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Improving Decisions of Situated Agents in Competitive Scenarios

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Abstract— **Environment's review, shared experiences and agents' self-analyze in the performance of cooperative tasks is a powerful set of resources that situated agents can use in hazardous, unpredictable and dynamic scenarios. Despite the importance of such information, nowadays, it handling suffer several carelessness when this knowledge is embodied. In fact, such consideration can be helpful by the agents to make suitable decision and to perform trustworthy individual commitments with other agents in order to benefit the collective execution performance. In light of this, we present a general structure for coordinating situated agents allowing both the individual agents' autonomy as well as explicit coordination. In this latter case, we pay particular attention to the possibility that agents with different abilities are aware on the needed to be focused on perceive the information aforementioned and used it in their individual reasoning process. We use the robot soccer test bed to express our method operatively. While several efforts are going towards take advantages of particular agent technologies, we think that simple consideration of the information aforementioned arise as bridge between the existence of such information and its embodiment as a whole system.**

Index Terms— **Situated Agents, Dynamics, Control Systems, Multi-agent Systems, Awareness, Coordination.**

I. Overview

Controlled systems are, in many cases, software applications that use high technologies that go beyond to the scope of a simple knowledge range. In fact, general trends in engineering control are pioneer using **artificial intelligence** methods jointly with traditional **control theory** to reach **Intelligent Systems**. In particular, some trends in this research line promote the management of complex systems using agent technology [1], [5], [6], [7]. These approaches consider all the process as a mutli-agent system that needs an effective coordination to achieve the desired goals [2]. Some promising results have been obtained when control systems are designed using agent technology [3]. Here, dynamic of such controlled system is understood as the skill of a situated agent to move throughout the scenario. Particularly, such dynamic is mainly related to: the **dynamic** intrinsic in the systems components and the **dynamic** produced in the execution of the required actions, which are established by the control engineer's criteria. In this sense, the set of such dynamics generates heterogeneity in the systems components. In particular, situated agents are a common application of controlled systems. From this point of view, a situated agent is any physical object "controlled" by an intelligent agent or group of intelligent agents. For instance, a physical object can be represented by a robot, an electronic device or machine. Such agent, must therefore, considers the physical features of the body that must manage (i.e., its dynamics) when they must achieve a commitment to perform a task or when they must agree to assume a specific behavior. It's mean, the dynamic limits and conditions the decisions, actions and cooperation among these agents. Diversity in dynamics abovementioned, gives origin to heterogeneous entities (i.e., heterogeneous situated agents). Such agents possess different characteristics both in their control structure as in their components. In this light, situated agents can perform the same action but in a different way. Inside a multi-agent scenario, interaction is one of the more transcendental challenges that must be solved. Interaction among agents allows perform tasks in a diverse and wide ways pursuing the achievement of a common goal. To perform these tasks coordination is needed. However, to work with situated agents has particularly; difference that to work with software agents because such situated agents must evaluate their bodies to reach individual decisions. Then, situated agents must take into account their physical capabilities and constraints in their decision-making structure (e.g., their dynamics). In addition, other relevant knowledge must be used to endow situated agent with a more set of information in order to improve their decisions. These information aims to be usefulness to situated agents at the moment when they must decide if are capable or not to perform a particular action [4], [8], [9], [10]. In particular, this paper shows three parameters to manage the dynamic aforementioned. Such parameters aim to be used as a simple but efficient coordination mechanism among situated agents. To mention, these parameters are: awareness, trust and world. But the scope of this work only the influence of one of these parameters is analyzed. In this sense, the relevance of the awareness in the development of complex problems is the analysis introduced. This parameter have been selected due to this knowledge is directly related to the physical representation of a situated agent and for thus, is related to the dynamic of the multi-agent system in a control-oriented background. To the end, the paper shows how this diversity can be modeled y generated using advanced control theories. This approach is particularly successful in an automatic control level, where situated agents must have a decision-making structure that takes advantages due to information obtained from the dynamics of the situated

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agents' bodies.

II. Control Structure & Diversity in Dynamics

A set of no-holonomic mobile robots has been used in this paper. The model of the robots is described in Fig. 1.

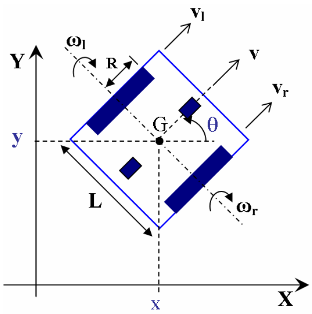

Fig. 1. Variables that describe the robots' state, L=9.5 cm, R=2.25 cm, G: geometric center.

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:

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

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, (1) provides the robot model used.

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

In particular, four different robots' movement behavior has been developed taking into account a particular set of control criteria, such that:

speediness refers to the velocity response of the physical agents to reach any desired target.

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.

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

Table 1 shows the dependence of each designed physical agent according to the four selected control design criteria.

TABLE I. PHYSICAL AGENTS' CRITERIA DESIGN DEPENDENCE
(↑: GREAT DEPENDENCE; ↓: MINOR DEPENDENCE)

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

Thus, 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.

III. Managing the Diversity

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[1]. 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 $\mathbf{PA}_\mathbf{j}$ 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 $\mathbf{PA}_\mathbf{j}$ is part of a cooperative group of

[1] 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.

physical agents $\mathbf{G_{PA}}$. A group of physical agents must generally involve more than one physical agent for the fulfillment of a task.

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

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 (2)

$$KB(PA_j, R_\varphi) = [EC(PA_j) \cup PK(PA_j) \cup TV(PA_j)] \quad (2)$$

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 (3).

$$\forall PA_j \in G_{PA} \; \exists \, KB(PA_j, R_\varphi)_{t_{S_\alpha}} =$$
$$[EC(PA_j, R_\varphi)_{t_{S_\alpha}} \; PK(PA_j, R_\varphi)_{t_{S_\alpha}} \; TV(PA_j, R_\varphi)_{t_{S_\alpha}}] \quad (3)$$

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 (4).

$$\Psi R(T_\beta) = [\Psi EC \; \Psi PK \; \Psi TV] \quad (4)$$
$$\text{where,} \quad \Psi EC, \Psi PK, \Psi TV \in [0,1]$$

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 (5).

$$\forall R_i \in R(T_\beta) \; \exists \, \psi R_i, S_\alpha \in \Psi R(T_\beta) \quad (5)$$

$$\psi R_i, S_\alpha = [\psi EC_{R_i,S_\alpha} \; \psi PK_{R_i,S_\alpha} \; \psi TV_{R_i,S_\alpha}]$$

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 (6).

$$\xi_{(PA_j, R_i)_{t_{S_\alpha}}} = \left(\frac{\sum_{b=1}^{3} kb(PA_j)_{(b)} * \psi(R_j, S_\alpha)_{(b)}}{\sum_{b=1}^{3} \psi(R_i, S_\alpha)_{(b)}} \right)_{t_{S_\alpha}} \quad (6)$$

IV. 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.

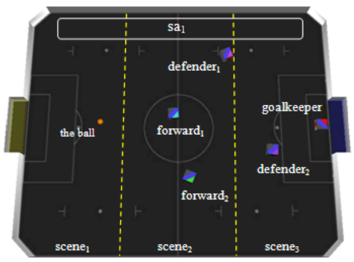

Fig. 2. General scheme of the simulated implementation.

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 (7)

$$P(PA_j, R_i)_{t_{S_\alpha}} = \left(1 - \frac{d(PA_j, R_i)}{d\max_{S_\alpha}} \right)_{t_{S_\alpha}} \quad (7)$$

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 (8)

$$d\max_{S_\alpha} = (d(PA_1, R_i), ..., d(PA_m, R_i))_t \quad (8)$$

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.

$$I(PA_j, R_i)_{t_{S_\alpha}} = (\max(I(PA_j, R_i)))_{t_{S_\alpha}} \quad (9)$$

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 (10).

$$T(PA_j, R_i)_{ts_\alpha} = \left(\frac{goods_{(PA_j,R_i)}}{goods_{(PA_j,R_i)} + bads_{(PA_j,R_i)}} \right)_{ts_\alpha} \quad (10)$$

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 II. Classification of the Decision Axes.

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

V. 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.

A. *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.

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. 3 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 ($case_R$).

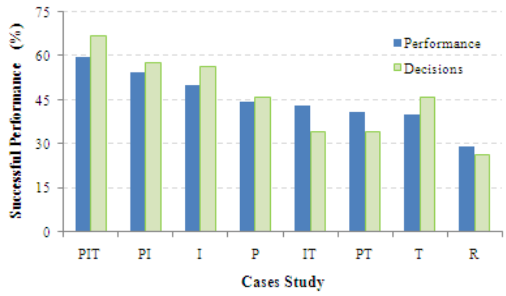

Fig. 3. Analysis Results of the Experiment 1.

B. *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.

1) Analyzing Results

Results are analyzed taking into account the average reached by the agents-teams in each championship. In this sense, Fig. 4 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%**.

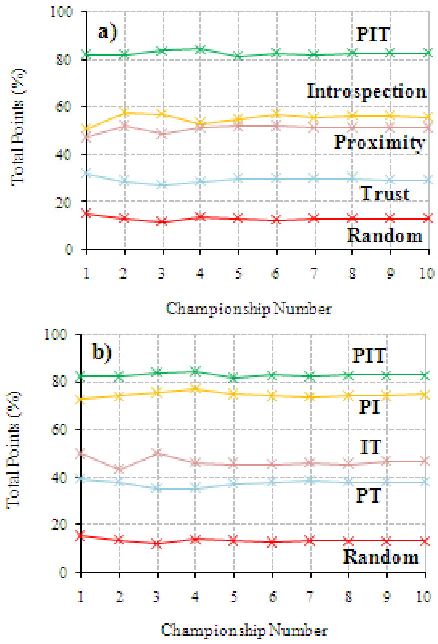

Fig. 4. Successful Performance of the Agents-Teams. a) Comparative Performance of the worst ($team_R$) the simple cases ($team_T$, $team_I$, $team_P$) and

the best case ($team_{P+I+T}$); b) Comparative Performance of the worst ($team_R$) the coupled cases ($team_{I+T}$, $team_{P+T}$, $team_{P+I}$) and the best case ($team_{P+I+T}$).

VI. 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; r**edundancy 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.

References

[1] Sanz Ricardo, Yela Adolfo and Chinchilla Rafael, (2003). A Pattern Schema for Complex Controllers. *IEEE Emergent Technologies for Factory Automation ETFA'2003*.

[2] Innocenti B., de la Rosa J. Ll., Vehí J., Muñoz I., Montaner M., Fàbregas M., Figueras A., Ramon J. A., (2001). Examples of Dynamical Physical Agents for Multi Robot Control. *2do Workshop Hispano-Luso de Agentes Físicos*.

[3] Jennings N.R., Bussmann S., (2003). Agent-Based Control Systems. Why Are They Suited to Engineering Complex Systems?, *IEEE Control Systems Magazine.*

[4] Sycara K., (1998). Multiagent Systems, *AI Magazine*, Vol. 10, No. 2, 1998, pp. 79-93.

[5] Matellán V., Borrajo D., (2001). ABC^2 an Agenda Based Multi-Agent Model for Robots Control and Cooperation, *Journal of Intelligent and Robotic Systems* 32: 93-114.

[6] Stone P., (1998). Layered Learning in Multi-Agent Systems. Ph.D. Thesis. CMU-CS-98-187.

[7] Kim Jong-Hawn and Vadakkepat P., (2000). Multi-agents Systems: A Survey from the Robot-Soccer Perspective, *International Journal of Intelligent Automation and Soft Computing*, 6: (1) 3-17.

[8] Oller A., de la Rosa J. Ll. and Del Acebo E., (1999). DPA^2: Architecture for Cooperative Dynamical Physical Agents. *9th European Workshop on Modelling Autonomous Agents in a Multi-Agent World MAAMAW '99*.

[9] De la Rosa J. Ll., Garcia R., Innocenti B., Muñoz I., Figueras A., Ramon J. A., Montaner M., (1999). Rational Dynamical Physical Agents. *3rd Robocup Workshop. Vol. on RoboCup-99: Robot Soccer World Cup III, Lecture Notes in AI Nº1395, Eds. Springer-Verlag*.

[10] De la Rosa J. Ll., Innocenti B., Oller A., Figueras A., Ramon J. A., Muñoz I., Montaner M., (2000). An Example of Dynamical Physical Agents. *European Robocup Workshop*.