Recognition and Prediction of Motion Situations Based on a Qualitative Motion Description

Andrea Miene, Ubbo Visser, and Otthein Herzog

TZI - Center for Computing Technologies
University of Bremen
Universitätsallee 21-23
D-28359 Bremen, Germany
{andrea,visser,herzog}@tzi.de

Abstract. High-level online methods become more and more attractive with the increasing abilities of players and teams in the simulation league. As in real soccer, the recognition and prediction of strategies (e.g. opponent's formation), tactics (e.g. wing play, offside traps), and situations (e.g. passing behavior) is important. In 2001, we proposed an approach where spatio-temporal relations between objects are described and interpreted in order to detect some of the above mentioned situations. In this paper we propose an extension of this approach that enables us to both interpret and predict complex situations. It is based on a qualitative description of motion scenes and additional background knowledge. The method is applicable to a variety of situations. Our experiment consists of numerous offside situations in simulation league games. We discuss the results in detail and conclude that this approach is valuable for future use because it is (a) possible to use the method in *real-time*, (b) we can *predict* situations giving us the option to refine agents actions in a game, and (c) it is *domain independent* in general.

1 Motivation and Related Work

When asking professional coaches in the soccer domain what they do after a game has started they tell us that the analysis of the opponents team is very important. First, the strategic information is considered. This can be the overall formation (e.g. 4-4-2) or whether the team is playing more offensive or defensive. The next step is to gather tactical information. One example is wing play or frequent use of the offside trap. Once this information is obtained the coach decides optional changes with regard to his own team.

If we would like to apply this to the RoboCup scenario, high-level online methods have to be developed. They become also more and more attractive with the increasing abilities of players and teams, preferably in the simulation league. The recognition or even better the prediction of strategies, tactics, and situations is an important feature that will improve a teams' performance.

In 2001, we proposed a method that interprets spatio-temporal relations based on motion direction and speed of single objects and spatial relations between two objects given by direction and distance. The approach assumes that

D. Polani et al. (Eds.): RoboCup 2003, LNAI 3020, pp. 77–88, 2004.

such information can be seen as time series. A threshold-based segmentation method is then used to derive temporal intervals from each time series. In addition, qualitative temporal relations between time intervals such as *before, meets, during* have been used. As a result, simple events such as *approaching, departing* and first complex events such as *player 1 passes ball to player 2* can be interpreted [8].

In this paper we describe a significant extension to this approach. First, a new monotonicity-based segmentation method will be described to derive more appropriate temporal intervals. Second, additional background knowledge about the problem domain is used for a better interpretation of the considered situation in a game.

Our approach is related to the work from Raines and colleagues [9] who describe an approach to automate assistants to aid humans in understanding team behaviors for the simulation league. Their approach ISAAC analyzes a game off-line using a decision tree algorithm to generate rules about the success of individual players. Also, the cooperation within a team is considered with the help of a pattern matching algorithm. ISAAC supports the analysis of so-called 'key events'. Key events are events which directly effect the result of the game. Therefore, single players are analyzed that directly shoot towards the goal. In case of the whole team, kicks of the ball by certain players which lead to a goal are analyzed. ISAAC has to be used off-line, thus the program is not able to support real-time conditions. The rules produced by ISAAC are intended to support the development of the analyzed team. Therefore, they show how successful the team is in certain situations. The approach is designed for the analysis of games to gain new experiences for the next game. The main difference to our approach is that this approach can be used off-line only. Also, key events are limited (e.g. only a single key event is used in the single player scenario).

Riley and Veloso in 2002 [10] use a set of pre-defined 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 approach can be used both off-line and on-line. The main difference to our approach described in this paper is that they analyze the movement of all players in set play situations.

Frank and colleagues [3] presented a real time approach which is based on statistical methods. The approach gathers information such as the percentage of ball-holding of a certain player or which player passes the ball to which team mate. The result is a thorough statistical analysis which can then be used to derive information about a game being played. This can help for new future developments of a team. The main difference to our approach is that this approach is designed to gather information that can be used after the game.

A hybrid approach to learn the coordinated sequential behavior of teams was presented by Kaminka and colleagues in 2002 [7]. The idea is to take time-series of continuous multi-variate observations and then parse and transform them into a single-variable categorial time-series. The authors use a set a behavior recognizers that focus only on recognizing simple and basic behaviors or the agents (e.g. pass, dribble). The data are then represented in a trie (a tree-like data structure) to support two statistical methods: (a) frequency counting and (b) statistical dependency detection. Experiments showed that the latter method is more suitable to discover sequential behavior. The main difference to our approach are the data the approach is based on and the fact that this approach is designed for unsupervised learning.

Huang and colleagues [6] recently published an approach for plan recognition and retrieval for multi-agent systems. The approach is based on observations of agents' coordinative behaviors. The basis are players' element behaviors sequences (e.g. pass, dribble, shoot) which are sorted in a temporal order. The field is decomposed into cells where each cell denotes one agent's behavior at a time slice. Interesting and frequent behavior sequences are considered as the team's plans on the assumption that the team's plan is embedded in those sequences. The discovery of significance of sequence patterns are based on statistical evidences. The promising results are plans based on observation. The difference to our approach is the analysis of the sequences. Huang and colleagues use a statistical-based analysis. Also, the interpretation of the results are different. The rules are obtained manually.

The remaining sections are organized as follows: the next section provides information about the qualitative description of motion scenes. Section 3 gives an overview about the background knowledge used and how we can use this knowledge to interpret the scene. The application and results of our approach within the soccer domain are discussed in section 4. Conclusions and future work are pointed out in the last section.

2 Qualitative Description of Motion Scenes

In this section we present our extended approach on a qualitative description of motion scenes that we presented first in [8]. The basic assumption of our approach is that we have a bird view of a motion scene. We further need a set of coordinates describing the positions of the moving objects for each moment (or cycle). Motion causes change not only for a single moving object but also for its spatial relations to other surrounding objects. To take into account both absolute (individual) movement and change in spatial relations (i.e., relative movement) of objects we calculate four types of time series from the raw positional information: the motion direction and speed of each object, and the spatial direction and distance for each pair of objects (see fig. 1).

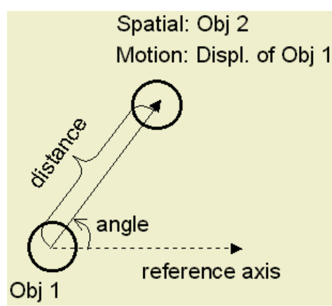

Fig. 1. Motion and spatial relations via direction and length.

These time series describe the motion within a scene on a quantitative level. In order to describe the motion on a qualitative level two steps of abstraction are performed:

– a temporal **segmentation** of the time series into time intervals of homogeneous motion and
– a **mapping** of the attribute values describing the intervals to qualitative classes.

The entire process is carried out online, i.e., at each time cycle one set of positional data is processed. Intervals are either extended or a new interval is started with the actual value if the homogeneity criterion fails.

Segmentation

In order to segment the time series into time intervals two different segmentation methods are used: a threshold-based segmentation method and a monotonicity-based segmentation method, which groups together strictly monotonic increasing intervals, strictly monotonic decreasing intervals and intervals of constant values. Each threshold-based segmented interval is described by a single attribute: the average of its values. A monotonicity-based segmented interval is described by its start value, its end value, and the run direction of values: increasing, decreasing or constant.

Both segmentation methods allow various interpretations of the resulting intervals. The monotonicity-based segmentation is useful to recognize dynamic aspects of motion, e.g., acceleration of a moving object. But due to the fact that the values are measured only at the start and the end of an interval its intermediate values are not known. Therefore, the threshold-based segmentation is more useful to find, e.g. an object that moves with a certain average speed.

Mapping into Classes

The second step of abstraction classifies the attributes of the intervals onto qualitative values for direction, speed or distance, respectively. The mapping functions have to be defined with respect to the domain. For the soccer domain the following mapping functions are used: For the directions (motion direction as well as spatial direction) eight classes as indicated by the dotted lines in fig. 2, i.e., from the viewpoint of object A, object B is in direction 5, object C is in direction 8 and so on. For the distances five classes are valid: *meets, very close, close, medium distance, far* and *very far* as indicated by the dashed circles in fig. 2. There object A meets object B and is very close to C, close to D and so on. For the speed also five classes are distinguished: *no motion, very slow, slow, medium speed, fast* and *very fast.* The speed and distance classes are organized in distance systems [5]. The radius of each distance class is double the size of the radius of the previous one.

For each pair of objects 12 sequences of temporal intervals describe their individual and relative motion: for each of the two objects we obtain one time

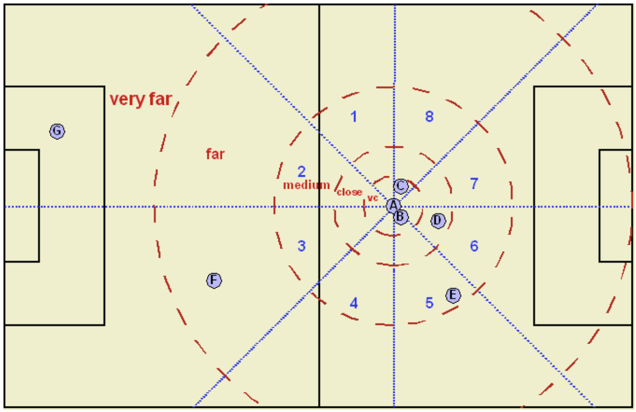

Fig. 2. Spatial relation classes in the soccer domain.

series concerning its motion direction and one concerning its speed (4 time series) and for the two objects one concerning the spatial direction and one concerning the distance (2 time series). Each of these 6 time series is segmented with the two different segmentation methods described in the previous section. Therefore, altogether we obtain 12 interval sequences.

The entire generation of motion descriptions is shown in fig. 3. The example shows the raw positional input data at the left. The time series calculated from the raw data and the results of the monotonicity-based segmentation method are illustrated in the middle (here: a single time series, the distance of two objects). One of the resulting intervals is shown with its attribute values as well as the mapping of values to classes. The single interval already allows a simple interpretation of the movement of the two involved objects: they approach each other and finally meet, which is expressed by the term HOLDS(approach-and-meet$(p, q), \langle t_n, t_{n+k} \rangle$). The predicate HOLDS expresses the coherence between a certain situation (movement or spatial relation), here approach-and-meet and the time interval $\langle t_n, t_{n+k} \rangle$ in which it is taking place or is valid [1].

3 Rule-Based Interpretation of Motion Scenes

These motion description intervals are used to recognize as well as predict motion situations with the help of a logic-based interpretation approach.

Domain knowledge is required for an interpretation of the motion. To know about the function or type of objects involved in a situation leads to more appropriate interpretations. For example, in the soccer domain the interpretation that two objects approach each other and finally meet can than be interpreted that a player gets in contact with the ball. To specialize the interpretation even more, different types of players can be distinguished, e.g., goalkeepers, defenders and offenders.

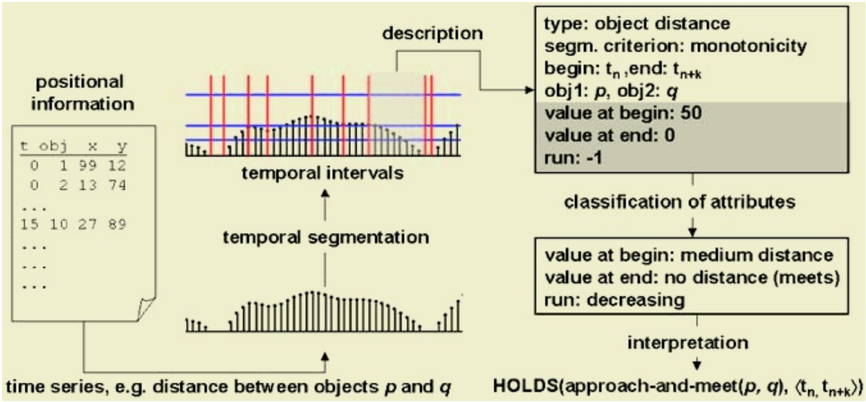

Fig. 3. Overview: Generation of motion description.

In some domains the location is important in which a certain motion situation takes place. For the soccer domain such locations are certain regions on the field of play, e.g. each half of the field, penally area, goal area and so on. E.g. the term HOLDS(region(*player, left-half*), $\langle t_n, t_{n+k}\rangle$) denotes that the object *player* is in the left half of the field of play during the time interval $\langle t_n, t_{n+k}\rangle$.

Currently, we have defined rules to recognize and predict 10 situations from the soccer domain. They include simple situations like a player kicking the ball as well as more complex ones like a one-two situation, a fight for the ball and offside.

For an experiment, we will have a closer look at the offside situation, because it is possible to predict an impending offside situation, that may occur while a team mate is planing to pass the ball. And, as we will show, both aspects of motion information – absolute and relative – are needed to detect and predict offside situations. In addition, further finer interpretations are possible, e.g., if an offside situation occurs it is possible to distinguish an offside trap from a situation that was caused by the offender himself.

Experiment: Offside Position

A player is in an offside position if he is nearer to his opponents' goal line than both the ball and the second last opponent. But he is not in an offside position in his own half of the field of play. For more details on the official offside rule refer to the FIFA rules [2], law 11 and appendix.

In order to recognize, whether a player is in an offside position we have to check if he is in the opponents' half of the field of play. If so, we have to analyze his spatial relation to the ball and the players of the opposite team. In detail we must determine if the ball is *behind* the player and count the amount of opponents that are *in front of* the player. If less than two opponents remain in front of the player, he is in an offside position:

$$\begin{aligned}
&\textsc{holds}(\mathsf{offsideposition}(player), \langle max(s_i), min(e_i)\rangle) \Leftrightarrow \\
&\exists\langle s_i, e_i\rangle, i \in \{1,2,3\} : \\
&\quad ((\textsc{holds}(\mathsf{region}(player, \mathit{right\text{-}half}), \langle s_1, e_1\rangle) \wedge \mathsf{team}(player) = 1) \vee \\
&\quad\ (\textsc{holds}(\mathsf{region}(player, \mathit{left\text{-}half}), \langle s_1, e_1\rangle) \wedge \mathsf{team}(player) = 2)) \wedge \\
&\quad \textsc{holds}(\mathsf{behind}(ball, player), \langle s_2, e_2\rangle) \wedge \\
&\quad \textsc{holds}(\mathsf{number\text{-}of\text{-}opponents\text{-}in\text{-}front\text{-}of}(player, n), \langle s_3, e_3\rangle) \wedge n < 2 \wedge \\
&\quad \forall i,j \in \{1,\ldots,3\} : s_i < e_j.
\end{aligned} \tag{1}$$

The term $\textsc{holds}(\mathsf{number\text{-}of\text{-}opponents\text{-}in\text{-}front\text{-}of}(p,n), \langle max(s_i), min(e_i)\rangle)$ denotes the number n of opponents located in front of a player p during the time interval $\langle max(s_i), min(e_i)\rangle$, where k is the number of players belonging to the opposite team:

$$\begin{aligned}
&\textsc{holds}(\mathsf{number\text{-}of\text{-}opponents\text{-}in\text{-}front\text{-}of}(p,n), \langle max(s_i), min(e_i)\rangle) \Leftrightarrow \\
&\exists\langle s_i, e_i\rangle, i \in \{1,\ldots,k\} : \\
&\quad \forall g_i \in \{g_1,\ldots,g_n\} : \textsc{holds}(\mathsf{in\text{-}front\text{-}of}(g_i, p), \langle s_i, e_i\rangle) \wedge \\
&\quad \forall g_i \in \{g_{(k-n)},\ldots,g_k\} : \textsc{holds}(\mathsf{behind}(g_i, p), \langle s_i, e_i\rangle) \wedge \\
&\quad \forall g_i \in \{g_1,\ldots,g_k\} : \mathsf{team}(g_i) \neq \mathsf{team}(p) \wedge \\
&\quad \forall i,j \in \{1,\ldots,k\} : s_i < e_j.
\end{aligned} \tag{2}$$

A complex situation like the above definition of offsideposition($player$) combines several time intervals. The term $\forall i,j \in \{1,\ldots,n\} : s_i < e_j$ postulates that all n intervals involved in the situation are contemporary. $\langle max(s_i), min(e_i)\rangle$ specifies the sub-interval covered by all n time intervals $\langle s_i, e_i\rangle, 1 \leq i \leq n$.

The spatial relations behind and in-front-of are generalizations of the 8 directions shown in fig. 2. Another object is in-front-of a certain player if it is between the player and the opponents' goal and otherwise behind the player. Therefore, the evaluation of the generalization rule depends on the team the player belongs to.

Eq. 3 specifies the spatial relation in-front-of. The spatial relation behind as well as the motion directions forward and backward are specified similarly.

$$\begin{aligned}
&\textsc{holds}(\mathsf{in\text{-}front\text{-}of}(object, player), \langle s, e\rangle) \Leftrightarrow \\
&\quad \textsc{holds}(\mathsf{spatdir}(player, object, dir), \langle s, e\rangle) \wedge \\
&\quad ((dir \in \{5,6,7,8\} \wedge \mathsf{team}(player) = 1) \vee \\
&\quad (dir \in \{1,2,3,4\} \wedge \mathsf{team}(player) = 2)).
\end{aligned} \tag{3}$$

The term $\textsc{holds}(\mathsf{spatdir}(player, object, dir), \langle s, e\rangle)$ denotes that $object$ is located in the direction dir from the viewpoint of $player$ during interval $\langle s, e\rangle$. This information is obtained from the threshold-based segmentation.

In order to predict an offside situation for player p, he has to be located in his own half, actually have the ball behind him and a small remaining number of k opponent defenders (e.g., k=3-4) in front of him. Then it depends on the relative movement of p and q if an offside position is impending or not. Therefore, we have to take into account the actual spatial direction between p and q (spatdir), obtained from the threshold based segmentation, and the development of the spatial direction between p and q (clockwise (change-spatdir-cw) or counterclockwise (change-spatdir-ccw), obtained from the monotonicity-based

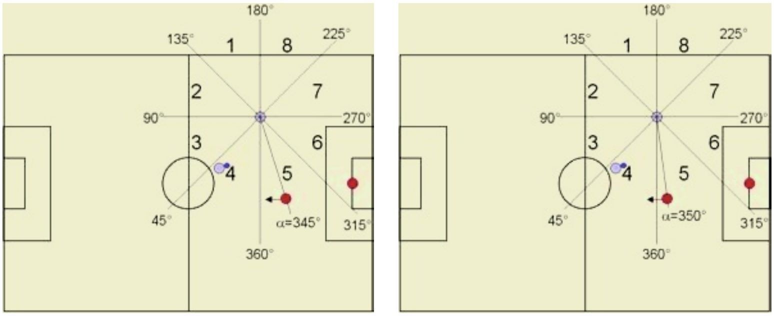

Fig. 4. Development of spatial directions between offender and defender announcing an impending offside position.

segmentation). If the spatial direction is already close to the change between the directions *in front of* and *behind*, and the values are increasing (clockwise change of spatial directions) or decreasing (counterclockwise change of spatial directions) an offside position is impending. For an illustration of this situation refer to fig. 4. The illustration shows the case of an increasing development of values. If the present trend lasts for some further time, an offside situation will occur in the moment the spatial relation changes to the next class (in the illustration from 5 to 4) and at the same point in time from *in front of* to *behind*.

$$\begin{aligned}
&\textsc{holds}(\mathsf{offside\text{-}danger}(p,q), \langle max(s_i), min(e_i)\rangle) \Leftrightarrow \\
&\exists \langle s_i, e_i\rangle, i \in \{1,\ldots,6\}: \\
&\quad ((\textsc{holds}(\mathsf{region}(p, \mathit{right\text{-}half}), \langle s_1, e_1\rangle) \wedge \mathsf{team}(p) = 1) \vee \\
&\quad\; (\textsc{holds}(\mathsf{region}(p, \mathit{left\text{-}half}), \langle s_1, e_1\rangle) \wedge \mathsf{team}(p) = 2)) \wedge \\
&\quad \textsc{holds}(\mathsf{behind}(\mathit{ball}, p), \langle s_2, e_2\rangle) \wedge \\
&\quad \textsc{holds}(\mathsf{in\text{-}front\text{-}of}(q, p), \langle s_3, e_3\rangle) \wedge \mathsf{team}(p) \neq \mathsf{team}(q) \wedge \\
&\quad \textsc{holds}(\mathsf{number\text{-}of\text{-}opponents\text{-}in\text{-}front\text{-}of}(p, n), \langle s_4, e_4\rangle) \wedge 2 \leq n < k \wedge \\
&\quad ((\textsc{holds}(\mathsf{change\text{-}spatdir\text{-}cw}(p,q), \langle s_5, e_5\rangle) \wedge \\
&\quad\; \textsc{holds}(\mathsf{spatdir}(p, q, 1 \vee 5), \langle s_6, e_6\rangle)) \vee \\
&\quad\; (\textsc{holds}(\mathsf{change\text{-}spatdir\text{-}ccw}(p,q), \langle s_5, e_5\rangle) \wedge \\
&\quad\; \textsc{holds}(\mathsf{spatdir}(p, q, 4 \vee 8), \langle s_6, e_6\rangle))) \wedge \\
&\quad \forall i, j \in \{1,\ldots,6\}: s_i < e_j.
\end{aligned} \tag{4}$$

Within the prediction phase we distinguish offside traps (see (6)) from offside situations caused solely by the movement of the offender himself. The temporal relation *contemporary* is defined as in [4]:

$$\begin{aligned}
&\textsc{holds}(\mathsf{prediction\text{-}offside\text{-}own\text{-}motion}(p,q), \langle max(s_1, s_2), min(e_1, e_2)\rangle) \Leftrightarrow \\
&\exists \langle s_1, e_1\rangle, \langle s_2, e_2\rangle: \\
&\quad \textsc{holds}(\mathsf{offside\text{-}danger}(p,q), \langle s_1, e_1\rangle) \wedge \textsc{holds}(\mathsf{forward}(p), \langle s_2, e_2\rangle) \wedge \\
&\quad \mathit{contemporary}(\langle s_1, e_1\rangle, \langle s_2, e_2\rangle).
\end{aligned} \tag{5}$$

An offside trap is caused by a forward movement of an opponent q remaining between the goal and the offender p. The offender is brought into an offside position by the movement of his opponents (with or without moving forward by himself).

$$
\begin{aligned}
&\textsc{holds}(\mathsf{prediction\text{-}offsidetrap}(p,q), \langle max(s_1,s_2), min(e_1,e_2)\rangle) \Leftrightarrow \\
&\exists \langle s_1,e_1\rangle, \langle s_2,e_2\rangle : \\
&\quad \textsc{holds}(\mathsf{offside\text{-}danger}(p,q), \langle s_1,e_1\rangle) \wedge \textsc{holds}(\mathsf{forward}(q), \langle s_2,e_2\rangle) \wedge \\
&\quad contemporary(\langle s_1,e_1\rangle, \langle s_2,e_2\rangle).
\end{aligned} \tag{6}
$$

A player p is in a punishable offside position, if he is in an offside position in the moment when the ball is kicked by his team mate p_2, and he approaches the ball while the ball is free, i.e. before another player obtains the ball (7).

$$
\begin{aligned}
&\textsc{holds}(\mathsf{offside\text{-}punishable}(p), \langle max(s_j,s_m), min(e_l,e_m)\rangle) \Leftrightarrow \\
&\exists j,k,l,m,p_2 : \\
&\quad \textsc{occur}(\mathsf{kick}(p_2), j) \wedge \textsc{holds}(\mathsf{offside\text{-}position}(p), k) \wedge \\
&\quad \textsc{holds}(\mathsf{ball\text{-}free}, l) \wedge \textsc{holds}(\mathsf{approaching}(p, ball), m) \wedge \\
&\quad starts(j,l) \wedge in(j,k) \wedge contemporary(l,m) \wedge \mathsf{team}(p) = \mathsf{team}(p_2).
\end{aligned} \tag{7}
$$

with $j = \langle s_j, e_j\rangle, k = \langle s_k, e_k\rangle, l = \langle s_l, e_l\rangle$ and $m = \langle s_m, e_m\rangle$.

The predicate $\textsc{occur}(e,t)$ states that an event $\mathsf{kick}p_2$ occurs at the moment j [1]. The temporal relations *starts* and *in* are defined in [1], *contemporary* in [4].

If the player comes to close to the ball this behavior should be penalized by the referee by interrupting the game for a free kick of the opponent team.

4 Results

To evaluate our approach we have chosen three games from the Robocup Worldcup 2002, which contain a reasonable amount of offside situations: FC Portugal vs. Puppets, TsinghuAeolus vs. FC Portugal and VW2002 vs. Cyberoos. Therefore, we have analyzed these three games in order to predict and recognize the occurring offside situations. Table 1 and 2 show the offside situations that occur in the games FC Portugal vs. Puppets and TsinghuAeolus vs. FC Portugal. For lack of space a table showing the table concerning the game VW2002 vs. Cyberoos is not included in this paper.

The first column (*ball contact*) denominates the player who kicked the ball before the penally offside situation occurred together with the time interval, at which he was in contact with the ball. The column *offside* contains the player numbers of his team mates which were already in an offside position before he obtained the ball. The next two columns contain our systems prediction of impending offside positions of further players. The column *mo.* contains the numbers of the players, who are moving in a direction that will possibly bring them into an offside position before the ball will be passed. The fourth column lists players who are possibly running into an *offside trap*. The column *offside/kick* lists the players who are in an offside position at the moment the ball is kicked. The column *penally* contains the players who have been in an offside position at the moment the ball is kicked and are approaching the ball during the following cycles. They are penalized by the referee if they come to close to the ball. The column (*break*) contains the cycle in which the game was interrupted by the referee. The tables contain all situations in which the game was interrupted by the referee due to offside. The last column s is marked with an ✓ if the situation was recognized by the system.

Concerning the prediction of offside situations there are also cases of impending offside situations that do not lead to an offside position before the ball is kicked the next time. Also there are situations in which a player, who was in an offside position at the moment the ball was kicked, starts approaching the ball in a penally way but another player gets the ball before the situation becomes critical. To keep them short, these situations are not included in the tables.

The game FC Portugal (FCP) against Puppets (see table 1) was interrupted 9 times by the referee due to offside. In 7 cases our system detected the offside situation. In two situations our systems is not in line with the referee. The first situations occurred from cycle 531 to 560. When player 7 of team Puppets kicks the ball (cycle 534), players 10 and 11 are in an offside position. In the following cycles player 11 approaches the ball, until he is in a very close distance to the ball (cycle 559), which was detected by our system. But in cycle 559 player 3 of the opponent team (FCP) gets in contact with the ball. In this moment our system stops looking for an penally offside for team Puppets, because FCP is already in possession of the ball. Nevertheless, the referee decided on offside and free kick in favor of FCP in cycle 560. According to our operationalization of the FIFA rules the referee should have interrupted the game before cycle 559 or should have let it go on after player 3 of FCP has reached the ball in cycle 559.

A comparable situation can be found from cycle 3844 to 3852. In cycle 3847 the ball is kicked by player 9 of FCP. Player 8 is in an offside position and approaches the ball in cycle 3850. This is detected by our system. But in the same cycle the ball touches player 4 of team Puppets. As before, we stop watching player 8 of FCP. But although the ball has touched a player of the opponent team the referee decides offside and penalizes player 8 of FCP in cycle 3852, which is obviously not in compliance to the FIFA rules.

Table 1. Offside situations FC Portugal (FCP) vs. Puppets (Pup).

Ball contact	offside	mo.	offside trap	offside/kick	punishable	break	s
Pup 7 474-478	10	11	$11_{Pup} \leftrightarrow 2_{FCP}$	10, 11	11	487	✓
Pup 7 531-534	10, 11			10, 11	11	560	
FCP 8 889-891	9, 10, 11			9, 10, 11	11	915	✓
FCP 10 1166-1168	6	7	$7_{FCP} \leftrightarrow 4_{Pup}$	6	6	1172	✓
Pup 5 2417-2422	10, 11			10, 11	11	2429	✓
FCP 9 3091-3094	10			10	10	3102	✓
FCP 9 3385-3386	10	11	$11_{FCP} \leftrightarrow 4_{Pup}$	10	10	3404	✓
FCP 9 3844-3847		8, 10	$8, 10_{FCP} \leftrightarrow 2_{Pup}$	8, 10	–	3852	
FCP 6 5589	10			10	10	5599	✓

Table 2. Offside situations TsinghuAeolus (TsA) vs. FC Portugal (FCP).

Ball contact	offside	mo.	offside trap	offside/kick	punishable	break	s
TsA 4 1279-1289		10	$9, 10, 11_{TsA} \leftrightarrow 2, 3, 5_{FCP}$	11	11	1304	✓
TsA 6 1547-1551		11	$11_{TsA} \leftrightarrow 2, 3_{FCP}$	9, 11	9	1554	✓
TsA 6 1575-1578		9	$9, 10, 11_{TsA} \leftrightarrow 4, 5_{FCP}$	9, 10, 11	9, 10	1584	✓
FCP 4 1650-1657	10, 11			10, 11	11	1673	✓
FCP 7 2944	9, 10, 11			9, 10, 11	9	2950	✓
TsA 8 3300-3302	9, 10		$11_{TsA} \leftrightarrow 5_{FCP}$	9, 10, 11	10, 11	3322	✓
TsA 2 4035-4038			$9, 10, 11_{TsA} \leftrightarrow 4_{FCP}$	10	10	4047	✓
TsA 6 4219-4226	9		$10, 11_{TsA} \leftrightarrow 5_{FCP}$	9, 10, 11	9	4228	✓
TsA 6 5047-5053	9, 10, 11			9, 10, 11	9	5056	✓

The game TsinghuAeolus (TsA) vs. FC Portugal (FCP) (see table 2) was interrupted 9 times by the referee due to offside. In all cases our system detected the offside situation.

The game VW2002 (VW) vs. Cyberoos (Cyb) was interrupted 35 times by the referee due to offside. In 29 cases our system detected the offside situation. In six situations the referee decides offside against a team A although a player of team B has touched the ball before the game was interrupted.

5 Conclusion and Future Directions

Spatio-temporal relations between objects within real-time environments are challenging by nature. We presented an approach for tracking single objects motion in combination with the changes in their pairwise spatial relations over time. The resulting motion description builds the basis for a qualitative interpretation of the dynamic scene.

This approach is domain independent and can therefore be used in various applications. We applied this idea to the soccer domain and argue that an implementation of this method within the online coach could enhance teams abilities. However, tests have been made off-line only at the moment. The additional background knowledge helps to interpret the analyzed motion scenes and significantly improves the results.

The described approach is valuable because it not only analyzes a past situation, it also is able to *predict* the next few steps of the opponents team to a certain extent. This will help the players of the own team to make better decisions at a certain cycle provided they have the information and can act accordingly. Also, when using this approach in an online scenario, the position data of the players have to be considered. For off-line analysis we use the data processed by the soccer server. These data can be quite different than those in the world model of a single player. Future tests have to be made in order to obtain valuable information about this problem. A possible solution to get all the information about the positions of both the opponents and the own team players is the based on the turn_neck-command and the aggregation of positions over a few cycles.

One of the biggest advantages of this approach is the independence from the domain. In the near future, we will also test other domains such as cell tracking in biological systems. Here, the objects are monitored with a camera and the method is able to track the objects over time and describe and store the spatial relations between them as well.

References

1. James F. Allen. Towards a general theory of action and time. *Artificial Intelligence*, pages 123–154, 1984.
2. FIFA. Laws of the game. Fédération Internationale de Football Association, FIFA House, 11 Hitzigweg, 8030 Zurich, Schweiz, July 2002.
3. Ian Frank, Kumiko Tanaka-Ishi, Katsuto Arai, and Hitoshi Matsubara. The statistics proxy server. In Tucker Balch, Peter Stone, and Gerhard Kraetschmar, editors, *4th International Workshop on RoboCup*, pages 199–204, Melbourne, Australia, 2000. Carnegie Mellum University Press.
4. C. Freksa. Temporal reasoning based on semi-intervals. *Artificial Intelligence*, 54(1):199–227, 1992.
5. D. Hernández, E. Clementini, and P. Di Felice. Qualitative distances. In *Proceedings of COSIT'95, LNCS 988*, Semmering, Austria, 1995. Springer.
6. Zhanxiang Huang, Yang Yang, and Xiaoping Chen. An approach to plan recognition and retrieval for multi-agent systems. In Mikhail Prokopenko, editor, *Workshop on Adaptability in Multi-Agent Systems, First RoboCup Australian Open 2003 (AORC-2003)*, Sydney, Australia, 2003. CSIRO.
7. Gal Kaminka, Mehmet Fidanboylu, Allen Chang, and Manuela Veloso. Learning the sequential coordinated behavior of teams from observation. In Gal Kaminka, Pedro Lima, and Raul Rojas, editors, *Proceedings of the RoboCup-2002: Robot Soccer World Cup VI*, pages 104–118, Fukuoka, Japan, 2002.
8. Andrea Miene and Ubbo Visser. Interpretation of spatio-temporal relations in real-time and dynamic environments. In Andreas Birk, Silvia Coradeschi, and Satoshi Tadokoro, editors, *RoboCup 2001: Robot Soccer World Cup V*, volume 2377 of *Lecture Notes in Artificial Intelligence*, pages 441–446. Springer, Seattle, WA, 2002.
9. Taylor Raines, Millind Tambe, and Stacy Marsella. Automated assistants to aid humans in understanding team behaviors. In *Fourth International Conference on Autonomous Agents (Agents 2000)*, Barcelona, Spain, 2000.
10. Patrick Riley and Manuela Veloso. Recognizing probabilistic opponent movement models. In *RoboCup-01, Robot Soccer World Cup V*, Lecture Notes in Computer Science, Seattle, Washington, 2002. Springer-Verlag. in print.