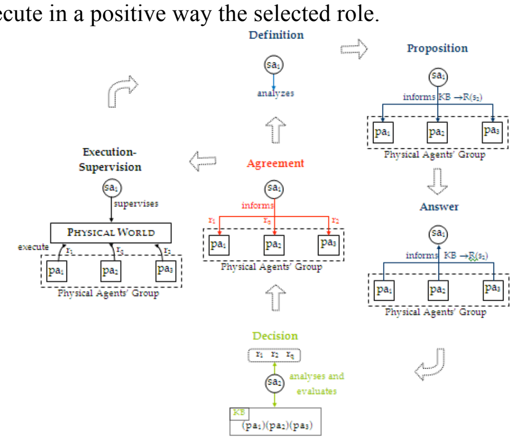

Fig. 1. General scheme of the problem-solving algorithm.

3. EXPERIMENTAL FEATURES

Robot soccer test bed simulates a soccer game where players (i.e., physical agents) must coordinate their individual actions to work aiming to achieve the global system's goal (i.e., to win a game). The features for the simulated soccer tournaments are here described as follow: a supervisor agent **SA,** five physical agents, **Gpa** = {goalkeeper, defender$_1$, defender$_2$, forward$_1$, forward$_2$} are involved in the cooperative actions related to a game match. Each physical agent has an obstacle-free movement trajectory controller [10] to move them in the environment. The supervisor agent have assigned three zone of the environment, such that, **SA** = {scene$_1$=attack; scene$_2$=midfield; scene$_3$=defense} as is showed in Fig. 2.

Fig. 2. General scheme of the simulated implementation.

Environment conditions, here called proximity **P**, are related to the distance between the current location of a physical agent and the current location of the proposed actions, and is provided by (6)

$$P(PA_j, R_i)_{t_{S_\alpha}} = \left(1 - \frac{d(PA_j, R_i)}{d\max_{S_\alpha}}\right)_{t_{S_\alpha}} \quad (6)$$

Where $d\max_{S_\alpha}$ means the maximal distance of a physical agent with the proposed roles in the scene S_α as is described in (7)

$$d\max_{S_\alpha} = (d(PA_1, R_i), \ldots, d(PA_m, R_i))_t \quad (7)$$

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, called introspection **I**. Introspection parameter is calculated implementing feed-forward back-propagation neural networks.

$$I(PA_j, R_i)_{t_{S_\alpha}} = (\max(I(PA_j, R_i)))_{t_{S_\alpha}} \quad (8)$$

Trust value, called trust **T**, refers to the social relationship among agents taking into account both the amount of "goods" actions which mean actions executed in a suitable way and the amount of and "bads" actions which mean actions that are executed in a negative way. In this sense, the trust of a physical agent is provided by (9).

$$T(PA_j, R_i)_{t_{S_\alpha}} = \left(\frac{goods_{(PA_j,R_i)}}{goods_{(PA_j,R_i)} + bads_{(PA_j,R_i)}}\right)_{t_{S_\alpha}} \quad (9)$$

To define how the relevance of the decision axes can influence in the calculus of the physical agents' suitability rates. We have designed a classification performed a binary combination of the three axes. In this sense, we have obtained eight cases study, as shown in Table 1. In particular, each case study denotes the behavior of each one of the agents-teams that we have used in the empirical experiments. It means that each agents-team uses of one of the cases study to enhance the information of the decision axes for each agents-team cooperative works.

Table 1. Classification of the Decision Axes.

$\Psi R(S_\alpha)$	P	I	T
$team_R$	×	×	×
$team_T$	×	×	✓
$team_I$	×	✓	×
$team_{I+T}$	×	✓	✓
$team_P$	✓	×	×
$team_{P+T}$	✓	×	✓
$team_{P+I}$	✓	✓	×
$team_{P+I+T}$	✓	✓	✓

4. EXPERIMENTS AND RESULTS

Empirical experiments featuring simulated cooperative scenarios have been established in order to put into practice the formalization of the problem-solving algorithm for situated agents described in this work. In addition, two experimental implementations have been developed; first, agents-teams (using each one of the cases study introduced in Table 1 versus a default opponent provided by the simulator; second, a set of games among the above agents-teams using the cases study.

4.1 Experiment 1

This implementation is constituted by predefined number of (10) championships, each one with predefined number of (30) games, where each agents-team plays versus a default opponent provided by the simulator. In addition, the initial state of each physical agent in the scenario was randomly set after each pause (due to the scored goals) and at ever game. The performance is measured as a radio between the total points (won: 3 points; tied: 1 point) reached by the proposed teams in each championship.4.1.1 Analyzing Results

The agents-teams performance is showed both from the average in the successful performance taking into account the number of obtained points and from the achieved successful decisions. In this sense, successful decisions mean that each physical agent selects the action for which it is the most suitable agent. Then, if the physical agent performs such action in a suitable way that increase the performance of the multi-agent system. In particular, Fig. 4 shows the agents' performance in a decreasing order (from left to right). To the end, the results identify an improvement rate of around 51% between the best case ($case_{PIT}$) and the worst case ($case_R$).

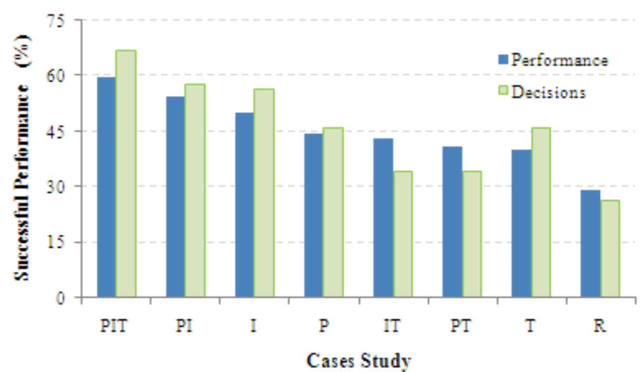

Fig. 4. Analysis Results of the Experiment 1.

4.2 Experiment 2

This experiment was predefined with number of (10) championships, each one with predefined number of (28) games, where each agents-team plays against the other agents-team denoted by its consideration of the three decision axes. In summary, each agents-team plays a set of (280) games and its performance is calculated in a radius of (won game: 3 points; tied game: 1 point). To mention, in all the experiments the initial state of the physical agents was randomly changed after each kick-off or after each finished game.

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4.2.1 Analyzing Results

Results are analyzed taking into account the average reached by the agents-teams in each championship. In this sense, Fig. 5 illustrates the agents-teams performance based on the successful number of obtained points along the championship. The progression of the cases shows that the performance does not improve significantly beyond about the championship 6. The number to initially confirm the agents-teams performance will be fixed in 10 championships. In particular, based on a critically comparison between the best and the worst cases, there is an improvement rate of around **51.40%**.

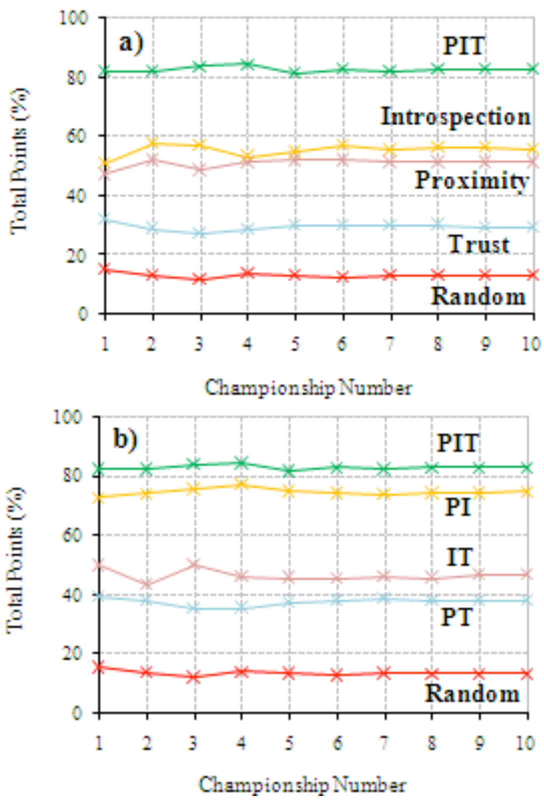

Fig. 5. Successful Performance of the Agents-Teams. a) Comparative Performance of the worst ($case_R$) the simple cases ($case_T$, $case_I$, $case_P$) and the best case ($case_{P+I+T}$); b) Comparative Performance of the worst ($case_R$) the coupled cases ($case_{I+T}$, $case_{P+T}$, $case_{P+I}$) and the best case ($case_{P+I+T}$).

5. FINAL REMARKS

A preliminary conclusion of the results is showed in the previous section 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, especially 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.

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.

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.

The paper shows 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.

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 allows agents to be only focused in those particular actions that they can execute taking into account its calculated estimation (suitability rate) regards such actions. For thus; **redundancy in the tasks execution is then avoided.** This new and effective approach contributes to enhance 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.

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