Dynamic Tracking of Multi-Agent Behavior Patterns Based on Topological Graphs

Huberto Ayanegui§ and Fernando Ramos‡

§ Universidad Autonoma de Tlaxcala
Facultad de Ciencias Basicas, Ingenieria y Tecnologia
Calzada de Apizaquito s/n, 90350,
Apizaco, Tlaxcala, Mexico.
‡ Tecnologico de Monterrey Campus Cuernavaca
Autopista del Sol, Km. 104, Col. Real del Puente.
Xochitepec, Morelos, Mexico. 62790
{huberto.ayanegui, fernando.ramos}@itesm.mx

Abstract. Two relevant problems are associated with behaviors of agents that cooperate in common tasks. The first one deals with adequate representations to recognize behavior patterns at several levels of abstractions. The second one deals with the tracking of behavior patterns. Both problems are confronted with the problem of dealing with multiple interactions submitted to dynamic conditions. This paper addresses the second problem through the construction of structures represented by topological graphs and their skeletons. Thus, behaviors of agents rely on structures formed by the relations between them. The topological graph is built by considering neighborhood relations between agents, where agents are represented by nodes and neighborhood relations by arcs. The topological conditions assure a planar graph, which is built by triangular sub-graphs, thus a structure where all the nodes can be connected. The problem of tracking behaviors is addressed by considering that, when the topological condition is broken, then a structure has changed, consequently the behavior has also changed. The skeleton of the primer topological graph allows a more abstract representation of structures that serves to reinforce the tracking of behavior patterns.

Key words: Pattern recognition, robotic soccer, formations, dynamic behavior.

1 Introduction

Multi-agent systems are one of the sub-disciplines of artificial intelligence which was introduced for the purpose of defining the rules and principles for developing complex systems and provides a mechanism for cooperating the agents [10]. The agents participating in a cooperative task, within real time environments, should be able to act autonomously an as a part of a team.

Two relevant problems are associated with behaviors of team agents that cooperate in common tasks. The first one deals with the discovery of behaviors patterns which is increasingly needed in a variety of tasks, as we develop more autonomous robots and general information processing agents. For example, in multi-agent environments, an agent may need to make decisions based on the behavior of the other agents. Automatic discovery of the team strategy is a challenging problem which implies to dispose of rich representations able to support tactical and strategic behaviors. Most of the research involved in the construction of multi-agent behavior models does not consider 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 aspects, tactical aspects involving at least two agents; strategic aspects involving the whole team. To dispose of an expressive representation model which takes into account different aspects exhibited in a team of agents is key to discover behavior patterns in a complex domain[8].

The second problem deals with the tracking of the behaviors already discovered. Such tracking task becomes very complex because the dynamic conditions of the game brings about dramatic changes of positions and multiple interactions between players, which difficult the construction of models capable of discovering behaviors of teams playing soccer matches[6]. Although multiple frameworks have been developed for single agent plan recognition, there has been less work on extending these frameworks to multi-agent scenarios. We propose a method for tracking the dynamically changed structures of groups of agents through the construction of structures represented by topological graphs (TG) based on triangular planar graphs and their skeletons (STG).

The TG is built considering neighborhood relations between agents, where agents represent nodes and edges neighborhood relations. Thus, the relations construct a structure that can be represented by a graph G. The topological conditions assure a planar graph, which is built by triangular sub-graphs, thus a structure where all the nodes can be connected. The skeleton of the primer topological graph (STG) allows a more abstract representation of relations. The problem of tracking behaviors is addressed by considering that, when the topological condition is broken, then a structure has changed, consequently the behavior has also changed.

We situate our work in the domain of robotic soccer, in which it is potentially advantageous to be able to discover and track the multi-agent behaviors. Robotic soccer has been developed in simulation and with real robots[4]. This work deals with soccer-simulation category, where the teams are composed of 11 players, such as in real matches, evolving within a terrain whose area is a scale of the original soccer-terrains. Important aspects of multi-agent modeling have been developed in simulation[12]. The real robots are physical robotic agent computer controlled either on-board or off-board through radio communication. In both simulation and real robots, the agents must be fully autonomous, as human operators are not allowed to interfere once the game has started. In general, robotic or simulation agents observe the state of the environment, including the position of the other robots, and select actions based on the observed state.

The paper is organized as follows. Section 2 discusses the related work. Section 3 presents how the agents are organized, particularly in domains of soccer-agents. Section 4 describes the topological graphs and their skeletons used to track behavior patterns. Section 5 deals with the method for tracking formations and tactical behavior patterns using topological graphs and their skeletons. The conclusions and future works are presented in Section 6.

2 Related Work

Although there has been considerable research on the problem of single-agent behavior recognition, there has been substantially less work on multi-agent behavior recognition. Most of the previous work makes one of two assumptions: (1) each agent is a decoupled entity that can be analyzed individually using a single-agent activity algorithm or (2) the agents are always working together and can be analyzed as a single cohesive entity represented by a high-dimensional feature vector [11]. In either case, team structure is generally assumed to be static; this paper specifically addresses the problem of behavior recognition for teams with dynamic team structure.

Devaney and Ram [3] have worked on identifying behaviors in the sort of two dimensional spatial environment. In particular they looked at the movement of military troops during battle to identify behaviors through a combination of object tracking and pattern recognition. However, they are more focused on the problem of identifying particular repeated patterns of movement among the large amount of given movement data rather than trying to identify a particular model which captures all of the agents' movements.

Bezek and Bratko[2] present a method to discover pass patterns incorporating domain knowledge and providing a graphic representation for detected strategies. This work is focused on the increase of human comprehension. 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 related with formations. Visser and colleagues recognized the formation of the opponent team using a neural networks model[13]. In the Visser's work observed player positions were the input of a neural network. The output was a predefined set of formations. If a classification can be done, the appropriate counter-formation is looked up and communicated to the players. The main difference with our approach is that Visser and colleagues did not represent relations between players. As Visser mentioned in his work, 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.

Riley and Veloso use a set of predefined movement models and compare these with the actual movement of the players in set play situation[9]. 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 approach uses probabilistic models and can be used in both off-line and on-line mode. The main drawback of Riley's model is that it is built based on individual movement of players without taking into account the relationships between agents. Raines and colleagues presented a system called ISAAC[7] which analyzes a game in mode off-line using a decision tree algorithm to generate rules about the success of players. ISAAC uses the individual, relational and global models in an independent way. It tries to discover patterns in each level based on 'key events'. Key events are events that affect directly the result of the game, for instance, a kick to goal. Some of the key differences between ISAAC and the work presented in this paper are: we build a model of a team based on behavior patterns, independently of success or failures events. The global behavior discovered by ISAAC is not based on the formation of a team but in a general performance of the team in a set of games played previously. Thus, ISAAC is unable to discover the strategic behavior of a team. ISAAC doesn't take into account variants of behavior patterns.

3 Organization of multi-agent systems

Von Bertalanffy [14] gives the meaning of the somewhat mystical expression: The whole is more than the sum of its parts, is simply that constitutive characteristics are not explainable from the characteristics of isolated parts. Given the total of parts contained in an organization and the relations between them, the behavior of the system is derived from the behavior of the parts. So, a cooperative multi-agent system (CMAS) is an organization focused on how a loosely-coupled network of problem solvers can work together to solve problems that are beyond their individual capabilities.

Two relevant elements to consider in CMAS:

- *Functional analysis,* which describes the functions of a multi-agent system in its different dimensions.
- *Structural analysis,* which distinguishes between the various possible forms of organization and identifies some essential structural parameters.

The functional analysis leads to the identification of the principal functions that the components should fulfill. In the context of such an analysis, a CMAS can be seen as a system of roles. It is possible to make this analysis more precise developing these functions in several levels corresponding to the different points of view from which an organization can be studied. For example, in the soccer domain, at individual level, the role of players can be as goal- keeper, left defender, right mid-fielder or left forward. At zone level, all defenders (left, central and right) form the defensive zone, all mid-fielders form the middle zone and forwards form the attack zone. At team level, the soccer team can be adopt formations determined by offensive or defensive strategies.

The structural analysis attempts to bring order to all possible interactions between agents by isolating the abstract relationships which connect them and the way in which they evolve over time. The relations between soccer-agents occur through the multiple interactions taking place between them at each instant of the game. For instance, an agent **A** can be related with the agent **B** because they interact through the exchange of passes to accomplish tactical plays. Another example of interactions occurs when several agents perform together a tactical play. In this situation, some of the relevant relations are determined by the structure that represents the distribution of soccer-agents accompanying the play. A formation is a structure based on positions of soccer-agents and relevant relations between them. For example, a code 5:2:3 represents a formation composed by five defenders, two mid-fielders, and three forwards. Goalkeepers are not counted because they are the one position forever. In general, strategies should be supported by formations in order to assure order, discipline and organization during a match [5].

3.1 Topological and Skeletons Graphs

Topological Graphs. 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 [1]. Two or more graphs are topologically the same if they can be transformed by elastic deformations until their form coincides, as shown in Figure 1.

The tactical plays are submitted to formations, in such a way that if a formation change or seems having changed, tactical plays are affected. Then, topological structures should guarantee that changes in formations have taken place if and only if the planar properties of the graph, representing structures, have been broken. Otherwise, formations have not changed.

This work uses a topological structure model based on relevant relations. The relevant relations used to build the topological structure are related with the notion of neighborhood. This way of doing supports well the idea of building formations, which is a key concept in this work. 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 2(a) and Figure 2(b). Figure 2(c) shows the integration of both kinds of relations for a 5:2:3 formation.

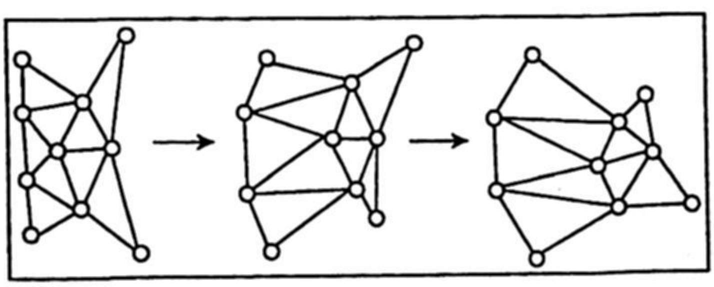
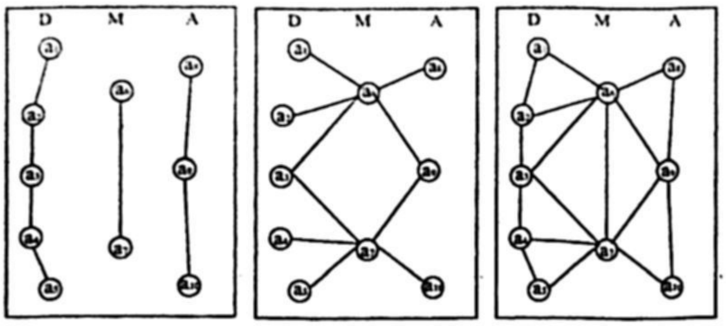


Fig. 1. Three representations of the same topological graph



(a) (b) (c)

Fig. 2. (a) Neighbor nodes of the same zone are linked. (b) Neighbor nodes for neighbor zones are linked. (c) Topological graph including both kind of links.

The Skeleton Graphs. Some of the most important team behaviors are related with strategic and tactical plays [8]. As discussed above, the structure of a team serve to track the players involved in tactical plays at each instant of the match. That is, 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 dynamic nature of soccer matches along with the multiple interactions between players difficult enormously the task of pattern recognition. On the one hand, the model based on topological graphs contributes importantly to manage the difficulties due to the dynamic nature of the soccer game to enable the tracking of formations. On the other hand, the skeleton of a topological graph serves in two ways: 1) to reinforce the break of topological conditions, because the skeleton suffers also of the break of topological conditions; 2) to facilitate the discovering of tactical plays with important information concerning the sub-structure participating in such plays.

4 Tracking of Formations and Tactical Plays

4.1 Tracking of Formations

Tracking of formations is important because a change of formation determine a potential changes of strategies and tactics.

The following example shows the break of topological conditions both for the *TG* and its *STG*, see Figure 3.

Frame 1 in Figure 3 shows a formation 4:3:3. Frame 2 is topologically similar to Frame 2 with the same formation 4:3:3. In Frame 3, player 7 moves down and player 8 moves right until almost it is aligned with forward players. However, we can verify that topological conditions are not yet broken. Frame 4 shows that the continuous movements of player 7 and player 8 have provoked the break of topological conditions of *TG*, because some intersections of arcs occur in

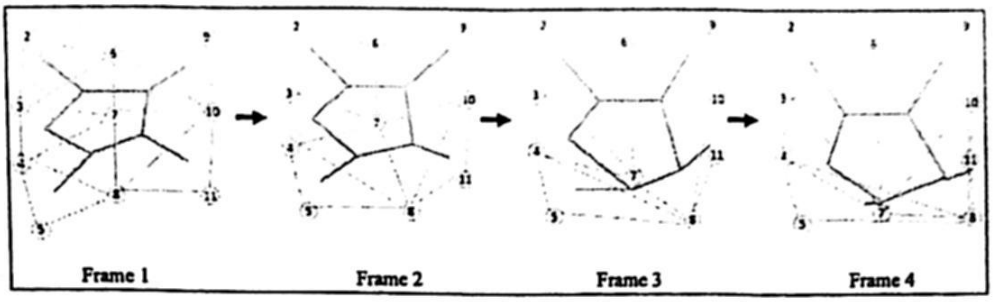


Fig. 3. Frame 4 shows the break of topological conditions for *TG* and *STG*.

the triangle formed by nodes 7,4,8. Given that, the *STG* is formed by linking neighbor nodes representing triangular graphs, the triangle formed by nodes 4,7,8 has not neighbor triangles well defined because the arc 4,8 is intersected by two other arcs. Thus, its topological conditions of the *STG* have been also broken. The construction of another *TG* and its *STG* is needed to represent the new formation, which is now a 4:2:4. This new formation corresponds to a more offensive strategy. We can verify that *STG* has reinforced the break of topological conditions, thus confirming a change of formation.

4.2 Tracking of Tactical Plays

Figure 4 shows a set of ball paths representing approaches, derived from offensive tactics, of the team located to the left to the opposite goal located at the right of the soccer terrain.

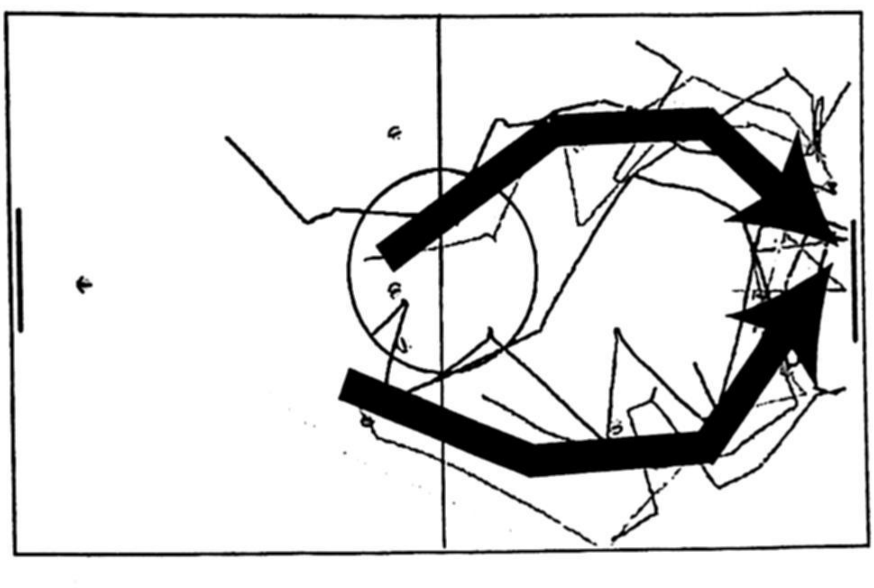


Fig. 4. Generalized paths obtained by applying the algorithm described in [8]. Generalized paths are drawn by thicker lines with an arrow at the end segment.

The details of the algorithm used to discover the tactical behaviors behind these ball paths are described in detail in [8]. Using freeman codes and generalization mechanisms, generalized paths were obtained from the set of paths illustrated in Figure 4. These generalized paths are represented by thicker lines with an arrow at the end segment of the path. This algorithm was not able to track the tactical plays and determine the structure of players associated with it. It is shown in the present work the method to track tactical plays and how the structure of players associated with it is determined. We argue that a tactical play relies on an adequate formation. Therefore, if the formation is represented by a structure, the tactical play should be also represented by a substructure, which is part of the formation structure. The substructure associated with the tactical play supports its performance.

In order to illustrate how the method to determine the structure associated with tactical plays works, let's consider the sequence of frames in Figure 5, which can be described as follows: ((frame1, cycle 1325), (frame2, cycle 1358), (frame3, cycle 1378), (frame4, cycle 1402), (frame5, cycle 1410), (frame 6, cycle 1418)). From the frame1 to frame5, there are a total of 93 frames, to complete the tactical play. Because of lack of space we do not show the 93 frames, but the most significant from the point of view of relevant moments of the tactical play. The sequence is extracted from a real match of the 2002 RoboCup World Championship. This sequence is one of the instances used to obtain the generalized paths shown in Figure 4.

These generalized paths do not provide neither information about players involved in the tactical play and nor a structure supporting the execution of the tactical play. The use of the TG and the STG cope with this problem. The fact of building the relations based on the concept of agents neighborhood relies on the fact that players pass the ball, most of the time, to a neighbor player and on the fact that semantically a more solid structure is made between neighbors of zones. Thus, the relations have two fold purposes: to build coherent structures representing correctly formations; to explicit relations that represent and support potential passes between players which could be linked to become tactical plays. Thus, recover a sequence of links (arcs) of the TG is a quite simple task. Meanwhile, STG's serve as reference to rebuild a structure, or reconnect a not connected graph, able to support a well performance of the tactical play.

The sequence of frames illustrated in Figure 5 can be described as follows: (frame1, player 5 $\rightarrow$ player 6) $\prec$ (frame2, player 6 $\rightarrow$ player 9) $\prec$ (frame4, player 9 $\rightarrow$ player 10) $\prec$ (frame5, player 10 $\rightarrow$ player 11) $\rightarrow$ (frame6, player 11 $\rightarrow$ goal). The character $\prec$ means that a frame X is before than frame Y. The arrow $\rightarrow$ means that a player X pass the ball to player Y. So, the play has been executed by following the sequence of passes: 5$\rightarrow$6, 6$\rightarrow$9, 9$\rightarrow$10, 10$\rightarrow$11, 11$\rightarrow$goal. If we link the passes, we obtain a path quite similar to the corresponding generalized path. The players executing the passes were extracted thanks to the TG. The arcs representing passes are arrowed showing the direction of passes. Thus, the substructures participating in the play will be the triangles associated with arrowed arcs. Figure 6(a) shows such substructure.

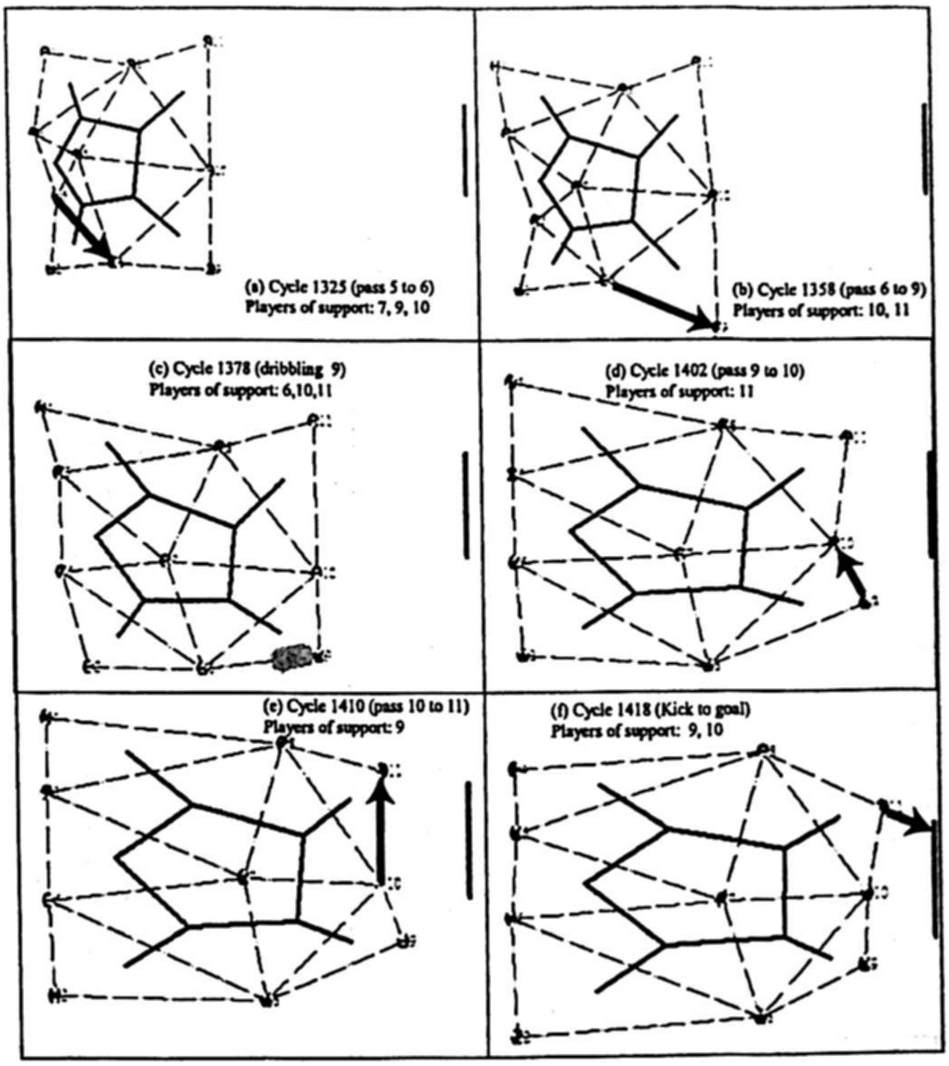
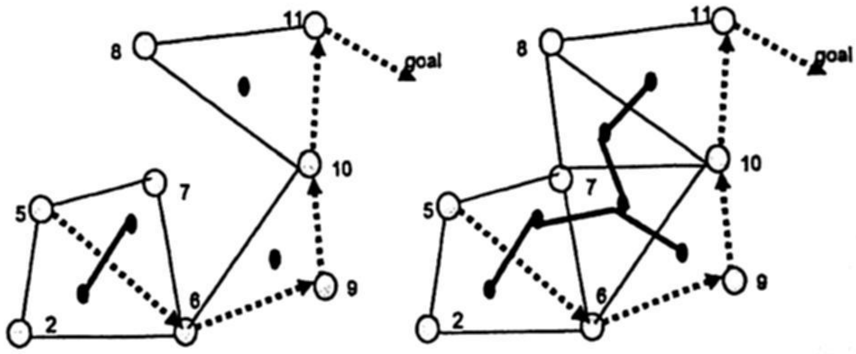


Fig. 5. Sequence of frames representing a tactical play



(a) (b)

Fig. 6. (a)STG not connected. (b)STG reconnected.

Based on Figure 6(a) above, the topological property of the *STG* has been broken, which can be interpreted that the play has not a connected support, thus the tactical play are not robust and if one of the players fails, the tactical play has an important risk of not being achieved. The *STG* serves as reference to convert the not connected graph into a connected one. Then, it results the subgraph illustrated by Figure 6(b), which represents the tactical play associated with players serving as support to improve the robustness of the play. For instance, if the tactical play takes place based on the graph of Figure 6(a), in case of an eventual fail of player number 9 or 10 the play is not supported by other players that could recover the failed tactic. Instead, the structure rebuilt once the part of the skeleton is added, player number 7 is incorporated automatically who can support the performance of the tactic play. Thanks to the operation of insertion of skeleton's links, the tactical play has been better characterized.

5 Conclusions

The discovery of tactical plays and formations supporting strategies of team represents 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 and their skeletons have contributed importantly to manage the difficulties for tracking behavior patterns as they evolve within dynamic environments such as soccer game. A relevant contribution in this work is the use of skeletons, which are also topological graphs. On the one side, skeletons can reinforce the break of topological conditions and confirm the change of formations. On the other side, skeletons serve to track tactical plays, with important information concerning the players participating in such plays and the sub-structure supporting them.

As future work the discovery of defensive tactics is necessary to have a richer spectrum of the tactics used in a match.

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