SELF-KNOWLEDGE BASED ON THE ATOMIC CAPABILITIES CONCEPT

A Perspective to Achieve Sure Commitments among Physical Agents

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Abstract: This paper presents a perspective based on the atomic capabilities concept (AC^2) to include control-oriented knowledge in the decision making structure of physical agents (e.g. mobile robots). These agents operate in a real environment managing physical objects (e.g. their physical bodies) in coordinated tasks. AC^2 guarantees an appropriate agent-oriented representation about the specifications of automatic controllers installed within the physical agents. This approach allows to each agent a reliable self-knowledge which concludes in achieving sure commitments and intelligent control in a cooperative system. Examples and conclusions are presented, emphasising the advantages of our proposal in a coordinated control scenario.

1 INTRODUCTION

Complex control systems are in most cases software-intensive applications that use advanced software technologies and have requirements that go well beyond the knowledge of single disciplines (Sanz *et al*, 2003). Currently, some results have been obtained when control systems are designed using technologies based on agents and multi-agent systems (Jennings *et al*, 2003). However, these agents lack an appropriate knowledge about physical aspects of the controlled system. This lack does not allow them to take the best decisions when these are requested. Namely, the control-oriented knowledge is not taken into account in the decision making structure of the controlled systems managed by agents. The above knowledge in a controlled system is directly related to the automatic controllers specifications established by any control engineer criteria. Nevertheless, all this embedded information needs from a suitable representation in understandable, comparable and computationally tractable terms that makes easy its management and improves the multi-agent system performance in a coordinated control scenario.

Particular cases are the physical agents (e.g. mobile robots). These agents need a reliable self-knowledge to avoid a loss of performance in cooperative decisions when perform coordinated tasks. This self-knowledge has to be based on an appropriate awareness about the physical features (e.g. the dynamics) of their physical bodies, namely, an agent-oriented representation of their automatic control architectures.

Along this research line, AC^2 is our proposal aimed at guaranteeing an appropriate agent-oriented representation about the specifications of automatic controllers installed within the physical agents. This approach provides to each agent a reliable self-knowledge about the physical features of their bodies, achieving sure commitments and intelligent control in a cooperative system.

In particular, AC^2 encapsulates enough control-oriented information that allows the physical agents to behave of an intelligent pattern when they acquire commitments in a coordinated task. Intelligence understood as the exploitation of this information to perform better (Sanz *et al*, 2001) and achieve enhanced levels of performance and autonomy (Sanz *et al,* 2000). This autonomy depends on the level of achieved consciousness (Sanz *et al*, 2001). In this sense, AC^2 contributes to increase this level of consciousness in the physical agents by means of a suitable representation of themselves in the world (Sanz *et al,* 2002), since high levels of intelligence imply not only do learning but also modelling and representation.

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According to (Sanz *et al,* 2004), the aim of the self-aware control systems research is to build systems that exhibit flexible, autonomous, goal-directed behaviour in response to changes in internal and external conditions based on a deep understanding of the world and the self. They will have integrated control architectures that generate and exploit world and/or self-awareness to solve some challenges presented in the modern control systems (Murray *et al,* 2003). Hence, how to introduce in the physical agent the self-knowledge about its physical features is an important issue to study and research in the intelligent systems field.

In this paper we show that AC^2 makes possible to obtain safer systems. These systems respond better to some undesired events and have a better coordinated control. Specifically, this paper shows the influence of AC^2 on the decision making structure of cooperative intelligent agents when executing coordinated tasks. In this implementation the offside manoeuvre in the robotic soccer testbed is used as coordinated task.

This approach is particularly effective at the level of automatic control. At this level is necessary to have a decision making structure about commitments between physical agents that takes into account physical features of their physical bodies. This allows the agents make physically feasible decisions and to get secure, reachable and physically grounded commitments.

2 THE ATOMIC CAPABILITIES CONCEPT (AC^2)

Physical agents that perform tasks in a multi-agent environment have to fulfil real time and real world requirements, such as situated behaviour, goal-oriented behaviour, efficiency and coordination. The DPA^2 (Oller *et al*, 1999) is a proposed layered architecture that joins the requirements of the control systems architectures with those of the multi-agent systems architectures using three principal modules (control, supervisor and agent) that integrate the above requirements. Figure 1 shows the different layers of the architecture and the different abstraction levels.

Physical agents have to check some external and internal parameters in order to decide their behaviours after other agents' requests in the commitments acquisition process in coordinated tasks. The external ones can be obtained by information interchange with other agents. The internal ones have to describe the different states of agents' physical body, in both low and high abstraction levels.

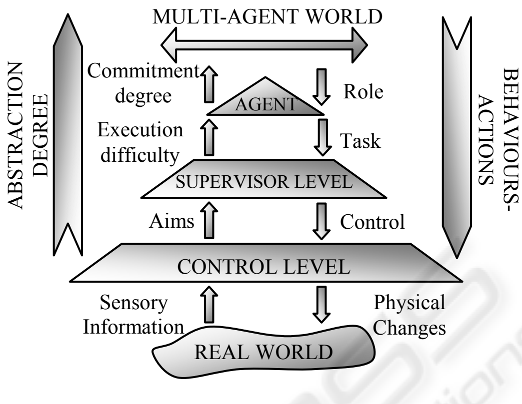

Figure 1: DPA² Architecture

The following capabilities depending on the abstraction level of the information were proposed in (Oller *et al*, 1999) and (Innocenti *et al*, 2001), in order to represent the internal parameters:

Atomic Capabilities: These contain control-oriented knowledge that describes the specifications of the controllers of the physical agent. This knowledge allows increasing the awareness about the agent's physical body and the perception of the environment through this body from a control-oriented viewpoint. This self-knowledge enhances the adaptation and learning skills of the physical agent in the environment.

Basic Capabilities: These contain task-oriented knowledge that emerges from different combinations of atomic capabilities sets. This knowledge allows selecting the most suitable resources (e.g. controllers) to perform a proposed task according to the task requirements.

Symbolic Capabilities: These contain role-oriented knowledge that emerges from different combinations of basic capabilities sets. This knowledge allows to perform collective behaviours among physical agents according to the certainty indexes related to the execution of the assigned roles in the commitments acquisition process.

The knowledge represented in these capabilities gives the physical agent the necessary information to decide with a high certainty level if its physical body can perform the requested tasks. Given the evident relevance of the atomic capabilities as key support of the DPA^2 architecture (delaRosa *et al*, 2004), (Quintero *et al,* 2004), (Zubelzu *et al*, 2004), (Quintero *et al*, 2005), it is necessary to obtain a general and enough definition that gathers control-oriented knowledge in an agent-oriented scenario.

We have summarized this definition in the atomic capabilities concept AC^2.

At a control level, the physical agents can interact in the world through different controllers (C_1, C_2, C_3,…, C_N) with different control algorithms and different control laws that modify the manner how their bodies answer in the execution of the proposed tasks, i.e., the controllers affect the dynamics of the agents' physical bodies. This fact makes necessary the association of each controller C_i to a set of atomic capabilities AC_i $\forall i = 1 \ldots N$, that represents this dynamics when this controller is utilized. All enclosed information in AC^2 can be extracted by the agents using introspective reasoning techniques (delaRosa *et al*, 2004), (Quintero *et al*, 2004), (Zubelzu *et al*, 2004), (Quintero *et al*, 2005) and handled using capabilities management techniques (Quintero *et al*, 2004), (Quintero *et al*, 2005).

The set of atomic capabilities used in this paper has been defined in (Quintero *et al*, 2005) to be applied in linear control systems (SISO, MISO, SIMO and MIMO).

3 AC2 APPLIED TO MOBILE ROBOTICS

We have used non-holonomic mobile robots to test our approach using a linearized second-order model of the robots dynamics. Thus, the movement of each robot [$x(t)$, $y(t)$, $\theta(t)$] is controlled such that the robot follows the horizontal axis x with a constant linear velocity v. A control law based on the poles location method in which the values of the angular velocity ω are obtained in terms of the robot position [$y(t), \theta(t)$] is proposed in (1):

$$\omega(t) = -\frac{\alpha_1\alpha_2}{v}y(t) + (\alpha_1 + \alpha_2)\theta(t) \quad (1)$$

Where $\alpha_{1,2} = -\zeta\omega_n \pm j\omega_n\sqrt{1-\zeta^2}$, $\alpha_{1,2}$ are the poles system, ζ is the damping factor and ω_n is the natural frequency of the characteristic equation of a second-order system. Thus, the stable linear controlled system for the movement variables (y, θ) of the robot can be written by using the following Laplace's expressions (2) and (3):

$$Y(s) = \frac{s^2 + 2\zeta\omega_n s}{s^2 + 2\zeta\omega_n s + \omega_n^2}y(0) + \frac{vs}{s^2 + 2\zeta\omega_n s + \omega_n^2}\theta(0) \quad (2)$$

$$\theta(s) = \frac{s^2}{s^2 + 2\zeta\omega_n s + \omega_n^2}\theta(0) - \left(\frac{\omega_n^2}{v}\right)\frac{s}{s^2 + 2\zeta\omega_n s + \omega_n^2}y(0) \quad (3)$$

Different dynamics can be designed using the step responses described in (4) and (5) of the above linearized model depending on the control engineer criteria. We have selected the following couples $\{\zeta, \omega_n\} = \{0.4, 6\}$, $\{0.6, 10\}$, $\{0.8, 4\}$ to design three movement controllers (C_1,C_2 and C_3) that generate different dynamics as it is shown in the figure 2.

$$y(t) = \frac{-\omega_n e^{-\zeta\omega_n t}}{\omega_d}\left[\begin{array}{l}\left(\sin\left(\omega_d t - \tan^{-1}\left(\frac{\omega_d}{\zeta\omega_n}\right)\right) - 2\zeta\sin\omega_d t\right)u_y(t) \\ + \frac{1}{\omega_n}\sin(\omega_d t)u_\theta(t)\end{array}\right] \quad (4)$$

$$\theta(t) = \frac{\omega_n e^{-\zeta\omega_n t}}{\omega_d}\left[\cos\left(\omega_d t - \tan^{-1}\left(\frac{\omega_d}{\zeta\omega_n}\right) + \frac{\pi}{2}\right)u_\theta(t) - \omega_n\sin(\omega_d t)u_y(t)\right] \quad (5)$$

Where $\omega_d = \omega_n\sqrt{1-\zeta^2}$. Some atomic capabilities using the definitions and constraints described (Quintero *et al*, 2005) and the above step responses were extracted. Table 1 shows the atomic capabilities associated to each movement controller.

Table 1: Atomic Capabilities of the Used Movement Controllers

Control	μ_A(%)	σ_A(%)	γ_A(%)	α_A(%)	ε_A(%)	κ_A
C_1	77.83	-42.6	57.54	93.14	81.62	1
C_2	86.25	39.10	59.46	88.93	75.20	1
C_3	87.48	-4.03	57.08	80.30	100	1

4 OUR STUDY CASE

In the proposed task as study case two physical agents are involved. *Defender1* and *Defender2* must coordinate between them to perform an offside manoeuvre and to avoid the passing a ball between two opposite physical agents. Figure 3 shows an example of this task.

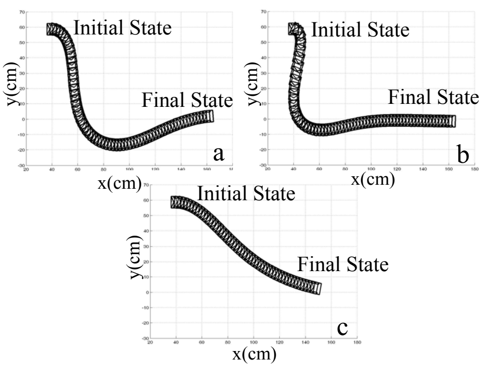

Figure 2: Different Dynamics generated with three different controllers. a). C_1; b). C_2; c). C_3

It is possible to describe the environment state using the time of the *passer* to strike the ball ($Time_P$), the distances (D_1) and (D_2) between each defender and the offside line as well as their respective orientations (θ_1 and θ_2). In order to use a more generic value, the orientation of the defenders is described in (6).

$$\theta_{1,2} = |\phi_1| + |\phi_2| = |\theta_L - \theta_I| + |\theta_L - \theta_F| \quad (6)$$

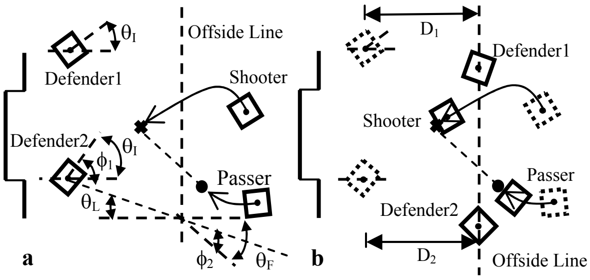

Figure 3: Offside Scheme. a). before, b). after

Besides, different situations can appear in order to execute the same coordinated task in a multi-agent environment. These situations have to be taken into account in the commitments acquisition process among physical agents to make a cooperative decision. We have used some situations that can be present in the above coordinated task. Space limitations *SL* (reduced space for movement due to the presence of other agents), motion disturbances *MD* (collisions with other physical agents), time constraints *TC* (deadlines in the tasks due to the environment dynamics), energy performance *EP* (different energy expenses according to the tasks) and special behaviours (like aggressiveness *AB* and quickness *QB* in the execution of the tasks) are analysed as well as examining their combinations. Every combination of these situations has a priority-order *PO* to establish the influence of each one on the decisions of the agents in relation to the task. The sum of all influence degrees *ID* of the examined situations is equal to 1 (100%).

5 AC2 TO ACHIEVE SURE COMMITMENTS AMONG PHYSICAL AGENTS

Our proposal for achieving sure commitments among physical agents based on AC^2 is drawn in figure 4. This approach based on the *CBR* methodology allows to the physical agent to be aware if it is able to do the expected task (introspective reasoning) by selecting the most suitable controller to perform it (managing the atomic capabilities associated with each controller).

5.1 Our CBR Methodology Structure

What is the problem to solve?. The physical agent has to be able of selecting the most suitable controller to perform the task (an offside manoeuvre) according to the control-oriented knowledge encapsulated on AC^2, taking into account the environment conditions (D_1, θ_1, D_2, θ_2) and the task requirements ($Time_P$).

What is our case definition?. A case represents both the temporal ($Time_A$) and spatial (D_A, θ_A) conditions under which the agent *A* can perform the task using the controller *C* being based on the information about the physical body's dynamics represented by AC^2. The cases base has enough and representative data continuously updated of the following type: Case = {$Time_A$ (s), D_A (cm), θ_A (°), C (C_1 or C_2 or…C_N), AC (μ_A, σ_A, γ_A, α_A, ε_A, κ_A)}.

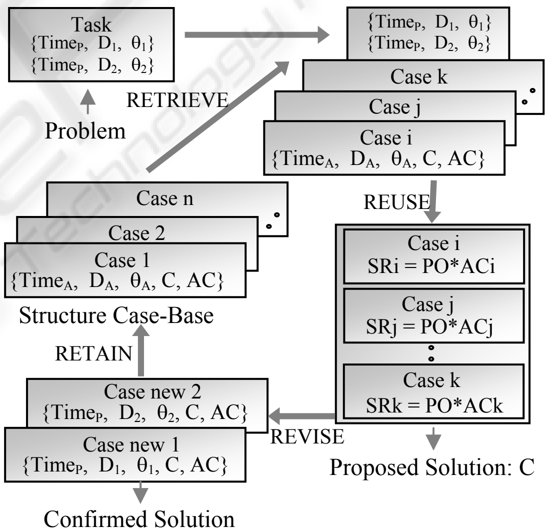

Figure 4: Scheme to achieve sure commitments and intelligent behaviours among physical agents

5.2 Our CBR Methodology Cycle

Retrieve: A progressive filtering using the task requirements and the environment conditions is performed in the cases base in order to extract the most similar cases to the problem. Table 2 shows the order and constraints of the filtering. The sequence of filtering is established, taking into account the relevance of the constraints.

Table 2: Filtering Process

Filter	Constraints
1	$Time_A \leq Time_P$?
2	D_1-10cm ≤ D_A ≤ D_1+10cm? D_2-10cm ≤ D_A ≤ D_2+10cm?
3	θ_1-30°≤ θ_A ≤ θ_1+30°? θ_2-30°≤ θ_A ≤ θ_2+30°?

This search allows selecting the controllers with which the agents could perform the task.

Reuse: A new solution is generated from the retrieved cases according to the problem conditions. In this approach is generated the suitability rate *SR* of each controller according to the associated atomic capabilities and the priority order *PO* established in the commitments acquisition process of the analyzed situation. Each atomic capability used in this study has a direct relation with one analyzed situation, (e.g. μ_A with *SL*, γ_A with *MD*, ε_A with *EP*, etc.). For instance, if it is taken into account the influence degrees *ID* of *SL, QB, MD, AB, and EP* respectively, the priority order coefficients come given by (7).

$$PO = [ID_{SL} \quad ID_{QB} \quad ID_{MD} \quad ID_{AB} \quad ID_{EP}]\%. \quad (7)$$

Therefore, *SR* can be obtained as it is described in (8).

$$SR = ID_{SL} \cdot \mu_A + ID_{QB} \cdot \sigma_A + ID_{MD} \cdot \gamma_A + ID_{AB} \cdot \alpha_A + ID_{EP} \cdot \varepsilon_A \quad (8)$$

In this sense, the controller with the highest suitability rate is the most suitable to be used in the task execution.

Revise: A revision of the proposed solution is done in order to evaluate the obtained results and verify if the solution has been satisfactory.

Retain: The problem conditions and the proposed solution are indexed in order to use them in successive iterations of the CBR cycle if the results after the evaluation have been satisfactory.

6 AN EXAMPLE USING AC2

Physical agents must reach an agreement that allows obtaining sure commitments in relation to the execution of a coordinated task. The sure commitments are necessary because they are directly related to a better response of the system to some undesired events and a better coordinated control in cooperative decisions. Therefore, each physical agent must be aware of its capabilities to perform the task, using the self-knowledge about the dynamics of their bodies included in their atomic capabilities. For instance if the agent *1* proposes to agent *2* to perform a task, both must inspect their physical limitations in accordance with the environment conditions and the task requirements before committing in the performing of this task. Thus, the agents have a high certainty about the correct performing of the task when they acquire commitments. In opposite case, the agents can make an alternative decision, repeating the commitments acquisition process again. In this sense, we have tested this approach using an offside manoeuvre in the robotic soccer testbed where each implicated physical agent has the same set of controllers designed in the section 3. The example scene involves the following situations, *SL*, *QB, MD*, *AB,* and *EP*. This situations set have the following *PO* = [5 30 20 40 5]% according to the features of the offside manoeuvre. Table 3 shows the introspection process and the capabilities management performed by the agents to solve this decision problem with the following requirements:

$Time_P$ = 1.6s, D_1 = 52cm, θ_1 = 80°, D_2 = 44cm, θ_2 = 35°.

Table 3: Introspection Process and the Capabilities Management

Physical Agent 1					
Filter	Case	$Time_A$	D_A	θ_A	C
1	1	1.23	30	15	C_1
	2	1.44	60	75	C_2
	3	1.05	20	45	C_3
	4	1.30	50	90	C_2
	5	1.25	50	30	C_3
	6	1.56	60	90	C_1
2	2	1.44	60	75	C_1
	4	1.30	50	90	C_2
	5	1.25	50	30	C_3
	6	1.56	60	90	C_1
3	2	1.44	60	75	C_1
	4	1.30	50	90	C_2
	6	1.56	60	90	C_1
	Case	Suitability Rate			
	2	SR_{case2} = PO*AC_1 = 0.5328			
	4	SR_{case4} = PO*AC_2 = 0.7616			
	6	SR_{case6} = PO*AC_1 = 0.5328			
Physical Agent 2					
Filter	Case	$Time_A$	D_A	θ_A	C
1	1	1.30	40	30	C_2
	2	1.25	50	30	C_3
	3	1.05	30	45	C_2
2	1	1.30	40	30	C_2
	2	1.25	50	30	C_3
3	1	1.30	40	30	C_2
	2	1.25	50	30	C_3
	Case	Suitability Rate			
	1	SR_{case1} = PO*AC_2 =0.7616			
	2	SR_{case2} = PO*AC_3 =0.5973			
Atomic Capabilities of the controllers: See Table 1					
Filtering Process: See Table 2					
Priority Order (PO) definition: See equation 7					
Suitability Rate (SR) definition. See equation 8					

The introspective reasoning is related to all inspection process performed by the physical agents in order to decide if their physical bodies allow them to execute a proposed task. This self-inspection is based on the control-oriented knowledge about their control systems architectures, namely, about their automatic controllers. Thus, the agents look for the controllers with which they can perform the task (e.g. agent 1: cases 2, 4 and 6, agent 2: cases 1 and 2). The capabilities management performed by the agents aids to choose among the controllers the most suitable according to task criteria established in the commitments acquisition process (e.g. agent 1: case $4 \rightarrow C_2$, agent 2: case $1 \rightarrow C_2$). Thus, the agents 1 and 2 find the most suitable controller (C_2) to perform the coordinated task and hence they commit to execute it.

The above results show a good decision tool established upon the introspective reasoning and the capabilities management that increase the autonomy and self-control of the agents. The introspection and the decisions based on capabilities give a trustworthy idea about the real reliability with which each agent can commit in cooperative systems.

7 CONCLUSIONS

This work presents a way of developing intelligent behaviours in physical agents by means of a suitable exploitation of the information of their control systems. This information should be exploited to enhance the autonomy and the decision ability of the physical agents for instance in coordinated tasks. Our proposal based on AC^2 makes possible to obtain safer systems taking into account control-oriented knowledge. Explicitly, this paper shows the need and influence of AC^2 on the decisions making structure of cooperative intelligent agents when executing coordinated tasks.

This proposal would open the research horizon towards an engineering perspective that could be used as an effective design methodology of physical agents based on AC^2. However, this approach is just one possible technique that can be used to extract the atomic capabilities. In this paper has been presented to remark the potential of AC^2 in the linkage of control systems with multi-agent systems. There are open studies on how to take advantage of this approach. Furthermore, to select one paradigm for the implementation of these concepts is not trivial at all, and its development is still open.

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