A Proposal to Manage Diversity in Robot Coordination

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***Abstract*—The paper present a way to manage and exploit the different capabilities of a team of mobile robots in a soccer scenario. To do this, each robot represents information by a set of data called "degrees of situation". In our approach the robots have different automatic controllers to generate dynamical diversity inside the group. Here, dynamic means dynamic temporal evolution of continuous variables of the controlled system. Therefore, a multi-robot system can be considered as a team of heterogeneous robots with different capabilities that work together to fulfill some cooperative tasks. In particular, this paper is related to studies about how the team-work performance improves by the "degrees of situation" management as a coordination strategy. Result and conclusions are shown, emphasizing contributions of the approach in the improvement of the cooperative team-work.**

***Index Terms*—Diversity in dynamic, robot coordination, soccer testbed.**

I. Introduction

According to the Distributed Artificial Intelligence (DAI) a Multi-agent Systems (MAS) is a team of entities able to solve problems by working jointly to find answers to problems that are beyond the capacity and the individual knowledge of each entity [1]. In particular, in this work the agent is an entity with goals, actions and domain knowledge, situated in an environment. Moreover, such agents must handle a physical body with different physical features (e.g. dynamics). In this sense, the MAS can be considered as a team of heterogeneous intelligent agents that must be coordinate in their actions to work jointly in a cooperative environment.

Therefore, studies about how the coordination mechanisms improve the performance in the above systems are necessary. Such mechanisms allow agents the interaction with other agents and make sure decisions in cooperative tasks. These studies are mainly based on Electronic Institutions foundations [2]. Some e-Institutions features have some similarities with the human relationships due to the agents cooperate through roles previously defined [3]. In this sense, each scene has an agent-behavior within the multi-agent system. The proactive agent-behavior in the scenes allows the system knows the aims of each scene and facilitates the coordination between agents within a specific scene. Such robot-behavior takes into account three parameters (proximity, introspection and trust) in its decision-making structure.

Proximity: Robots take in account their position within the environment regarding other agents.

Introspection: Robots are able to analyze their physical body and know the tasks they can perform according to their physical capabilities [4]. Such knowledge can be extracted by the robots using introspective reasoning techniques [5-6].

Trust: Robots make their decisions based on the results of past interactions with other agents.

According to the above parameters, have been established eight degrees of situation and some study cases in the robot soccer testbed. Currently, robot soccer is considered a good research platform for cooperative multi-robot systems at both simulation and real environments. It emulates a soccer game, which the agents must interact among them in a dynamic, surrounding, cooperative and competitive environment [7].

This approach shows how robots can use the proposed degrees of situation to exploit their heterogeneous skills for improving the collective decisions in cooperative environments.

Section 2 presents our approach to generate dynamical diversity from a control-oriented perspective. Section 3 shows the main idea of our coordination mechanism. Section 4 explains our coordination mechanism approach on the robot soccer simulation platform. Section 5 shows experimental result. Finally, some conclusions are drawn in section 6.

II. Control Structure and Dynamic Diversity

Our tests used the robot models of the *SimuroSot* simulator available from the web page: http://fira.net/contents/sub03/sub03_7.asp. The simulator facilitates extensive training and testing of this proposal. The robot model is described by the equations (1) and (2) that represent the linear and angular velocities of each robot respectively.

$$V_{robot} = \frac{2.3}{0.2833s+1} V_{give} \qquad (1)$$

$$\omega_{robot} = \frac{2.07}{0.0687s+1} \omega_{give} \qquad (2)$$

We designed four different *PID* controllers with suitable control laws for our agents. Based on the *PID* controller designed, we have created four different physical agents:

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Precise, *Disturbed*, *Fast* and *Fast-Disturbed*. Table 1 shows the dependence of each designed physical agent with four selected control design criteria: *speed, precision, persistence and control effort.*

Table 1. Definition of the physical agents according to designed controllers. (↑ : great dependence; ↓ : minor dependence)

Robots behavior	*speed*	*precision*	*persistence*	*control effort*
precise	↓	↑	↑	↓
disturbed	↓	↓	↓	↑
fast	↑	↓	↑	↑
fast-disturbed	↑	↓	↓	↑

The *Precise*-robot is the most precise in the team for achieving any desired target. However, the *precise*-agent is slow, persistent and it has a minimal control effort.

The *Disturbed*-robot performs aggressive movements to achieve any desired target. In addiction, it is slightly persistent, slow, imprecise and it has a high control effort.

The Fast-robot is rapid to reach any target in a persistent way but with a high control effort.

Finally, the *Fast-disturbed*-robot has some features between the *fast*-agent and the *disturbed*-agent.

The Fig. 1 shows the spatial evolution of the physical robots with their controllers.

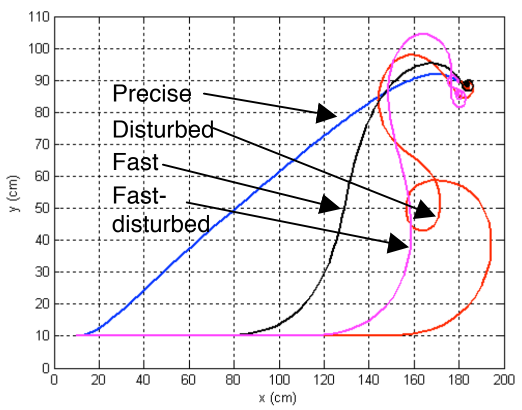

Fig 1. Spatial evolution of each physical agent.

III. Coordination

Distributed intelligence on computer science is, currently, focused to generate systems of software agents, robots, sensors, computer systems, and even people that can work together with the same level of efficiency and expertise as human teams [8]. Agents must, for example, be able to reason about goals, actions, when to perceive and what to look for, the cognitive state of other agents, times, resources, collaborative task execution [9]. Agents are therefore, defined as computer systems capable of flexible and autonomous actions in dynamic, unpredictable and typically cooperative environments [10]. One typical implementation of the agent technology is the physical agent paradigm. A physical agent is an intelligent entity which is embodied in some environment (i.e., has a physical representation) and which must take its decisions based on the capabilities of the physical body its must manages. Even when a single physical agent can achieve any given task, the possibility of deploying a physical agents' team can represent a significant improvement in the performance of the overall systems. A huge single robot, no matter how powerful it is, will be spatially limited while smaller robots could achieve a given goal more efficiently [11]. The control and coordination of multiple autonomous mobile agents (i.e., physical agents) is a challenging task; particularly in environments with multiple, rapidly changing conditions and agents [12]. In fact, the objective of the cooperation is to maintain maximum utilization of multi-agent resources while ensuring job performance at the highest productive level. But, a general theory of cooperation for multi-agents domains remains elusive [13]. In recent years, cooperation in multi-agent systems is an increasingly and essential element for managing systems with enormous amount of data to process and communicate, providing high performance, high confidence, and reconfigurable operation in the presence of uncertainties [14]. For example, different cooperative schemes of an individual agent can constrain the range of effective coordination regimes; different procedures for communication and interaction have implications for behavioral coherence [15]. Generally speaking, one the most transcendent topic in the literature is the **coordinated task** problem-solving algorithm. **Agents can improve cooperation by planning the execution of complex problems.** Planning for a single agent is a process of constructing a sequence of actions considering only goals, suitability rates, capabilities, and environmental constraints [16]. To the end, a proper alternative is that agents can interact aiming to achieve a successful cooperative agents' performance. Indeed, such lack represents a significant impediment to reduce complexity and to achieve appropriate levels of coordination and autonomy in multi-agent systems [16-17].

The coordination among robots is a challenge to improve the performance of heterogeneous teams in cooperative environments. In this way, we have developed a method based on the Electronic Institution Foundations [2] where the robots have meetings (scenes) in specific zones of the environment. These scenes have a set of well-defined goals to perform the team-work. Thus, the system activates the scenes by means of target's locations in the environment. The scenes aid and facilitate the execution of coordinate tasks by using the coordination mechanism previously selected.

In this paper, we have used some coordination mechanisms to improve the performance of a team of heterogeneous robot based on three parameters: *proximity, introspection and trust.* To reach sure commitments and make better decisions improving the team performance, the robots uses such information in their decision-making structure.

Thus, the *proximity* is related to the distance between the current location of each robot and the location of desired target. Such knowledge is regarding to the environment, and represents the physical situation of the every robot in this environment.

The knowledge about the physical robot' bodies (*introspection*) is obtained through the representation of them on a capabilities base. All this enclose information can be extracted by the robots using introspective reasoning techniques and handled using capabilities management techniques. These approaches get to guarantees sure commitments and improve of this way the team-work

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achievements, because a robot can develop a better self-control improving in this way its performance in coordinate tasks. Finally, the social relationship of a robot takes into account the result of past interactions of a specific robot with others.

The above parameters then aid the robots to coordinate among them. These parameters are useful when a lot of robot must interact and operate effectively within an environment with changing circumstances and a great quantity of information [3].

IV. The Approach

In our approach, a scene is defined, as a momentary situation where a particular set of actions must be executed. To do that, a robot (or group of robots) should be capable of selecting what to do. These meetings facilitate the execution of tasks in certain areas of the field, because they define momentary roles for each robot, which allows the best robot to perform the activity most appropriate to their abilities. The robot soccer simulator has been used as experimental platform. In particular, the field has been segmented in three zones (see Fig. 2). Thus, every zone has a defined a set of actions which determine the behavior of each robot within the active scene.

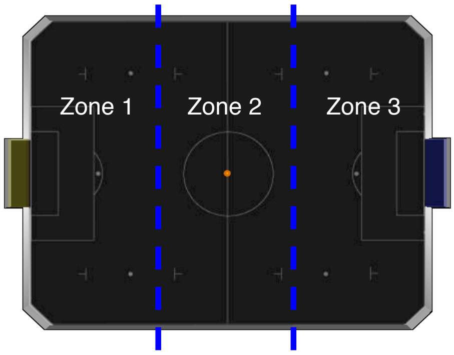

Fig 2. Zones in the environment.

4.1 Scene Activation.

The scenes' activation is determinate by the target's location in the environment (in this case, the current ball position). The system uses a selection of the three parameters to perform the goals of the scene when it is activated. These parameters define the decision making structure of the agent within the scenes.

Table 2. Scenes and roles in the scenes.

Scene	*Role*
Defense	Central Defense
	Left Defense
	Right Defense
Midfield	Mid-center
	Mid-left
	Mid-right
Attack	Forward
	Left wing
	Right wing

The active scene makes the roles allocation for the robots by means of the same selected parameters (*proximity, introspection, trust*).

In this sense, the roles are the behaviors of the robots in every scene. In particular, the roles have been designed depending on the features of the active scene (e.g. robots' locations, amount of robots, etc.). Table 2 shows the scenes and roles established in this approach.

The system's zones and the scenes' activation have been defined by mean of the ball's position. Likewise, the changes between zones are also determined by the same consideration. Studies about the changes between zones are necessary to update the agents' roles in every zone. In this sense, the changes between zones are performing when the goals of the active scene are achieved and the system identifies a new target in another zone of the environment. This process is performing through the coordination between the definite zones, due to the agents must know so much the zone to which they will go and their physical situation in this new zone.

In other hand, the entrance of the agents in the scenes depends on match between the task requirements of the active scene and the agents' capabilities to perform the proposed task. In addition, the scene chooses the most suitable agent to execute the main task (kick the ball) by using the same selected parameters. This selection depends on the certainty index (*CI*) related to the three parameters. Equation (3) shows the *CI* calculation.

$$CI_{(k,i)} = (PC_{(k,i)}) * (IC_{(k,i)}) * (TC_{(k,i)}) \quad (3)$$

where:

$CI_{(k,i)}$: certainty index of the robot k in the scene i.
$PC_{(k,i)}$: proximity coefficient of the robot k in the scene i.
$IC_{(k,i)}$: introspection coefficient of the robot k in the scene i.
$TC_{(k,i)}$: trust coefficient of the robot k in the scene i.

Proximity Coefficient (PC) is related to the distance between the current location of each robot and the ball's current location. Equation (4) shows the *PC* calculation.

$$PC_{(k,i)} = (1 - d_{(k,i)}/dmax_{(i)}) \quad PC \in [0\text{-}1] \quad (4)$$

where:

$d_{(k,i)}$: distance between the robot k and the ball in the scene i.
$dmax_{(i)}$: maximal distance between robot and the ball in the scene i.
If PC is great is better.

Equation (5) shows the $dmax_{(i)}$ calculation.

$$dmax_{(i)}=max(d_{(1,i)},\ldots,d_{(p,i)}) \quad (5)$$

Introspection Coefficient (IC) represents the knowledge of the robot about their physical capability to perform a proposed task. In particular, a backpropagation neural network model is used to represent the introspection data of a robot. The input data is the robot' locations, ball's locations and tasks requirements (e.g. kick the ball towards

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the goal). The output is related to $IC \in [0\text{-}1]$ so that while is great represents a good agent's performance.

Trust Coefficient (TC) represents the social relationship among robots. It takes into account the past interactions with other robots. The team decide how perform the proposed task based on the *TC*. Equation (6) shows the *TC* calculation if the aim is reached. Otherwise, equation (7) shows the *TC* calculation if the aim is not reached.

$$TC_{(k,i)} = TC_{(k,i)} + \Delta A_{(i,a)} \qquad (6)$$

$$TC_{(k,i)} = TC_{(k,i)} - \Delta P_{(i,b)} \qquad (7)$$

where:

$TC_{(k,i)}$: trust coefficient of the robot k in the scene i.
$\Delta A_{(i,a)}$: is the *award* given by the scene i.
$\Delta P_{(i,b)}$: is the *punish* given by the scene i.
$a = 1,\ldots,Q_{(i)}$ $Q_{(i)}$:number of awards in the scene i.
$b = 1,\ldots,R_{(i)}$ $R_{(i)}$: number of punishes in the scene i.
$TC \in [0\text{-}1]$ so that if more great is better.

Then, from combination among the three parameters have been abstracted eight robot's behaviors (degrees of situations) using as coordination mechanisms. Table 3 shows the defined Degrees of Situation (*DS*).

Table 3. Three parameters' classification (Degrees of Situations: *DS*) in our approach.
(0: is not considered; 1: is considered).

D.S.	*proximity*	*introspection*	*trust*
0	0	0	0
1	0	0	1
2	0	1	0
3	0	1	1
4	1	0	0
5	1	0	1
6	1	1	0
7	1	1	1

In this way, the proposed degrees of situations attempt to provide to the agents with a set of awareness to perform coordinate task taken into account the agent situation in the environment.

V. Experiments

By using the robot soccer testbed, the model presented in section 3 have been used to form a team of heterogeneous robots. This team was tested in two different experiments. In the first experiment, our team competed against an opposing team of homogeneous robots in thirty games for every degree of situation shown in table 3. In addition, the initial values of the coordination parameters for each case in all the experiments were change of a random way at the beginning of each game.

In the second experiment, a league of twenty-eight games was performed. In this league, teams with different degrees of situations competed among them.

In particular, for all the games in the two experiments, the scenes used only one of the *DS*.

Table 4 shows the obtained results of the first experiment. In this case, the team performance is improved when our team takes into account the three proposed parameters as coordination mechanisms. Specifically, the team with the degree of situation 7 (all the parameters taken into account) shows a better average (improvement rate: +81% better) than the degree of situation 0 (any parameter taken into account).

Table 4. Results of the first experiment.

Position	*Degree of Situation*	*Win Games*	*Average (%)*
1	7	21	70
2	3	16	55.3
3	6	14	46.7
4	4	12	40
5	5	12	40
6	2	10	33.3
7	1	9	30
8	0	4	13.3

Table 5 presents the obtained results of the second experiment. In these results is shown how when our team use jointly all parameters (degree of situation 7) as coordination mechanism the system performance is increased. For this case, the degree of situation 7 (the best case) shows a better average (improvement rate: + 92%) than the degree of situation 0 (the worst case).

Table 5. Results of the second experiment.
(WG: Win Games)

Position	*Degree of Situation*	*WG*	*Average (%)*
1	7	25	89,3
2	6	21	75,0
3	3	19	67,9
4	5	16	57,1
5	2	13	46,4
6	4	9	32,1
7	1	7	25,0
8	0	2	7,1

VI. Conclusions and Future Work

This work shows how artificial intelligence techniques aid to improve the coordination of heterogeneous multi-robot systems. Our approach contributed with three parameters (*proximity, introspection* and *trust*) as coordination mechanisms for heterogeneous teams.

We emphasize the robot-behavior given to the scenes with which it is possible to consider them like a part of the team.

Besides, we have worked with combinations of the Degrees of Situations to show how the cooperative team performance is different according to this selection. In particular, the best performance is obtained when our team took into account all the parameters in its decision-making structure.

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At the moment, in all the experiments the scenes used only one of the *DS* at the same time. Then, a combination among the *DS*s in the same experiment is something interesting to study how to take advantages when the system is able to selecting the best behaviour in a determine scene according to the current goals.

Finally, we plan to implement the main contributions of this paper in a real robot soccer testbed in order to extrapolate and corroborate the obtained results. It is also interesting to compare this coordination mechanism approach with other techniques, in order to evaluate the usefulness and advantages of our proposal. However, at present we perform studies about how take advantage of this approach but its development is still opened.

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