INTRODUCTION ON CONTROL-GROUNDED CAPABILITIES

A Task Allocation Study Case in Robot Soccer

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Abstract: Our proposal is aimed at achieving reliable task allocation in physical multi-agent systems by means of introspection on their dynamics. This new approach is beneficial as it improves the way agents can coordinate with each other to perform the proposed tasks in a real cooperative environment. Introspection aims at including reliable physical knowledge of the controlled systems in the agents' decision-making. To that end, introspection on control-grounded capabilities, inspired by the agent metaphor, are used in the task utility/cost functions. Such control-grounded capabilities guarantee an appropriate agent-oriented representation of the specifications and other relevant details encapsulated in every automatic controller of the controlled systems. In particular, this proposal is demonstrated in the successful performing of tasks by cooperative mobile robots in a simulated robot soccer environment. Experimental results and conclusions are shown, stressing the relevance of this new approach in the sure and trustworthy attainment of allocated tasks for improving multi-agent performance.

1 INTRODUCTION

In recent years, *A*rtificial *I*ntelligence *(AI)* approaches have been combined with traditional control theory to obtain intelligent systems. In this sense, the advances of the *AI* community, together with the new techniques in the control community, have presented a fresh path for further progress (Halang *et al.*, 2005) (Murray *et al.*, 2003). In particular, complex control systems (Sanz *et al.*, 2003) have been managed using agents. Nowadays, a complex control system is a distributed, asynchronous and networked framework and the whole process must be considered as a multi-agent system that requires coordination and cooperation to perform the proposed tasks (Luck *et al.*, 2005) (Stone and Veloso, 2000). Specifically, agent technology helps to solve task allocation problems in real control scenarios by means of its distributed and cooperative problem-solving paradigm (Jennings and Bussmann, 2003). However, these agents lack appropriate reasoning on knowledge related to the physical features of the controlled system (*physical knowledge mainly related to dynamics*). In addition, such relevant knowledge is not appropriately reflected and communicated by the agents. These lacks do not facilitate more suitable task allocation by the agents in a multi-task scenario. Explicitly, lack of appropriate reasoning on physical knowledge results in a lower number of successful coordinated tasks performed by agents. In fact, this lack is currently a significant impediment to reducing complexity and achieving appropriate levels of control, coordination and autonomy in task allocation problems (Murray *et al.*, 2003). That is to say, agents don't reflect on their control-oriented knowledge and this knowledge is not currently properly taken into account in the utility/costs functions used in the agents' decision-making for allocating tasks. Physical agents are particular examples of controlled systems. In recent years, mobile robots - one typical representation of physical agents - have become progressively more autonomous and cooperative. So we have used mobile robots in this approach without loss of general applicability. Such autonomous cooperating robots must then have reliable self-knowledge if they are to improve the task allocation performance in a multi-robot environment. Specifically, this self-knowledge must be based on an appropriate agent-oriented representation of their automatic controllers in the utility/cost functions used for allocating tasks. With this representation, the physical agents can consider their bodies in a better and more reliable

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way, whenever it is necessary to allocate and perform tasks in a multi-agent system. In this sense, the paper proposes an introspection-based approach to provide agents a cognitive ability for reasoning on their physical knowledge, aiming at making physically feasible task allocation to improve the cooperative multi-agent performance.

2 RELATED WORK

Several authors (Goldberg and Matarić, 2000) (Gerkey and Matarić, 2002) (Scheutz, 2002) (Balakirsky and Lacaze, 2002) (Goldberg *et al.*, 2003) (Gerkey and Matarić, 2004) (Dahl *et al.*, 2004) (Lagoudakis *et al.*, 2005) (Koenig *et al.*, 2006) (Sariel and Balch, 2006) (Ramos *et al.,* 2006) have studied the problems related to task allocation in multi-robot environments based on utility/cost functions. These approaches present suitable approaches to task/action selection mainly take into account domain knowledge in the agents' decision-making. However, an approach based on control-oriented knowledge has not been completely carried out. In this sense, we want to show how introspection on the physical agents' dynamics contributes to a more suitable task allocation by considering the physical agents' bodies in a better and more reliable way. Such consideration is directly related to the automatic controllers of the physical agents. Thus, reliable information is extracted from the controllers to obtain appropriate control-oriented knowledge of the physical agent's body. In this sense, such knowledge is represented by means of specific attributes (*control-grounded capabilities*) focused mainly on the physical agents' dynamics.

3 OUR APPROACH

Before an agent starts a task, it should make a plan for how to reach a given goal. This planning requires the agent to have knowledge about the environment, knowledge that can be represented in the agent's knowledge base. It is the agent's ability to model its own environment that makes it able to reason about this environment, to plan its actions and to predict the consequences of performing these actions. However, much intelligent behavior seems to involve an ability to model not only the agent's external environment but also itself and the agent's own reasoning. Such ability is called introspection (Bolander, 2003).

Introspection is yet another aspect of human reasoning in artificial intelligence systems (Wilson *et al.,* 2001). To have introspection in an artificial intelligence system means that the system is able to reflect on its own knowledge, reasoning, tasks and planning (Bolander, 2003). For instance, before an agent commits in the execution of a task, the agent should register the fact of knowing if it can or cannot perform the task, this needs introspection, due to the agent has to look introspectively into its own knowledge base and from it to arrive at a suitable decision. In addition, in order to decide how well the agent is doing or will do the proposed task, an agent will also need this self-examination capability (*introspection*) (McCarthy, 1999).

The *agent is non-introspective when no information in the knowledge base expresses facts concerning the agent itself. Any non-introspective agent only models its external environment.* Otherwise, *introspective agents differ from non-introspective ones by modelling not only their external environment but also themselves. It is by also have models of themselves they are given the ability to introspect* (Bolander, 2003).

In particular, introspection on the physical agents' dynamics is a previously unexplored research area. So we have focused our work just on this topic for examining its impact in the performance of cooperative multi-agent systems.

3.1 Introspection on the Physical Agents' Dynamics

Physical agents require a sense of themselves as distinct and autonomous individuals able to interact with others, i.e. they require an identity (Duffy, 2004). A complete concept of identity therefore constitutes the set of internal and external attributes associated with any given physical agent based on introspection of its physical and "mental" states and capabilities. In this work, the notion of internal and external relates to the attributes of a physical agent analogous to Shoham's notion of capabilities in multi-agent systems (Shoham, 1993). Thus, there are two distinct attributes that are local and particular to each physical agent within a cooperative system:

- Internal Attributes: beliefs, desires, intentions, the physical agent's knowledge of self, experiences, a priori and learned knowledge.

•External Attributes: the physical presence of the agent in an environment; its actuator and preceptor capabilities (e.g., automatic controllers) and their physical features.

In particular, a subset of internal attributes (*control-grounded capabilities*) is used to describe the physical agents' dynamics.

Introspection on physical agents' dynamics refers then to the self-examination by a physical agent of the above capabilities to perform tasks. This self-examination mainly considers the agent body's dynamics.

In this sense, an agent's knowledge of its attributes therefore allows a sufficient degree of introspection to facilitate and maintain the development of cooperative work between groups of agent entities (Duffy, 2004). When an agent is "aware" of itself, it can explicitly communicate knowledge of self to others in a cooperative environment to reach a goal. This makes introspection particularly important in connection with multi-agent systems.

In this context, physical agents must reach an agreement in cooperative groups to obtain sure and trustworthy task allocation. Sure and trustworthy task allocation refers to an allocation accepted by the agents only when they have a high certainty about correctly performing the related tasks.

To achieve sure and trustworthy task allocations, each physical agent must introspect, consider and communicate their physical limitations before performing the tasks. Without introspection, physical agents would try to perform actions with no sense, decreasing the number of successful tasks performed by them.

3.2 Formalization Aspects

Let us to suppose that a physical agent A_α is a part of a cooperative group *G*. A cooperative group must involve more than one physical agent. That is,

$$\exists A_i, A_j \in G \mid A_i \neq A_j \wedge G \subseteq AA$$

Where *AA* is the set of all possible physical agents in the environment. Let us to define the set of control-grounded capabilities *CC* to represent the physical agent's dynamics as a subset of the internal attributes *IA* of a physical agent A_α such that:

$$CC(A_\alpha) \subseteq IA(A_\alpha)$$

A capability is part of the internal state of a physical agent that must be useful to represent the physical agent's dynamics, must allow computational treatment to be accessible and understandable by agents and must be comparable and combined with other capabilities to be exploited as a decision tool by agents.

Let us to define the set of automatic controllers *C,* whose actions provoke the physical agent's dynamics, as a subset of the external attributes *EA* of a physical agent A_α such that:

$$C(A_\alpha) \subseteq EA(A_\alpha)$$

The controllers allow and limit the tasks' executions. So they are key at the moment physical agents *introspect* on their control-grounded capabilities to perform tasks.

Let us to consider the domain knowledge *DK* for a physical agent A_α made up of a set of environmental conditions *EC* (e.g., agents' locations, targets' locations), a set of available tasks to perform *T*, and a set of tasks requirements *TR* (e.g., achieve the target, avoid obstacles, time constraints, spatial constraints,) as is described by (1).

$$DK(A_\alpha) = EC(A_\alpha) \cup T(A_\alpha) \cup TR(A_\alpha) \quad (1)$$
$$DK(A_\alpha) = \{ec_1, \ldots, ec_o, task_1, \ldots task_p, tr_1, \ldots, tr_q\}$$

Each physical agent has associated a subset of controllers for the execution of tasks of the same kind such that:

$$\forall task_k \in T(A_\alpha),\ \exists C_{task_k}(A_\alpha) \subseteq C(A_\alpha)$$

All controllers involve in the same task has associated the same kind on capabilities such that:

$$\forall c_i \in C_{task_k}(A_\alpha),\ \exists CC_{c_i,task_k}(A_\alpha) \subseteq CC(A_\alpha)$$

The capabilities $CC_{c_i,task_k}$ for a controller *i* in the execution of a particular task *k*, are obtained, as in (2), taking into account the agent's domain knowledge DK_{task_k} related to the proposed task such that:

$$CC_{c_i,task_k}(A_\alpha) \subseteq CC(A_\alpha) \subseteq IA(A_\alpha)$$
$$DK_{task_k}(A_\alpha) \subseteq DK(A_\alpha) \mid$$
$$CC_{c_i,task_k}(A_\alpha) = \Psi_{c_i,task_k}(DK_{task_k}(A_\alpha)) \quad (2)$$

$\Psi_{c_i,task_k}$ is a self-inspection function that allows physical agents *introspect* on their capabilities using the controller *i* for the task *k*.

A self-evaluation function $\Phi_{c_i,task_k}$ uses the capabilities in an appropriate way to allow physical agents *know* a certainty index $ci_{c_i,task_k}$ related to the correct execution of the proposed task *k* using the controller *i* as is described in (3).

$$ci_{c_i,task_k}(A_\alpha) = \Phi_{c_i,task_k}(CC_{c_i,task_k}(A_\alpha)) \quad (3)$$

The set of all certainty indexes for a specific task *k* is constituted by all $ci_{c_i,task_k}$ of the controllers in this task:

$$\forall c_i \in C_{task_k}(A_\alpha),\ \exists ci_{c_i,task_k}(A_\alpha) \subseteq CI_{task_k}(A_\alpha)$$
$$\text{Where } CI_{task_k}(A_\alpha) \subseteq CI(A_\alpha)$$

CI constitutes the set of all certainty indexes related to the available tasks *T* for the agent A_α. A certainty index provides physical agent a degree of conviction concerning the truth of its knowledge and ability to perform a particular task.

In summary, the functions (Ψ,Φ) provide physical agents powerful tools for introspection-level reasoning and suitable model of themselves.

Currently, there are several alternatives to implement independently or jointly the above functions. Thus, soft-computing techniques (e.g., neural networks, case-based reasoning and fuzzy logic) and control techniques (e.g., model-predictive control, multiple model adaptive controllers and switching control systems) are commonly used.

3.3 Task Allocation Algorithm

There are several coordination parameters to take into account in the utility/cost functions for allocating tasks. Our approach considers jointly with the introspection, the proximity and the trust.

The introspection parameter $I_{task_k}(A_\alpha)$ refers to a comparative analysis between all possible certainty indexes CI_{task_k} of the controllers in a specific task that allows physical agent, if it is possible, to select a controller for the execution of this task as is described in (4).

$$I_{task_k}(A_\alpha) = \max(CI_{task_k}(A_\alpha)) \quad (4)$$

$$I_{task_k}(A_\alpha) \in [0,1]$$

A high $I_{task_k}(A_\alpha)$ value represents that the agent A_α can perform the task *k* correctly. A low $I_{task_k}(A_\alpha)$ value indicates that the agent cannot perform the task.

Proximity represents the physical situation of each agent in the environment. The proximity parameter $P_{task_k}(A_\alpha)$ is related to the distance between the current location of the agent A_α and the location of the target as is described in (5).

$$P_{task_k}(A_\alpha) = (1 - d_{task_k}(A_\alpha)/d\max) \quad (5)$$
$$P_{task_k}(A_\alpha) \in [0,1]$$

Where $d_{task_k}(A_\alpha)$ is the distance between the physical agent A_α and the target $task_k$ and *dmax* establishes a fixed maximal radius limit according to the target's location.

Trust represents the social relationship among physical agents that rule the interaction and behavior of them. The trust parameter $T_{task_k}(A_\alpha)$ takes into account the result of the past interactions of a physical agent with others. The performance of the proposed task is then evaluated based on $T_{task_k}(A_\alpha)$. Equation (6) shows the reinforcement calculus if goals are correctly reached by the agent. Otherwise, the agent is penalized if goals are not reached using (7).

$$T_{task_k}(A_\alpha) = T_{task_k}(A_\alpha) + \Delta A_{task_k}(A_\alpha) \quad (6)$$
$$T_{task_k}(A_\alpha) = T_{task_k}(A_\alpha) - \Delta P_{task_k}(A_\alpha) \quad (7)$$
$$T_{task_k}(A_\alpha) \in [0,1]$$

Where $\Delta A_{task_k}(A_\alpha)$ and $\Delta P_{task_k}(A_\alpha)$ are the awards and punishments given to A_α in the task *k* respectively. A high $T_{task_k}(A_\alpha)$ value represents a more trusted physical agent in the task.

The utility/cost function $U_{task_k}(A_\alpha)$ is therefore constituted as a proper average of the element-by-element multiplication of the tuples as in (8).

$$U_{task_k}(A_\alpha) = \frac{\sum\left(Th_{task_k} \cdot Ok_{task_k} \cdot Pa_{task_k}(A_\alpha)\right)}{\sum Ok_{task_k}} \quad (8)$$

Where $Pa_{task_k}(A_\alpha)$ is a tuple formed by the coordination parameters such that:

$$Pa_{task_k} = [I_{task_k}(A_\alpha)\ P_{task_k}(A_\alpha)\ T_{task_k}(A_\alpha)]$$

Th_{task_k} is a set of flags (1 or 0) that establishes if the above coordination parameters fulfill their respective decision thresholds such that:

$$Th_{task_k} = [I\_th_{task_k}\ P\_th_{task_k}\ T\_th_{task_k}]$$

We have selected appropriate decision thresholds to set or not the above flags.
Ok_{task_k} is a set of flags (1 or 0) that establishes if the above coordination parameters are currently taking into account in the utility/cost function such that:

$$Ok_{task_k} = [I\_ok_{task_k}\ P\_ok_{task_k}\ T\_ok_{task_k}]$$

Thus, the tasks are allocated to physical agents according to the value of their utility/cost functions (see Equation 8).

4 CASE STUDY

We have used a simulated robot soccer environment to evaluate our approach. Here, task allocation is related to achieve targets with different time and spatial constraints.

In particular, the environment is divided is several *scenes* S = {$scene_1$, $scene_2$, $scene_3$,…, $scene_N$}, each one with a specific set of tasks to allocate $T = \{task_1, task_2, task_3, \ldots, task_{M(scene_j)}\}$. Here, scenes refer to the spatial regions where agents must meet and work jointly to perform the proposed tasks. Physical agents are represented by nonholonomic mobile robots. The robots have just one controller to control its movements in the environment. These physical agents must therefore coordinate their moves to increase the system performance by means of a suitable task allocation in each scene. At the beginning of each simulation, the physical agents are not moving. In addition, the agents' locations are set randomly in each simulation.

5 IMPLEMENTATION

In our implementation, we have designed a heterogeneous team such that G = {A_1, A_2, A_3, A_4, A_5} where each agent has a different movement controller such that: $C(A_1) = \{c_1\}$, $C(A_2) = \{c_2\}$, $C(A_3) = \{c_3\}$, $C(A_4) = \{c_4\}$ and $C(A_5) = \{c_5\}$. There are three scenes S = {attack, midfield, defense} in the environment as is shown in Figure 1. The current scene is established taking into account the current ball's location. For the sake of simplicity, the main task to allocate is to kick the ball in each scene toward the opposite goal. In this sense, for each physical agent is calculated its utility/cost function $U_{task_k}(A_\alpha)$ in the current scene. Such function allows selecting the most suitable agent for that task while the other remaining agents follow a fixed strategy. Specifically, the introspection approach was implemented by using feed-forward back-propagation neural networks. Similarly, the awards and punishments of the trust parameter are different in each scene.

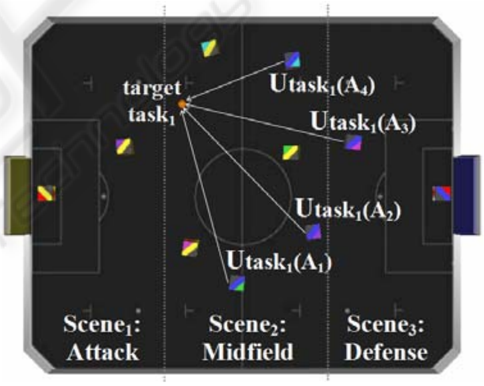

Figure 1: Robot soccer simulator environment.

6 EXPERIMENTAL RESULTS

We established empirical experiments featuring simulated robot soccer tournaments to test system performance when introspection on physical agents' dynamics is used. Our tests used models of the *MiroSot* robots simulator. The selected simulation experiments consist of a predefined number of championships (10), each one with a predefined number of games (10). The performance is measured as a ratio between the total points (*won game: 3 points, tied game: 1 point*) achieved by our team in each championship and the all possible points (30) in this championship where our team play versus a blind opponent robotic team. The initial state of each physical agent was randomly set at every game.

We have compared the system performance highlighting the influence of the introspection in the decisions of our team. In particular, we compared the following teams R vs. I, P vs. P + I, T vs. T + I and P + T vs. P + T + I by modifying the set of flags Ok_{task_k} such that, e.g., $Ok_{task_k} = [0\ 0\ 0]$ for R and $Ok_{task_k} = [1\ 0\ 0]$ for I, where R: random, I: introspection, P: proximity and T: trust.

Figure 2 illustrates how the best system performance is achieved by using introspection in all cases. Here follows a preliminary conclusion: the composition of any parameters with introspection increase the performance as the result of most suitable task allocation in the system. The system performance always improves when the physical agents take into account their physical capabilities based on introspection. The figure also confirms that successful decisions related to task allocation increase when agents use introspection: agents can make better decisions and can consequently make more sure and trustworthy task allocations. In addition, it should be noted that the improvement rate of the introspection approach over the other approaches is a result of the possibility of including the misses in the agents' decisions. In fact, this is an advantage of introspection. Agents can discriminate between the trials in which they have a chance of successfully performing the tasks and those in which they have no chance. In summary, all the above results show that a good decision tool based on introspective reasoning can increase the autonomy and self-control of agents and obtain reliable utility/costs functions in task allocation problems. Introspection and decisions based on capabilities give a trustworthy indication of the real reliability with which each agent performs tasks in cooperative systems.

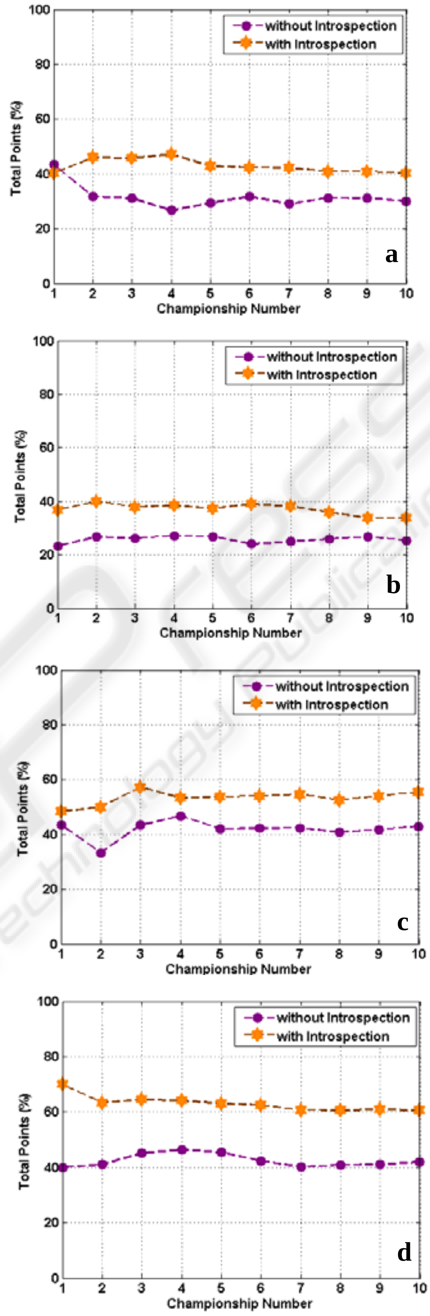

Figure 2: Performance comparison a) R vs. I, b). P vs. P + I, c). T vs, T + I, d). P + T vs. P + T + I.

7 CONCLUSIONS

We argue the need for introspective skills in relation to control-oriented knowledge in physically grounded agents to improve the physical agents' decision-making performance in task allocation problems. Introspection allows physical agents to achieve sure and trustworthy task allocations in cooperative systems, thereby improving the performance of agents in a multi-task environment.

We considered a representation based on capabilities related to the agent body's dynamics. These capabilities were managed in an introspective manner when agents were required to select the most suitable task to perform. Nevertheless, it is still difficult to choose the necessary information to include in the capabilities to represent control-oriented knowledge. In spite of this, our experimental results show that introspection on control-oriented features helps physical agents to make a reliable task allocation and to form sure, achievable and physically grounded commitments for these tasks. Here, introspection on control-oriented features is closely related to the automatic controllers of physical agents. From the controllers, suitable information was extracted to obtain reliable control-oriented knowledge of the physical agent's body. There is still much to explore about how to take advantage of this approach. In the future, we want to extend the contribution to other controlled systems with a larger number of tasks, physical agents, controllers and capabilities, as well as to include introspection-based approaches in auction-based methods for coordination. Furthermore, selection of a paradigm for the implementation of these concepts is not at all trivial, and its development is still an open question.

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