Coordination in Competitive Environments

I. González, S. Ibarra, J. A. Castán, J. Laria, J. Guzmán

Abstract—**Despite several researches in autonomous agents important theoretical aspects of multi-agent coordination has been largely untreatable. Multiple cooperating situated agents support the promise of improved performance and increase the task allocation problems in cooperative environments. We present a general structure for coordinating heterogeneous situated agents that allows both autonomy of each agent as well as explicit coordination of them. Such situated agents are embodied for taking into account their situation to solve any action. Indeed, organizational features have been used as metaphor to achieve highest levels of interactions in an agent system. Then, a decision algorithm has been developed to perform a match between the situated agent knowledge and the requirements of an action. Finally, this paper presents preliminary results in a simulated robot soccer scenario.**

Index Terms—**Multi-agent coordination, e-Institutions, Interactive Norms, Soccer Robotics.**

I. Introduction

COORDINATION depends on how autonomous agents make collective decisions to work jointly in real cooperative environments [1]. Nowadays, several researchers have proposed that autonomous agent systems are computational systems in which two or more agents work together to perform some set of tasks or satisfy some set of goals. Research in multi-agent systems is then based on the assumption that multiples agents are able to solve problems more efficiently than a single agent does [2]. Special attention has been given to MAS developed to operate in dynamic environments, where uncertainty and unforeseen changes can happen due to presence of other physical representation (i.e., agents) and another environmental representations that directly affects the agents' decisions. Such coordination allows agents to reach high levels of interaction and increase their successful decisions, improving the performance of complex tasks. Agents must therefore work in some way and under a wide-range of conditions or constraints. In fact, an agent system will have to be handled with a great level of awareness because the failure of a single agent may cause a total degradation of the system performance. For thus, this paper aims to introduce a decision algorithm based on the electronic Institution (e-I) features [3], which it represents the rules needed to support an agent society. Specifically, such algorithm uses knowledge of the agent situation regards to three perspectives: interaction with social information and other relevant details to entrust in other agents or humans; **awareness** representing the knowledge of the physical body reflecting in the body's skills; and **world** including information perceived directly from the environment. But each type of agent reacts to its perception of the environment in different ways, modifying the overall system performance. In particular, a match function has been formulated to reach a suitability rate based on the situated agents' capabilities and the actions' requirements. In fact, agents can select those actions for which they are the best qualified. The effectiveness of this work is illustrated by developing several examples that analyze cooperative agents' behavior considering different situations in a real cooperative environment.

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II. Procedure for Paper Submission

A group of situated agents are here presented as cooperative systems constituted by a group of autonomous agents who must cooperate among themselves in order to reach specific goals within real cooperative environments. When agent interaction exists, each element of the agent group must be able to be differentiated from the others. These agents require a sense of themselves as distinct and autonomous individuals obliged to interact with others within cooperative environments (i.e., they require an agent identification) [14]. This identification refers to the property of each agent to know who it is and what it does within the group. In this sense, this work proposes two agent classifications: Coach Agents (*CA*) and Situated Agents (*SA*)

A. Adopting e-Features

In order to imitate the ideology of the *e-I* (i.e., *e-I* uses a set of rules to manage the action performance in groups of agents), the paper describes how agents that work in temporal groups, are able to achieve collective behaviour. Such behaviour is possible by using communication among agents. Let us suppose a scene s_α as a spatial region where a set of actions must be performed by a group of situated agents s_α.

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

S is the set of all possible *Scenes*.

Let us define a coach agent ca_α in charge of supervising the execution of the actions in a particular s_α.

$$\exists ca_i, ca_j \in G_{CA} \mid ca_i \neq ca_j \wedge G_{CA} \subseteq CA$$

$$\text{where } CA = \{ca_1, ca_2, ca_3, \ldots, ca_n\}$$

Where CA is the set of all possible Supervisor Agents.

When sa_α has identified its s_α, it must claim information in order to know which actions must be achieved in such s_α. It is possible, then, to define a sa_α as sensitive to the events that happen in real cooperative environments based on the agent paradigm [15].

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Let us define a situated agent sa_i as an entity that has a physical representation on the environment and through which the systems can produce changes in the world.

$$\exists sa_i, sa_j \in G_{SA} \mid sa_i \neq sa_j \wedge G_{SA} \subseteq SA$$

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

SA is the set of all possible Situated Agents.

In this sense, sa_i could be represented in many ways, (i.e., one autonomous robot with arms, cameras, handles, etc) but for the scope of our proposal; sa_i is embodied for an entity that is characterized by the consideration of three parameters refer to: interaction, awareness and world.

In fact, the paper argues coordination at two meta-levels (cognitive level - supervision of the intentions; physical level – execution of the action in the world), where the coach agents coordinates among them to allocate of a set of actions for a group of situated agents.

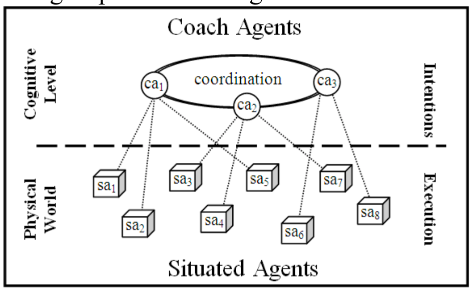

Fig. 1. Levels of Interaction.

Let us define a norm n_i that is denoted as a rule that must be respected or must fix the behaviour that a sa_i must keep at trying to perform an action in a s_α. We indicated the conception of a *norm* within a *scene* following a set of rules such that:

$$\textbf{if } (n_i) \textbf{ do/dont } \{\textbf{action}\}$$

$$\exists n_i, n_j \in N(s_\alpha) \mid n_i \neq n_j \wedge N(s_\alpha) \subseteq N$$

$$\text{Where } N(s_\alpha) = \{n_1, n_2, n_3, \ldots, n_a\}$$

Let us define an obligation *obl* as the imposition given to some sa_i to perform some action, which it is established following a set of rules. In order to denote the notion of obligation *obl* the predicate [3] is present as follows:

$$obl(pa_i, \psi, s_\alpha)$$

Where a sa_i is obligated to do ψ in s_α.

1) Cooperative Actions

Studies about which actions are involved in determine scene are needed to perceive knowledge that make possible the organization of any determined scene. Once a *coach* knows in which scene it will develop its function, it must identify the goals to be accomplished in such spatial region, indicate the tasks that must be performed to achieve these goals, and what roles are necessary for the task achievement.

Then, a *coach* is defined in its knowledge base $KB(ca_\alpha)$ by the consideration of a set of goals *G*, a set of tasks *T* and a set of roles *R*.

$$KB(ca_\alpha) = G(s_\alpha) \cup T(s_\alpha) \cup R(s_\alpha)$$

Where $KB(sa_\alpha)$ is the information of all the issues regarding to a specific *scene* s_α, such that: $G(s_\alpha)$ is the set of goals, $T(s_\alpha)$ is a set of all tasks, and $R(s_\alpha)$ is the set of all roles involved in determined scene s_α.

Indeed, it is necessary to propose a priority index p_i that represents the importance of every action. A sa_α will know both the order in which the goals and the tasks must be performed and the order of the role allocation process regarding its supervised s_α. Such priority index will be established according to system requirements (i.e., timeline) in order to achieve the sa_α aims.

Goals then embody the overall system purpose; however a ca_α could achieve a particular goal without the necessity of performing another goal at the same s_α.

$$\exists g_i, g_j \in G(s_\alpha) \mid g_i \neq g_j \wedge G(s_\alpha) \subseteq G$$

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

$$\forall g_i \in G(s_\alpha)\ \exists\, p(g_i) \in P_{G(s_\alpha)} \mid 0 \leq p(g_i) \leq 1$$

Where *G* is the set of all possible *Goals* and $G(s_\alpha)$ is g_β involved in s_α.

Let us to define a set of tasks *T* which represent the issues that must be performed to achieve a specific g_β. Goal then could be achieved without the implicit necessity of performing all its involved tasks. Therefore, the tasks selected are independent, but their development could affect in a positive or negative way the development of other tasks.

$$\exists t_i, t_j \in T(g_\beta) \mid t_i \neq t_j \wedge T(g_\beta) \subseteq T(s_\alpha) \subseteq T$$

$$\text{Where } T(g_\beta) = \{t_1, t_2, t_3, \ldots, t_p\}$$

$$\forall t_i \in T(g_\beta)\ \exists\, p(t_i) \in P_{T(g_\beta)} \mid 0 \leq p(t_i) \leq 1$$

Where *T* is the set of all possible *Tasks*.

Let us to define a set of roles *R* which represent the actions that a pa_i must fulfil to perform a t_γ within a s_α.

$$\exists r_i, r_j \in R(t_\gamma) \mid r_i \neq r_j \wedge R(t_\gamma) \subseteq R(s_\alpha) \subseteq R$$

$$\text{Where } R(t_\gamma) = \{r_1, r_2, r_3, \ldots, r_q\}$$

$$\forall r_i \in R(t_\gamma)\ \exists\, p(r_i) \in P_{R(t_\gamma)} \mid 0 \leq p(r_i) \leq 1$$

Where *R* is the set of all possible *Roles*.

In order to illustrate how this process is performed, let us suppose a scene s_1 which is supervised by the coach ca_1 performing a decision process to define which goal must be attended firstly (Fig. 2).

$\exists G(s_1) = \{g_1, g_2\} \mid p(g_1) = 0.78 \wedge p(g_2) = 0.72$

//decision process is performed following the //condition:

if $(p(g_1) > p(g_2))$

then (g_1 is the first performed)

else (g_2 is the first performed)

//the g_1 presents a higher $p(g_1)$, therefore, is //performed before that g_2.

Fig. 2. The coach ca_1 defines which goal must be performed first.

2) Embodying Situated Agents

Suppose that a situated agent lives in a real environment, therefore, it has the ability to consider its physical representation in such world. Although these characteristics could supposedly take a lot of "things" regarding the environment our proposal takes three kinds of knowledge that seek to reference all the information that characterize the perception of particular sa_i.

a) Interaction

Interaction I refers to the certainty that an agent wants to interact with other agents to assume a specific behavior with successful and high reliability to achieve any action proposed within any determined scene. Such information is

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useful in the interaction process of the agents because they can trust in other agents based on the result of their previous interactions. Obviously, if a sa_i has a positive performance of its actions, its interaction level increases; but if the outcome of the action is negative, its interaction level decreases. Such knowledge is obtained when a sa_i has a direct relationship with a ca_α.

$$\forall\, sa_i \in G_{SA}\ \exists\, I_{r_\gamma, s_\alpha}(sa_i) \subseteq I(sa_i)$$

Where $I_{r_\gamma, s_\alpha}(sa_i)$ is the *interaction* level of a sa_i to perform r_γ in the s_α.

b) Awareness

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

Physical agents could be any physical object "*handled*" by an intelligent agent (i.e., an autonomous robot, a machine or an electric device). Such pa_i has features that consider their physical body properties (i.e., their dynamic, their physical structure) usually when they commit to perform some task or to assume a specific behaviour within a cooperative environment. This fact represents the skill of the physical agents to know that actions will be performed based on the knowledge of the physical agents' bodies, which is achieved through representation of them on a capabilities basis.

$$\forall\, pa_i \in PA\ \exists\, A_{t_\gamma, s_\alpha}(pa_i) \subseteq A(pa_i)$$

Where $A_{t_\gamma, s_\alpha}(pa_i)$ is the Awareness of pa_i to perform t_γ in the s_α.

a) World

World W refers to the set of environmental knowledge that physical agents have to perform the proposed set of actions. Such domain representation is considered as the embodiment of the environment knowledge that represents all the physical information that has influence in the physical agents' reasoning process

Let us to define a set of world conditions that represent information about empirical knowledge of the environmental state, such that:

$$\forall\, pa_i \in PA\ \exists\, W_{t_\gamma, s_\alpha}(pa_i) \subseteq W(pa_i)$$

Where $W_{t_\gamma, s_\alpha}(pa_i)$ is the environmental condition of pa_i to perform t_γ in a s_α; sa_α uses the above information to know the physical situation of each pa_i.

All knowledge of a particular pa_i $KB(pa_i)$ is then constituted by the information provided for the three modules, such that:

$$\forall\, pa_i\ \exists\, KB(pa_i) = [I(pa_i)\quad A(pa_i)\quad W(pa_i)]$$

In particular, all knowledge related to a specific t_γ in s_α is given such that:

$$KB(pa_i)_{t_\gamma, s_\alpha} = [I_{t_\gamma, s_\alpha}(pa_i)\quad A_{t_\gamma, s_\alpha}(pa_i)\quad W_{t_\gamma, s_\alpha}(pa_i)]$$

3) Communication Process

The humans have a communication process that allows transmit information or ideas in a common language to make sure and reliable commitments between us. Likewise, artificial intelligence has several approaches showing the same process [15], [17] to exploit the advantages of expressing communication. To accomplish an action, a group of agents must establish communication (to coordinate them). On such coordination agents must "converse" among them to agree who is who within the group. Then, a communication with three simple dialogues based on the *KQML* specification is presented as follows:

$$\mathrm{Request}(sa_\alpha, sa_\beta, \theta, s_n)$$

Where sa_α asks to sa_β its θ in the scene s_α

$$\mathrm{Reply}(sa_\beta, sa_\alpha, \phi)$$

Where sa_β responds to sa_α its decision ϕ based on the information dispatched.

$$\mathrm{Inform}(sa_\alpha, sa_\beta, \delta, s_\alpha)$$

Where sa_α informs sa_β its state δ in the scene s_α.

This process helps to the sa_α to communicate among them and with a pa_i.

//we presents the follow situation.
sa_1:$G(s_1)=\{g_1, g_2\} \mid p(g_1)=0.78 \wedge p(g_2)=0.72$;
sa_2:$G(s_2)=\{g_3, g_6\} \mid p(g_3)=0.71 \wedge p(g_6)=0.68$;
//the dialog between these agents is performed such as:
REQUEST(*sa_1, sa_2, $p(g_1)=0.78$, s_1*) ;
//the sa_2 compare this information with its p, then:
REPLY(*sa_2, sa_1, $p(g_1)$_ok*) ;
//the sa_1 receive this information and notify its actions:
INFORM(*sa_1, sa_2, g_1, s_1*) ;

Fig. 3. Conversation between the sa_1 and sa_2.

Otherwise, some concepts have been explained throughout this research work, but none of them has clarified how a sa_α could decide who is the pa_i (or group) that will take part in the action of its responsible s_α. sa_α then considers an *I*nfluence *D*egree *ID* to all these actions involved in a s_α by the tupla $ID(s_\alpha)$ based on the consideration of the aforementioned parameters to generate an utility function that helps them in their decision making structure.

$$ID(s_\alpha) = [id_{EC}(s_\alpha)\quad id_{PK}(s_\alpha)\quad id_{TV}(s_\alpha)]$$

Where $id_{EC}(s_\alpha)$, $id_{PK}(s_\alpha)$ and $id_{TV}(s_\alpha)$ are values that establish the relevance of each parameter related to a s_α. These values are in the range [0,1]. In this sense, the sa_α responsible in s_α uses the $KB(pa_i)_{t_\gamma, s_\alpha}$ and the $ID(s_\alpha)$ to perform a match function by means of (1).

$$\mathrm{match}(ID(s_\alpha), KB(pa_i)_{t_\gamma, s_\alpha}) = \frac{\sum_{j=1}^{3} ID(s_\alpha)_{(j)} \times KB(pa_i)_{t_\gamma, s_\alpha (j)}}{3 - \sum_{j=1}^{3}(1 - ID(s_\alpha)_{(j)})} \quad (1)$$

A sa_α uses the match to determine which pa_i must perform r_q in a s_α, assigning the higher pa_i for the most prior r_q in s_α.

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$$\mathrm{ID}(s_1) = [0.5 \quad 0.8 \quad 0.2]$$
$$\mathrm{KB}(pa_1)_{t_3,s_1} = [0.61 \quad 0.48 \quad 0.73]$$
$$\mathrm{KB}(pa_2)_{t_3,s_1} = [0.19 \quad 0.62 \quad 0.21]$$

//using the eq. (1) we have:

$$\mathrm{match}(\mathrm{ID}(s_1), \mathrm{KB}(pa_1)_{t_3,s_1}) = 0.5667$$
$$\mathrm{match}(\mathrm{ID}(s_1), \mathrm{KB}(pa_2)_{t_3,s_1}) = 0.4220$$

//then, the role allocation process is perform based on the rule

$$\textbf{if } (\mathrm{match}(\mathrm{ID}(s_1), \mathrm{KB}(pa_1)_{t_3,s_1}) > \mathrm{match}(\mathrm{ID}(s_1), \mathrm{KB}(pa_2)_{t_3,s_1}))$$
$$\textbf{then } (\mathrm{ID}(s_1) \rightarrow pa_1)$$
$$\textbf{else } (\mathrm{ID}(s_1) \rightarrow pa_2)$$

//then, the match serves to identify the *pa* with higher coefficient, and so, the //*pa₁* is the selected to perform the proposed action.

Fig. 4. Empirical example of a match process.

B. Decision Algorithm

An important criterion for the development of collective actions within real cooperative environments is the traffic of the information available from the perception of the intentions to the execution of them. We have therefore determined a particular decision algorithm of four simple stages.

Stage 1. Refers to the property of a sa_α to *perceive* which s_α must manage, therefore, a sa_α then knows its goals, tasks, roles (the priority of every item is also perceived) and ID involved in its s_α. Hence, the knowledge base of each sa_α could be achieved.

Stage 2. All the *sa* (of the entire *SA*) must organize them to define which will be the order in that they could begin the recruitment of *pa* to perform the actions within its s_α. For thus, the sa must converse among them using the developed dialog (see II.5)

Stage 3. Based on the order obtained above, a sa_α is approved to starts the communication with the entire *PA* to determine that pa_i will be the selected to perform every action. For thus, a sa_α must obtain the physical knowledge of each pa_i by means of directly communication with they; the environment conditions and trust value of each pa_i are obtained when the sa_α uses the modules aforementioned (respectively for each parameter).

Once a sa_α completes the $\mathrm{KB}(pa_i)$ of the entire *PA*, takes such information to perform the match using the equation (1), considering the priority index of all the roles. Then, sa_α has a list detailed (form higher to lowest coefficient) of the entire *PA*. After, sa_α knows that pa_i must perform that role; therefore, it is able to obligate a determine pa_i to perform a role which it represent that action must be performed.

Hence, the best pa_i (of the entire *PA*) will chose to perform the most prior role and so successively until finish with all the roles in such s_α. Such process guaranty us a suitable role allocation because the r_q always will allocated to the best pa_i. Indeed, a sa_α knows how many *PA* needs because it needs the same amount of *PA* such as $R(s_\alpha)$. Suppose that the system has enough amount of *PA* to take all the defined roles. To know, every sa_α is able to exclude a pa_i that presents a lowest action capability.

Stage 4. Show-time. A pa_i knows the r_q that must perform. This involves physical changes in the environment. Now, the environment has been modified. So, a new consensus among the *SA* could be performed to adjust it to the current changes in the environment.

III. Implementation

In our implementation, each *physical agent* has a different movement controller which differentiates from others. Then, we have segmented the scenario into three spatial regions (Fig. 5) to represent each s_α.

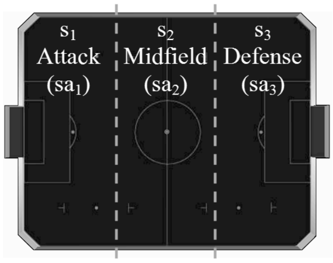

Fig. 5. Geographic segmentation of the experimental environment.

For sake of simplicity, we only have defined one goal per scene $G(s_1)=g_1$; $G(s_2)=g_2$ and $G(s_3)=g_3$. The consensus to define the execution order of the scenes is derived as follow (Fig. 6).

if (*cbp is* [2,60]) then {s_1}
else if (*cbp is* [61,140]) then {s_2}
else if (*cbp is* [141,220]) then {s_3};

Fig. 6. Supervisor Agent Consensus.

Where *cbp* is the current ball position on the environment. So, the spatial regions are limited according to the simulator dimensions (axis *x*: [0 220]; axis *y*:[0 180]). Moreover, specific tasks are defined in order to accomplish each g_i such that:

$$T(g_1) = \{t_1, t_2\} \wedge T(g_2) = \{t_3, t_4\} \wedge T(g_3) = \{t_5, t_6\}$$

Where t_1 is make-pass, t_2 is shooting, t_3 is player-on, t_4 is kick-ball, t_5 is protect-ball and t_6 is covering a position.

Following the rule presented for the goals, the tasks also use the *cbp* as a reference to determine its execution order.

Then, using the ranges above, a sa_α may decide the task to perform at any time. But, to attempt to achieve such tasks a sa_α must define which roles it must perform and the priority order of such roles. Therefore, by means of human analysis we have proposed four roles that could be used to perform any task such that:

$$R(t_\gamma) = \{r_1, r_2, r_3, r_4\}$$

Where r_1 is go to the ball, r_2 is kick the ball, r_3 is cover a zone and r_4 is take a position to be used in each t_γ.

In addition, we have performed a combination with the information involved in the *environment-based knowledge*. Such combination is used by sa_α to perform the match process considering the aforementioned parameters. Then, a binary combination lets us generate eight influence degrees (Table I).

Table I. Influence Degree Consideration (0: is not considered; 1:is considered)

Influence Degree	TV	PK	EC
ID0	0	0	0
ID1	0	0	1
ID2	0	1	0
ID3	0	1	1
ID4	1	0	0
ID5	1	0	1
ID6	1	1	0
ID7	1	1	1

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We present a review to show how we have implemented these parameters in the robot soccer testbed.

Interaction here called *Trust* TV represents the social relationship among agents taking into account the result of past interactions of a sa_α with a pa_i. Equation (2) shows the *trust* calculation if the aim is reached. Otherwise, using (3) shows the *trust* calculation if the aim is not reached.

$$tv_{t_\gamma,s_\alpha}(pa_i) = tv_{t_\gamma,s_\alpha}(pa_i) + \Delta A(s_\alpha,\sigma) \quad (2)$$

$$tv_{t_\gamma,s_\alpha}(pa_i) = tv_{t_\gamma,s_\alpha}(pa_i) - \Delta P(s_\alpha,\omega) \quad (3)$$

Where the $tv_{t_\gamma,s_\alpha}(pa_i) \in [0,1]$ and higher $tv_{t_\gamma,s_\alpha}(pa_i)$ represent the best pa_i to perform t_γ in s_α, $\Delta A(s_\alpha,\sigma)$ and $\Delta P(s_\alpha,\omega)$ are the awards and punishments given in s_α respectively and σ is from 1 to $Q(s_\alpha)$ and ω is from 1 to $Q'(s_\alpha)$; that are the number of awards and punishments in s_α.

Awareness here called *Physical Knowledge PK* represents the knowledge of the agents about their physical capabilities to perform any proposed task. In particular, the introspection process is performed by using neural networks taking into account the knowledge that a pa_i has related to perform t_γ in s_α. Consider that a high $PK_{t_\gamma,s_\alpha}(pa_i) \in [0,1]$ by representing a suitable pa_i.

World here called *Environmental Conditions EC* is a value related to the distance between the current location of a pa_i and the location of the ball. Equation (4) shows the calculation:

$$ec_{t_\gamma,s_\alpha}(pa_i) = (1 - d(pa_i, r(t_\gamma, s_\alpha)) / d\max(s_\alpha)) \; ec_{t_\gamma,s_\alpha}(pa_i) \in [0,1] \quad (4)$$

Where $ec_{t_\gamma,s_\alpha}(pa_i)$ is the value of a pa_i to perform a t_γ in s_α; $d(pa_i, r(t_\gamma,s_\alpha))$ is the distance between the pa_i with $r(t_\gamma,s_\alpha)$ and $d\max(s_\alpha)$ is the maximal distance of all *pa* in s_α. Then, equation (5) shows the $d\max(s_\alpha)$ calculation where *m* is the total number of *pa* in *IAS*.

$$d\max(s_\alpha) = \max(d(1,s_\alpha),...,d(m,s_\alpha)) \quad d\max \in [0,1] \quad (5)$$

In order to show how our approach performs the role allocation process we present a possible situation (Fig. 7 where the ball is within the s_2 and we use all the influence degrees generated to perform the *pa* selection. Then, we only showed the allocation for one action (kick the ball).

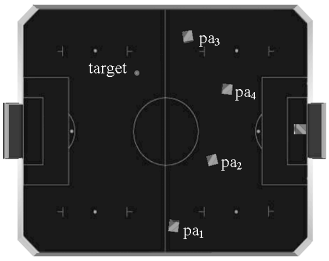

Fig. 7. Possible situation for the PA in the environment.

In (Table II) we present the values of a pa_i regarding to the proposed action. In (Table III) we show the match values obtained by means of the equation (1). Then, is possible to see will be the pa_i selected by the sa_2 to perform the proposed action. Additionally, the remained physical agents follow a fix strategy which was defined to consider actions to the entire *PA*.

TABLE II. PHYSICAL AGENTS' KNOWLEDGE BASES

pa	*Trust*	*Intro.*	*Prox.*
$KB(pa_1)_{t_{kickball},s_2}$	0.43	0.47	0.31
$KB(pa_2)_{t_{kickball},s_2}$	0.65	0.52	0.46
$KB(pa_3)_{t_{kickball},s_2}$	0.71	0.69	0.79
$KB(pa_4)_{t_{kickball},s_2}$	0.83	0.77	0.63

TABLE III. SOME EXAMPLES OF PHYSICAL AGENT SELECTION

ID(s_2)	pa_1	pa_2	pa_3	pa_4	pa selected
ID2(s_2)	0.31	0.46	0.79	0.63	**pa_3**
ID3(s_2)	0.47	0.52	0.69	0.77	**pa_4**
ID4(s_2)	0.39	0.49	0.74	0.70	**pa_3**
ID5(s_2)	0.43	0.65	0.71	0.83	**pa_4**
ID6(s_2)	0.37	0.55	0.75	0.73	**pa_3**
ID7(s_2)	0.45	0.58	0.70	0.80	**pa_4**
ID8(s_2)	0.40	0.54	0.73	0.74	**pa_4**

IV. RESULTS AND CONCLUSIONS

We ran two experimental evaluations to validate the proposed approach. In particular, in the experiments our IAS uses all the binary combination of the ID to perform the match process. In Exp. 1, our IAS competed against a blind opponent in 30 games. Here, the IAS performance is improved when all the parameters are considered. So, IAS(ID_7) shows a better average (improvement rate: +81% better) than IAS(ID_0) (any parameter considered). Then, in the Exp. 2, a league of 28 games was performed to confront the IAS among them. So, the IAS performance increases when uses jointly all the parameters. In fact, the IAS(ID_7) shows a better average (improvement rate: +92%) than IAS(ID_0).

As conclusions we argue the need of agent meta-coordination to exploit the advantages of abstract the environment knowledge (by the supervisor agents) and use it to influence the reasoning process of the physical agents. In addition, a combination (named Influence Degree) describes the consideration among these parameters giving to the sa_α the ability to determine a decision process to perform a match between the scene requirements and the physical agent capabilities. In fact, the best performance is obtained when our team agent took into account all the parameters in its decision process.

But it is really interesting to analyze how the cooperative IAS performance increases when the system takes the parameters into consideration. In conclusion, the situation matching approach is a promising method to be used as utility function between task requirements and physical agent capabilities in MAS. In (Table IV) we show some approaches regarding architecture for multi-agent cooperation. In particular, these architectures express behavior by implementing different kinds of knowledge which can be related to our approach.

TABLE IV. OUR APPROACH VS OTHER APPROACHES

ID	T	I	P	VS
0	0	0	0	References take at least one of these parameters.
1	0	0	1	No references yet
2	0	1	0	[4], [5], [6], [7]
3	0	1	1	[2], [10], [14]
4	1	0	0	No references yet
5	1	0	1	[9], [11]
6	1	1	0	[8]
7	1	1	1	No references yet

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