A Multi-Layered Representation Model to Recognize and Discover Multi-Agent Behavior Patterns

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Abstract. The complex interactions of agents immersed in dynamic environments make extremely difficult for human beings the understanding and analysis of agent-team behaviors. This paper focuses on the discovery of behavior patterns in multi-agent teams, more precisely, in robot soccer teams. The discovery of behavior patterns requires expressive models able to represent relevant aspects of multi-agent systems. The hypothesis of this work states that an expressive representation model at different levels of abstraction, each one dealing with a different aspect, facilitate the discovery of behavior patterns in complex domains. In this work, a multi-level representation model is proposed, which includes: individual level, relational level and formation level. The multiple interactions between agents are modeled as relations represented by a topological graph which is able to manage the dynamic changes of structures of formations. Such structures serve to track the players involved in tactical plays at each instant of the match. The results show that the expressive representation model described in this work can facilitate the discovering of patterns.

1 Introduction

Multi-agent teamwork is critical in a large number of agent applications, including training, education, virtual enterprises and collective robotics [8]. However, in multi-agent domains, agent interactions become the domain highly complex for the analysis of agent-team behaviors, such is the case of robotic soccer. We consider "complex domains" to be those with enormous state action spaces, dynamic environment, competitive and real time. Obviously, when the multiple interactions of both teams are considered the task of analysis for modeling is even more complex.

Most of the research involved in multi-agent modeling is based on building models considering partial aspects and non relevant aspects of the team. Nevertheless, relevant aspects associated with any team should be taken into account in order to model its behaviors. These aspects include: individual actions (individual aspect), relationships between agents (tactical aspect) and formation behaviors (strategy aspect). This paper emphasizes on the fact of having an expressive representation model which takes into account different aspects exhibited in a team of agents. The adequate representation of these aspects enables the discovery of behavior patterns at different levels of abstraction in a complex domain. Thus, the hypothesis of this work states that an expressive representation model at different levels of abstraction facilitates the discovery of behavior patterns in a complex domain such as robotic soccer. Some of the most important behaviors are related with strategic and tactical plays [12]. On the one hand, a team that presumes to play by following certain strategies should play under the context of formations to assure order, discipline and organization during a match [5]. On the other hand, tactical plays occur, most of the time, under the context of formations. The discovery of tactical or team behaviors needs the tracking of both the positions of players at any instant of the game and relevant relations able to represent particular interactions between players. Nevertheless, the tracking task becomes very complex because the dynamic conditions of the game brings about drastic changes of positions and interactions between players, which difficult the construction of models capable of recognizing and discovering behaviors of teams playing soccer matches [1]. We propose in this work a model able to manage the constant changes occurring in the game, which consists in building topological structures based on triangular planar graphs. Thus, based on this model tactical behavior patterns have been discovered in spite of the dynamic conditions. The test domain for this research is simulated robotic soccer, specifically, the Soccer Server System [7], used in the Robot World Cup Initiative [4], an international AI and robotics research initiative. A total of 10 matches have been analyzed. The results obtained have been shown that the model has been able of recognizing and discovering behaviors satisfactory.

2 Related Work

Riley and Veloso [9] used a set of predefined movement models and compare these with the actual movement of the players in set play situation. In new set play situations the coach then uses the gathered information to predict the opponent agent's behavior and to generate a plan for his own players. The main drawback of Riley's model is that it is built based on individual movements of players without taking into account the relationships between agents. Raines and colleagues [8] presented a system called ISAAC which analyzes a game in mode off-line to generate rules about the success of players. ISAAC used the individual and relational models in an independent way. It tries to discover patterns in each level based on events that affect directly the result of the game. Two key differences between ISAAC and this paper are: we build a model of a team based on behavior patterns, independently of success or failures events; ISAAC is unable to discover the strategic behavior of a team. Bezek and Bratko [2] presented a method to discover pass patterns incorporating domain knowledge and providing a graphic representation for detected strategies. Although their approach obtains tactical behavior patterns, they only consider the players involved in the passes without taking into account the notion of team behaviors. Visser and colleagues [10] recognized the formation of the opponent team using a neural networks model. The output was a predefined set of formations. The main difference with our approach is that Visser and colleagues did not represent relations between players. As Visser menstioned in his work [14], his approach is unable of tracking the changes of formations. This is because the lack of structures due to the absence of relations between players.

3 Multi-Level Representation Model

We emphasize on the fact of having an expressive representation model which takes into account different aspects exhibited in a team of agents. The adequate representation of these aspects enables the discovering behavior patterns at different levels of abstraction in a complex domain. In this paper, we present an expressive representation model able to discover behavior patterns by taking into account various aspects such as individual aspects about agents, relationships between agents (tactical aspect) and formation behaviors (strategy aspect). In order to facilitate the discovery of behavior patterns, we need to have a representation model able to express relevant aspects at different abstraction levels. Such model should endow a reasoning system, through an expressive representation model, with the capacity of discovering strategic, tactical and individual behavior patterns.

The different levels of abstraction, each one representing a different aspect of the team, are built in a bottom-up mode, that is, higher levels are constructed based on lower levels. For instance, the representation of formations of a team is based on the relational level, which is composed of relations between zones. At the same time, each zone represents a relationship between individuals (players). As an example, the formation 4:3:3 represents four defenders, three midfielders and three forwards. The proposed multi-layered representation model is shown in Figure 1.

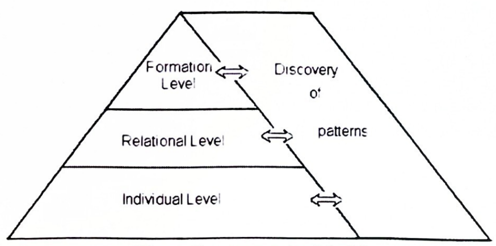

Fig. 1. Representation Model

Individual level. It represents the individual information of the objects in the field, such as players and ball. Such information can be acquired from the Soccer Simulator System directly.

Relational level. It represents the relationship between players.

Formation level. A formation represents the relation among defenses, midfielders and forwards of a team. The formation reveals part of the general strategy of a team. Formations are the way a soccer team lines up its defense, midfield, and attack line during a match. When talking about formations, defenders are listed first and then midfielders and forwards. For example, a code 5:3:2 represents a formation composed by five defenders, three midfielders, and two forwards (see Figure 2). As in the real soccer game, the goalkeeper is not considered as part of the formation. Usually, teams playing in strategic and organized ways search for respecting predefined structures or formations.

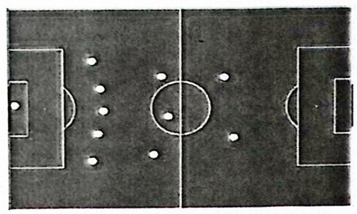

Fig. 2. A 5:3:2 formation

4 Recognition of Formations

The focus of this work is on teams that play following patterns of high level of abstraction (formations) based on a distribution of zones named Defensive (D), Middle (M) and Attack (A), as in classic soccer game. These patterns will be represented as follows: D:M:A. Due to the dynamic conditions of the soccer game, the players are in constant movement and temporally breaking the alignment of players belonging to a zone. To handle the constant changes without an expressive representation of the relations between players can result in an inefficient way of recognizing formations submitted to a dynamic environment. In the next section will be explained how the zones and the players belonging to them are recognized in this work.

4.1 Recognition of Team Zones

As in human soccer domains the players in robotic soccer should tend to be organized. That is, each player has a strategic position that defines its movement range in the soccer field. The role of a player is quite related with a predefined area within which an individual player can play basically in the field. Any behaviors of a player depend on its current role. According to the position of the player, roles in robotic soccer can be divided into four types: goalkeeper, defenders, midfielders and forwards. Different roles are associated with different positions and different behaviors that players assume. However, due to the dynamic changing conditions of a match, a defender could become a forward temporarily as his team is trying to attack. So the roles of a player are dynamically changing. Consequently, the recognition of formation patterns is difficult due to the dynamic and real time conditions of the environment. In a first step, we will discover what players belong to what zone. For this, the clustering algorithm, K-means [6], is applied. K-means classifies a given data set through a certain number of clusters (assume k clusters) fixed a priori. In this work, k=3 such that three zones will be defined: defensive, middle and attack zones. From the log file (game film), the data from one team is extracted and K-means is applied in each simulation cycle of the game. The positions of each player, with respect to the x axis, are taken as the input of the clustering algorithm and the output of clustering is the classification, according to their x position, of all players of the team in the three clusters. Clustering algorithm is useful to determine the three zones of a team but it is not able to represent the multiple relations between players of each zone. Given that patterns of formations are based on relations that determine structures then an additional model is crucial for the recognition of patterns of formations. The next section describes an adequate representation model able to facilitate the recognition of formation patterns.

4.2 Topological Structure Model

A formation is represented by a set of relations between players. Thus, the relations represent the structure that supports a formation. So, a change of relations between players entails a change of formation. It is needed at least the change of one relation to transform one structure into another one. Constant changes of relations could occur because the multiple relations in a formation and the dynamic nature of a match. Figure 3(a) illustrates the relations of each one of the players with the rest of their teammates. A total of 90 relations are obtained by $n(n-1)$, where n represents the number of players. This formula considers two relations by each pair of players. Thus, one relation is represented by the link from player A to player B and the second one from player B to player A. For practical reasons, just one of these relations is considered. Thus, the total of relations is 45. Figure 1(b) illustrates these 45 relations.

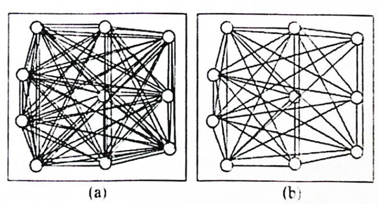

Fig. 3. All possible relations between players of a soccer team.
(a) 90 relations and (45) relations.

On the one hand, the control of such number of relations becomes very difficult to be managed because any change of relations would produce a change of structure. In addition, it could happen that several changes of relations occur at the same time then the problem of detecting what relations are provoking changes of structures becomes much more difficult to be managed. On the other hand, the 45 relations are not relevant in a real match, because a relevant relation is the one in which a player uses to exchange passes and positions in a strategic way. In this work, the goal is to build a simple but robust structure based on relevant relations modeled by a planar graph. A graph *G* is planar if it can be represented on a plane in such a way that the nodes represent different points and two edges should be encountered only at their ends. The intersection of two edges out of their ends breaks the planar property of the graph G. This graph *G* is also named as planar topological graph [11]. Two or more graphs are topologically the same if they can be transformed by elastic deformations until their form coincides. The relevant relations used to build the topological structure are related with the notion of neighborhood. Thus, an agent remains related with his closer neighbor belonging to his zone (defensive (D), medium (M) or attack (A)), and his closer neighbor belonging to the neighbor zone as illustrated in Figure 4(a) and Figure 4(b). Figure 4(c) shows the integration of both kinds of relations for a 4:3:3 formation.

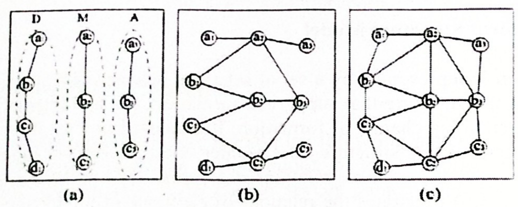

Fig. 4. (a) Step 1. Neighbor nodes of the same zone are linked. (b) Step 2. Neighbor nodes of neighbor zones are linked. (c) Planar graph obtained from step 1 and step 2.

Figure 4(c) shows the planar graph represented by triangular sub-graphs as result of applying the previous two steps. The total number of relations of a graph, which has been built based on the method described above, is given by N_m +15; where N_m is the number of nodes of the middle zone (Due to the lack of space the deduction of this formula is not described in this work). For instance, for a formation 4:4:2, the number of relations will be 19, because $N_m = 4$. The advantages of this method that the number of relations has been reduced from 45 to 19 for the formation 4:4:2. Then, 26 relations have been eliminated. Triangular graphs are able to assume a topological behavior [12]. That is, even if a structure is deformed because positional changes of nodes, the topological property of the triangular graphs helps to preserve the structure.

4.3 Pattern Recognition Process

Figure 5 shows the process to recognize patterns of formations and changes of structures that support the formations. The first module serves to determine the zones by using a clustering algorithm; the second module builds the multiple relations which are expressed by a topological graph and finally in the third module the changes of structures are detected if topological properties of a defined structure have been broken.

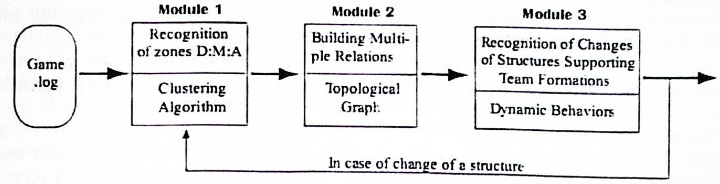

Fig. 5. Process to recognize pattern formations

Module 1. *Recognition of team zones.* The algorithm of clustering is performed during the first cycles of the match and it is stopped until the number of players in each group does not change. In this way, the three zones of a team, defensive, middle and attack zones are recognized.

Module 2. *Building multiple relations and a topological graph.* Based on the three zones recognized by the clustering algorithm and relevant multiple relations a topological planar graph is built.

Module 3. *Recognition of Changes of Structures that support Team Formations.* Changes of structures are detected if topological properties of a defined structure have been broken. A topological graph is, by definition, a planar graph [11]. In a planar graph any pair of nodes belonging to the graph can be linked without any intersection of links. Otherwise, if the topological property of the graph has been broken then another structure supporting a formation should be built. Intersections occur when players change their roles in order to build a new formation or due to reactive behavior in response to the opponent. If intersections of links occur, clustering algorithm should redefine the zones and a new topological graph should be built.

5 Discovering of Tactical Behavior Patterns

The process to discover tactical behavior patterns is illustrated in Figure 6. The following six steps describe such process:

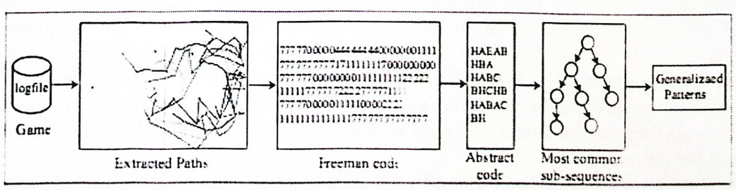

Fig. 6. The steps to discover the tactical behavior patterns

Step 1.Read *logfile*. Input data mainly related with players and ball positions;

Step 2.Extraction of similar paths. A set of ball's paths occurring under similar contexts are extracted. The extracted paths in Fig.6 shows paths starting from the middle zone of the field and then distributed either to the right or to the left side until ball reach a zone close to the goal;

Step 3.First Freeman codification. The set of extracted paths are coded to be represented by a sequence of orientations using a Freeman codification [3] which is composed of eight orientations.

Step 4.Second Freeman codification. The sequence of step 3 is recoded to obtain a more abstract code. Let A,B,...,H be the new abstract segments where each one represents a freeman code sequence with the same orientation, such that, A represents the sequence of 0's, B represents the sequence of 1's, and so on. Thus, a path coded as 7-7-7-1-1-1 can be represented by the code HB;

Step 5.Identification of most frequent sub-sequences. A method based on a generalization of a tree is applied to discover the general behavior patterns representing the paths of tactical plays. For instance, let's take two paths: BAH and ABA. Let's suppose that the trie is empty. It will first insert BAH into it. It will then insert the two remaining su□xes of BAH: {AH, H}. Next, it will then insert the next path and its su□xes: {ABA, BA, A}, into the trie. The most common single sub-sequence is A, the most common two subsequences is BA.

Finally, the players and zones are associated to the generalized paths. The topological structures used to track formations have been a very good support to determine the players participating in tactical plays, as well as the zones through which the plays have taken place. Thanks to the topological graph, we are able to know at each instant of the game the players and their relations participating in a play.

6 Experimental results

In this section, important experimental results are analyzed. They are derived from two teams: The TsinghuAeolus soccer team, who won the Simulation RoboCup Championship in 2002. It is presented an analysis of the match between TsinguAeolus vs. Everest; and theWrightEagle team, who won the second place in the same competition that held in 2007. The model has been proven in nine matches, but for the relevance of the teams, we present the analysis of results of two matches, one for the TsinguAeolus and one for the WrightEagle. Figure 7 shows a sequence simulation cycles that represent the structures involving the soccer-agents in a path of a tactical play. Because of the lack of space it is shown some of the sub-graphs that compose the total sequence of sub-graphs representing the path (in fact, there are approximately 50 sub-graphs for this tactical play). As can be seen, the shadowed sub-graphs contain the soccer agents involved in the tactical plays. They are in this case: the middle center, the right middle, the right forward, the center forward and the left forward.

As first step, the paths of the ball were extracted to be analyzed and coded by the code of Freeman. In this way the set of paths can be compared numerically by measuring the similarity between them. Another advantage of this codification is that we can have an idea about how long the paths are. However, what is interesting in this analysis is not exactly how long a path is, but, from the point of view of behavior, the form adopted by the path and obviously the properties associated with the intention or purpose of it, in this case to get close to a position of shooting to the goal. Due to these reasons, it is proposed in this work a more abstract representation. Then the paths coded by the code of Freeman have been recoded to obtain a more abstract code. The paths represented by abstract codes have facilitated the application of the model to discover behavior patterns related with tactical plays. It is important to point out that similar paths are not necessary those to end in a goal, but those that assume a similar behavior from the start of the path to the final objective. Figure 8 illustrates two shapes of generalized paths of tactical behaviors played through the right and left side of the terrain. These generalized paths correspond to the TsinghuAeolus team.

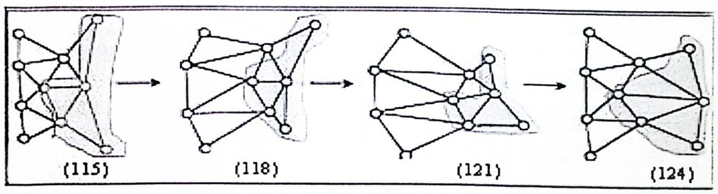

Fig. 7. Sequence of sub-graphs representing a tactical play incorporating agents and field zones

(a) (b)

Fig. 8. Generalized paths of tactical behaviors: a) Attacks by right side and b) Attacks by left side

For the case of the WrightEagle team, they played in the right side, Figure 9 shows the extracted paths that get close to the opposite goal and Figure 10 shows two shapes of discovered generalized paths. Based on the results obtained, it is observed that the model to obtain the paths representing the tactical plays do not depend on the analyzed team. The topological structures used to track formations have been a very good support to determine the players participating in tactical plays, as well as the zones through which the plays have taken place.

7 Conclusions

The discovery of tactical plays and the recognition of formations supporting strategies of team represent relevant information to implement counter strategies or tactics to reduce the performance of the opposite team or, in the best of cases, to beat it. Nevertheless, the dynamic nature of soccer matches along with the multiple interactions between players difficult enormously the task of discovery. The model based on topological graphs has contributed importantly to manage the difficulties due to the dynamic nature of the soccer game. It can facilitate the tracking of formations. In addition, it provided the algorithm of discovery tactical plays with important information concerning the players participating in such plays. Another contribution described in this paper is related with the double codification of the paths, which has facilitated the interpretation of paths to implement the algorithm described in section 3.2. The discovered paths can be considered as generalized because they were obtained from a set of paths by applying the generalization algorithm described in section 3.2. As future work the discovery of defensive tactics is necessary to have a richer spectrum of the tactics used in a match.

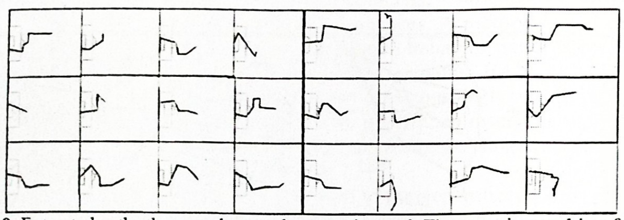

Fig. 9. Extracted paths that get close to the opposite goal. The team is attacking from left to right side.

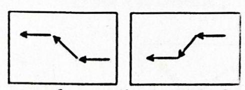

Fig. 10. Two shapes of generalized paths of tactical behaviors

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