KickOffTUG - Team Description Paper 2009

Stephan Gspandl, Werner Arnus, Julia Gebetsberger, Gerwin Gsenger, Andreas Hechenblaickner, Michael Reip, Christian Wagner, Máté Wolfram, Christoph Zehentner

Institute for Software Technology, Graz University of Technology, Inffeldgasse 16B/II
8010 Graz, Austria,
`sgspandl@ist.tugraz.at`,
`http://kickofftug.tugraz.at`

Abstract. In the past months KickOffTUG developed its agent code in many directions. On an abstract level we focus on developing methodologies to define and adapt behaviour of agents or robots. We thus propose a system to transform tactics graphs from books on soccer strategies or tablet-pcs and digital whiteboards into behavioural plans as intuitive and easy as sketching on paper.
Furthermore our research comprises new and optimized ways of diagnosing the behaviour and execution of agents or robots. Costs of collaboration, debugging and testing should be minimized by enhancing usability and motivating all members to actively participate. Our Diagnosis Tool makes it even possible to evaluate adaptions offline (i.e. without having to run a game).
Concerning the agents' skills, we have been researching into ways of improving dribbling skills by identifying appropriate features as well as positioning and marking methods. Latter shows empiric results over several algorithms.

1 Automatic Derivation of Behavioural Models

1.1 Introduction

One important task in the RoboCup soccer league is to build up soccer domain-knowledge. Most teams of the RoboCup soccer leagues are engaged in adapting soccer knowledge for their robots. Because soccer is a well-covered domain, there exists a broad variety of books and strategic knowledge from soccer experts (like [1] or [2]). Teams use such knowledge to develop their agents' behaviour. This is mostly done by a manual transformation into specific plans or algorithms.
In our view, adapting the agents' behaviour should be as easy and fast as scanning diagrams from expert books or scribbling circles and lines onto a piece of paper or a tablet-pc. We therefore propose a system for an easy translation of soccer strategic graphs to plans defining the agents' roles and abstract behaviours.
The input to the system is a graph (a scan) or a seqence of strokes (from a tablet-pc or a digital whiteboard) depicting an agent's behaviour in a concrete

situation. Our approach is based on several transformations and models of representation. In the first stage we recognize the strategic graph and translate it to a spatial-temporal representation of the described situation. This model typically contains a set of circles representing the own, the opposing players and the ball and a set of different arrows standing for the actions to be performed by the players, respectively. By using a domain-model the spatial-temporal model is then transformed into a domain-specific situation model. This model in turn comprises a set of literals describing the situation given by the strategy graph, the actions which are applied to this situation and a set of conditions describing the situation after application of the actions. A combination of such strategic models creates an overall model of the agents' behaviour.
Fig. 1 sketches this process. As this is work in progress we will discuss only the first approach in this paper.

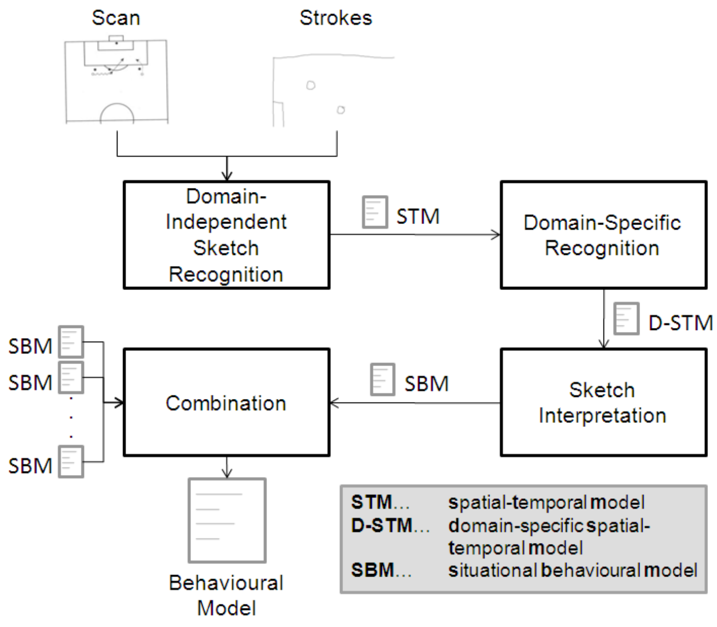

Scan
Strokes
Domain-Independent Sketch Recognition
STM
Domain-Specific Recognition
D-STM
SBM
SBM
SBM
Combination
SBM
Sketch Interpretation
Behavioural Model
STM... spatial-temporal model
D-STM... domain-specific spatial-temporal model
SBM... situational behavioural model

Fig. 1. The process of automatically deriving a behavioural model from several tactics graphs.

1.2 First Approach

Our first approach is based on the decision-making system in the 2D RoboCup Simulation League team KickOffTUG and a first version of a scan-recognition module built in Matlab. We are using an adaption of T-R-Programs (see [3]) combined with a STRIPS notation (see [4]) to generate plan trees which define the agents' behaviour (see [5], [6] and [7]). At the moment these plans are created by hand using expert knowledge. Simply spoken, a plan tree consists of action nodes, each path in this representation corresponds to a goal in the T-R-notation and the tree is traversed in a depth-like way to find a node whose postconditions (or effects) are false (to denote that the outcome of this action has not yet been fulfilled) and the corresponding preconditions are met (i.e. the action is indeed executable). Invariants help to maintain deliberativity of a decision as an action is executed as long as the invariant remains satisfied. In order for the agent to be reactive, the tree is traversed from the root otherwise (thus, the whole search space is again examined).

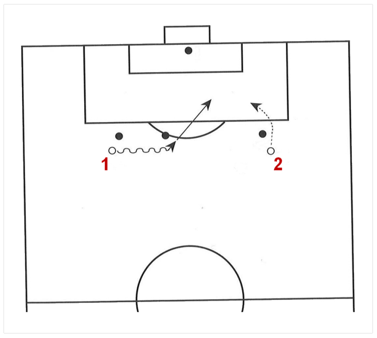
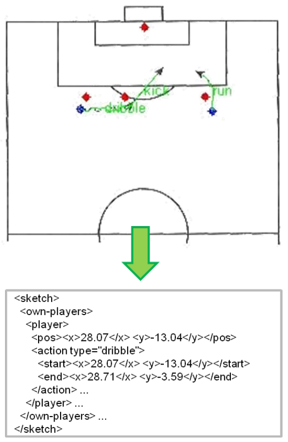


Fig. 2. An example for a tactics graphs from [1].

Input to the recognition engine is a tactics graph from [1] like the example shown in Fig. 2 which results in a simple domain-specific spatial-temporal model with players and the ball recognized and annotated with field positions as well as actions to be performed. This transformation applied to the example is shown in Fig. 3. The interpretation step is based on a knowledge domain derived from the set of conditions used to evaluate the environment (the world state) the agent is faced with. Applying this domain yields a qualitative description which is employed to build tree plans described before as they provide a predicate basis for pre-, postconditions and invariants. Fig. 4 yields the resulting plan of the transformation process for the given example.

In the simplest case this qualitative model will be directly inserted into an overall plan tree by attaching it as sibling. As each situation broadens the tree further, this will probably turn out to be very inefficient. Therefore, techniques to deepen the tree have to be implemented. One approach would be binary ramification, i.e. using common predicates as anchor points to ramify the tree.



```
<sketch>
 <own-players>
  <player>
   <pos><x>28.07</x> <y>-13.04</y></pos>
   <action type="dribble">
    <start><x>28.07</x> <y>-13.04</y></start>
    <end><x>28.71</x> <y>-3.59</y></end>
   </action> ...
  </player> ...
 </own-players> ...
</sketch>
```

Fig. 3. The recognized graph is transformed into a simple spatial-temporal representation.

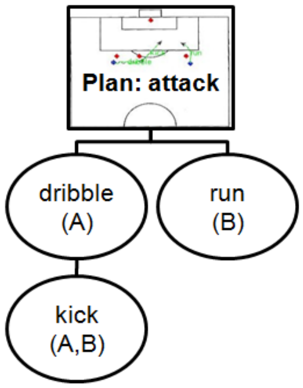


Fig. 4. The resulting plan.

2 Diagnosis Environment

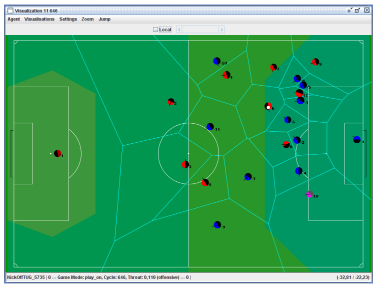
2.1 Introduction

Our GUI for diagnosing the agents' behaviour and execution (Diagnosis Tool) has recently experienced several major improvements, including a new datasource management system and advanced methods for visualizing all kinds of data associated with the agent's decision process. Aim of this project was to improve this tool's usability to motivate all team members to actively participate in our analysis and debugging process.

2.2 Diagnosis Features

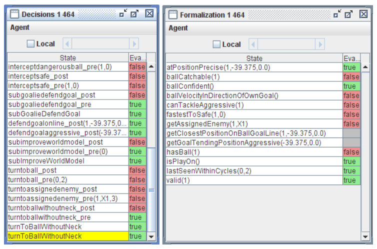
Visualizations The window for visualizing the agents' world states after each game has been enhanced to include all kinds of overlapping visualizations that can be individually written, integrated and activated. Several convenience methods are available to ease this process and to offer the developer a mighty tool for individual debugging, especially if compared to simple system output or logging. Any information presented in the visualization frame is such a visualization, from the world state as we see it through a soccer monitor to Delaunay and Voronoi diagrams or calculations for higher level actions such as passing, dribbling and positioning, to name a few (see Fig. 5).

Another useful and often interesting feature is the mirrored world state that allows us to generate all visualization overlays based on the opposing team. That way, we can compare their actual behaviour to the calculations our agents would have come up with.



KickOffTUG_5735 | 0 --- Game Mode: play_on, Cycle: 646, Threat: 0,110 (offensive) --- 0 | (-32,81 / -22,23)

Fig. 5. Visualization Frame

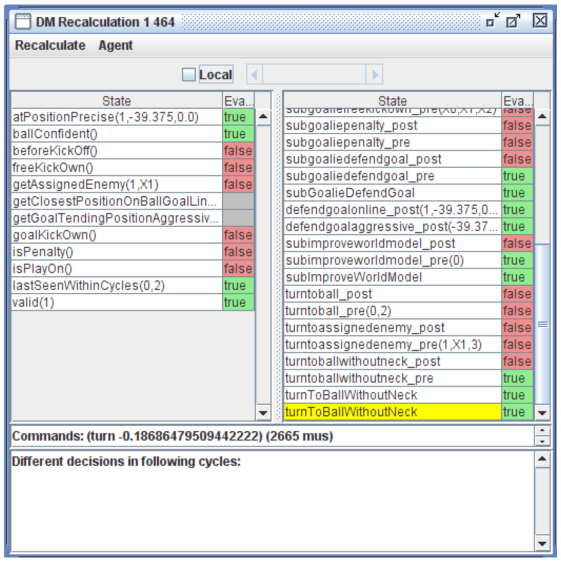


State	Eva...
interceptdangerousball_pre(1,0)	false
interceptsafe_post	false
interceptsafe_pre(1,0)	false
subgoaliedefendgoal_post	false
subgoaliedefendgoal_pre	true
subGoalieDefendGoal	true
defendgoalonline_post(1,-39.375,0...	true
defendgoalaggressive_post(-39.37...	true
subimproveworldmodel_post	false
subimproveworldmodel_pre(0)	true
subImproveWorldModel	true
turntoball_post	false
turntoball_pre(0,2)	false
turntoassignedenemy_post	false
turntoassignedenemy_pre(1,X1,3)	false
turntoballwithoutneck_post	false
turntoballwithoutneck_pre	true
turnToBallWithoutNeck	true
turnToBallWithoutNeck	true

State	Eva...
atPositionPrecise(1,-39.375,0.0)	true
ballCatchable(1)	false
ballConfident()	true
ballVelocityInDirectionOfOwnGoal()	false
canTackleAggressive(1)	false
fastestToSafe(1,0)	false
getAssignedEnemy(1,X1)	false
getClosestPositionOnBallGoalLine(1,-39.375,0.0)	
getGoalTendingPositionAggressive(-39.375,0.0)	
hasBall(1)	false
isPlayOn()	true
lastSeenWithinCycles(0,2)	true
valid(1)	true

Fig. 6. Formalizations and Decisions

Formalizations and Decisions Whenever the appropriate logging level is enabled, our agents record their decisions and formalizations in every cycle. After the game, this information is written to logfiles that can be interpreted and displayed by the Diagnosis Tool (see Fig. 6).
If such information isn't available or needs recalculation due to changes in the agent's plans, the missing (or new) information can always be recalculated, by invoking a passive instance of an agent from within the Diagnosis Tool to request new decisions (see Fig. 7).



State	Eva...
atPositionPrecise(1,-39.375,0.0)	true
ballConfident()	true
beforeKickOff()	false
freeKickOwn()	false
getAssignedEnemy(1,X1)	false
getClosestPositionOnBallGoalLin...	
getGoalTendingPositionAggressiv...	
goalKickOwn()	false
isPenalty()	false
isPlayOn()	false
lastSeenWithinCycles(0,2)	true
valid(1)	true

State	Eva...
subgoaliefreekickown_pre(X0,X1,X2)	false
subgoaliepenalty_post	false
subgoaliepenalty_pre	false
subgoaliedefendgoal_post	false
subgoaliedefendgoal_pre	true
subGoalieDefendGoal	true
defendgoalonline_post(1,-39.375,0...	true
defendgoalaggressive_post(-39.37...	true
subimproveworldmodel_post	false
subimproveworldmodel_pre(0)	true
subImproveWorldModel	true
turntoball_post	false
turntoball_pre(0,2)	false
turntoassignedenemy_post	false
turntoassignedenemy_pre(1,X1,3)	false
turntoballwithoutneck_post	false
turntoballwithoutneck_pre	true
turnToBallWithoutNeck	true
turnToBallWithoutNeck	true

```
Commands: (turn -0.18686479509442222) (2665 mus)
```

```
Different decisions in following cycles:
```

Fig. 7. Decision-Making Recalculation

Log Data, Actions, Statistics In addition to the aforementioned features, the Diagnosis Tool offers a large amount of various views to inform the developer about exact positioning, agent actions or match statistics. The available frames are not limited to a certain set, but the developer is rather encouraged to contribute new views to the system, that can be added as easily as new visualizations for the visualization frame. The data that's necessary for these views is managed by the Diagnosis Tool's datasource management system, as described in chapter 2.3.

2.3 Datasource Management

Since our team uses a farm of simulation servers for tournaments to evaluate our agents' skills, all the diagnosis information written during and after simulated matches is stored on these servers and can be accessed online. To enable the developer to quickly overlook and access this huge amount of data, the Diagnosis Tool is able to fetch data from various datasources, including our servers of course, and present it to the developer in a simplified form. Fig. 8 shows how the user can choose among various datasources and open corresponding diagnosis elements.

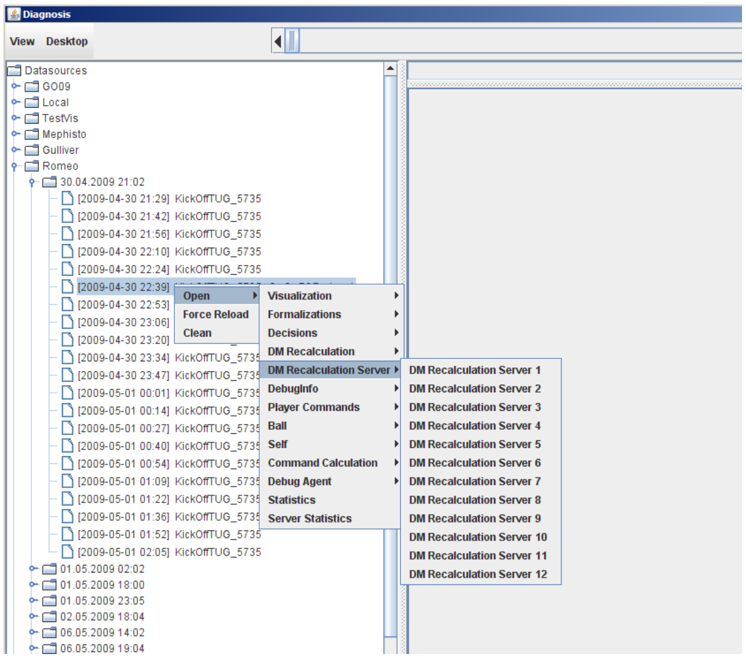
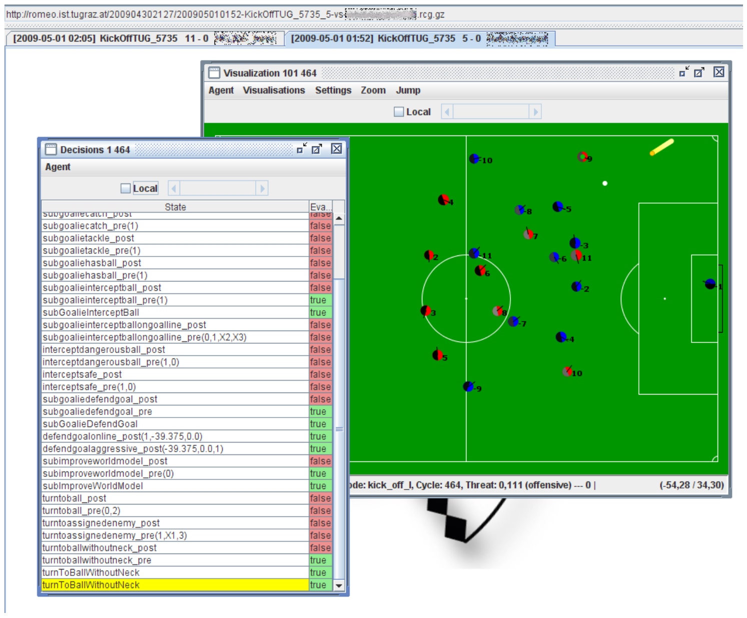

Diagnosis
View
Desktop
Datasources
GO09
Local
TestVis
Mephisto
Gulliver
Romeo
30.04.2009 21:02
[2009-04-30 21:29] KickOffTUG_5735
[2009-04-30 21:42] KickOffTUG_5735
[2009-04-30 21:56] KickOffTUG_5735
[2009-04-30 22:10] KickOffTUG_5735
[2009-04-30 22:24] KickOffTUG_5735
[2009-04-30 22:39]
[2009-04-30 22:53]
[2009-04-30 23:06]
[2009-04-30 23:20]
[2009-04-30 23:34] KickOffTUG_5735
[2009-04-30 23:47] KickOffTUG_5735
[2009-05-01 00:01] KickOffTUG_5735
[2009-05-01 00:14] KickOffTUG_5735
[2009-05-01 00:27] KickOffTUG_5735
[2009-05-01 00:40] KickOffTUG_5735
[2009-05-01 00:54] KickOffTUG_5735
[2009-05-01 01:09] KickOffTUG_5735
[2009-05-01 01:22] KickOffTUG_5735
[2009-05-01 01:36] KickOffTUG_5735
[2009-05-01 01:52] KickOffTUG_5735
[2009-05-01 02:05] KickOffTUG_5735
01.05.2009 02:02
01.05.2009 18:00
01.05.2009 23:05
02.05.2009 18:04
06.05.2009 14:02
06.05.2009 19:04
Open
Force Reload
Clean
Visualization
Formalizations
Decisions
DM Recalculation
DM Recalculation Server
DebugInfo
Player Commands
Ball
Self
Command Calculation
Debug Agent
Statistics
Server Statistics
DM Recalculation Server 1
DM Recalculation Server 2
DM Recalculation Server 3
DM Recalculation Server 4
DM Recalculation Server 5
DM Recalculation Server 6
DM Recalculation Server 7
DM Recalculation Server 8
DM Recalculation Server 9
DM Recalculation Server 10
DM Recalculation Server 11
DM Recalculation Server 12

Fig. 8. Datasource View

To enable the user to analyze multiple games at the same time, open matches are presented in a tabbed view (as shown in Fig. 9).



http://romeo.ist.tugraz.at/200904302127/200905010152-KickOffTUG_5735_5-vs[redacted].rcg.gz

[2009-05-01 02:05] KickOffTUG_5735 11 - 0 [redacted]
[2009-05-01 01:52] KickOffTUG_5735 5 - 0 [redacted]

State	Eva...
subgoaliecatch_post	false
subgoaliecatch_pre(1)	false
subgoalietackle_post	false
subgoalietackle_pre(1)	false
subgoaliehasball_post	false
subgoaliehasball_pre(1)	false
subgoalieinterceptball_post	false
subgoalieinterceptball_pre(1)	true
subGoalieInterceptBall	true
subgoalieinterceptballongoalline_post	false
subgoalieinterceptballongoalline_pre(0,1,X2,X3)	false
interceptdangerousball_post	false
interceptdangerousball_pre(1,0)	false
interceptsafe_post	false
interceptsafe_pre(1,0)	false
subgoaliedefendgoal_post	false
subgoaliedefendgoal_pre	true
subGoalieDefendGoal	true
defendgoalonline_post(1,-39.375,0.0)	true
defendgoalaggressive_post(-39.375,0.0,1)	true
subimproveworldmodel_post	false
subimproveworldmodel_pre(0)	true
subImproveWorldModel	true
turntoball_post	false
turntoball_pre(0,2)	false
turntoassignedenemy_post	false
turntoassignedenemy_pre(1,X1,3)	false
turntoballwithoutneck_post	false
turntoballwithoutneck_pre	true
turnToBallWithoutNeck	true
turnToBallWithoutNeck	true

ode: kick_off_l, Cycle: 464, Threat: 0,111 (offensive) --- 0 | (-54,28 / 34,30)

Fig. 9. Tabbed Browsing

2.4 Benefits

As mentioned before, the main goal of the Diagnosis Tool is to ease the debugging process and therefore motivate all team members to actively participate in it. However, it's also helpful in terms of team-internal communication of detected issues. Since all team members are working on a central repository of matches and associated logged data, issues can be communicated by simply pointing to a simulated match and a certain cycle, instead of having to send logged data in large files. Also, issues can be easily stored for later reference.
The large amount of available features, especially the visualization frame, offers the developer a way to quickly pinpoint errors or try new code without even having to actually start an agent. Deployment times of new features are dramatically reduced while increasing the quality of the resulting source.

3 Dribbling: Skill of Handling the Ball

Dribbling is an action, where the player runs with the ball without loosing it. Therefore he should be able to move into various directions and with different kinds of speed. These features have been derived empirically and are subject of discussion in the next paragraphs. Fig. 10 shows an example of applying concrete parameters to the dribbling algorithm.

3.1 Speeds

Three different dribbling speeds are implemented. These are accomplished by calculating the velocity appropriatly.

1. **Normal:** The player kicks the ball with the maximum velocity so that he is able to reach the ball each cycle. Thus, it is possible to change the direction each cycle to avoid opponents.
2. **Fast:** Fast dribbling is used to enable the agent to attack opponents faster. Therefore the ball is kicked in a way that the velocity is equal to the maximal acceleration of the player after some cycles. So the player is not able to reach the ball each cycle which makes the move more risky.
3. **Slow:** When the player uses slow dribbling he has to save stamina or wait until his colleagues are positioned to be able to execute a pass. He accelerates the ball with the half of the velocity of the normal dribbling speed.

3.2 Directions

The dribble directions are given as absolute coordinates on the soccer field. The player should be able to run to a strategic position, but also to avoid opponents. Therefore three different dribbling direction were implemented:

1. **Position to go:** The player should move primarily to this position which could be used to implement different soccer tactics. For instance, if the player is inside the offensive area, he should move, if possible, to the opponent's goal or the corner.
2. **Dodge direction:** The dodge direction is a calculated position where the player should move when opponents are near but not very near. This direction is used to avoid them as early as possible. The direction is calculated with aid of the widest angle between the near opponents.
3. **Wide dodge direction:** This direction is used, when the opponents are very near and the player has to dodge with a larger angle than the normal dodge angle. That angle could be inside the full range of $0°$ to $360°$.

4 Comparing Several Positioning and Marking Methodologies

4.1 Introduction

Handling the ball while in ball possession or to intercept the ball are important skills in (human or digital) soccer, but most of the time a player takes only part

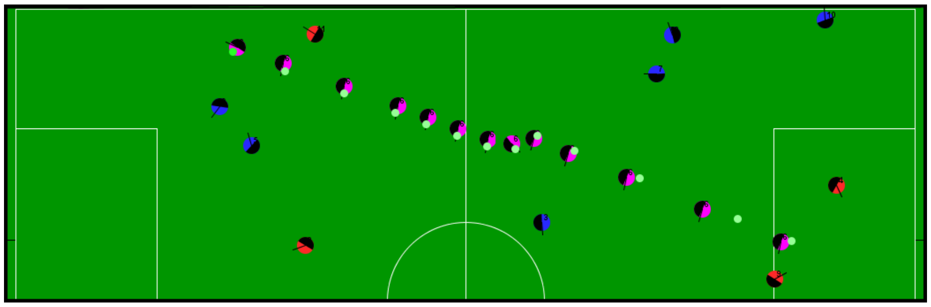


Fig. 10. Slow dribbling over time - the player is painted every tenth cycle avoiding the opponents in blue.

in a passive way without having the ball. During this periods, its main task is to run to a good position an the field depending on the current situation (offensive or defensive play) and to keep the team formation.
Depending on the current ball position and the role of the player, a position on the field can be calculated known as the players home position or strategic position.
While some simple algorithms to calculate these positions are presented in [8] and [9], a more flexible implementation using Delaunay triangulation and linear interpolation was presented in [10].

4.2 Offensive Positioning

To improve position selection during offensive situations the player should find the best position within its reachable area that allows him to receive passes and gives him a good scoring probability.
Based on [11] an algorithm considering the following criteria was implemented:

- Keep formation given by the strategic position.
- Maximize distance to opponents.
- There should be a free way to the opponents goal.
- Direct pass should be possible.
- Keep near offside line.
- Avoid positions near the outlines.

The weights of each criterion depends on the players role (striker, midfielder, defender), the current play mode and the position of the ball.

4.3 Defensive Positioning and Opponent Assignment

To successful defend opponents attacks each attacking player must be marked by one defender. To avoid single opponents to be addressed by more than one player or to leave an attacker unattended, a collaborative assignment of attackers to

defenders must be negotiated in the defending team.
To solve this problem, an algorithm presented in [12] that minimizes the costs (a weighted function of the attackers threatness, the distance to the attacker and the distance to the strategic position), of marking all attackers was implemented, giving a good assignment for a man-to-man marking defense strategy.
As in modern soccer zonal marking is very successful, a second algorithm selects the attacker to take care of based on the zones around each players strategic position.

4.4 Experimental Results

All implemented algorithms are compared in a set of matches against other teams released binaries from 2008 RoboCup competitions.
Table 1 shows the strong advantage of the Delaunay triangulation based strategic positioning algorithm against the simple one presented by UvA.

Implementation	Goal difference	Ball possession
UvA [8]	-5,07	59,08 %
Delaunay triangulation [10]	-2,71	57,86 %
Delaunay with offensive positioning	-2,02	59,56 %

Table 1. Comparision of different positioning implementations.

For defensive situations two opponent assignment algorithms explained in the previous section are compared against a simple one that assigns each defender the attacker with the shortest distance and does not avoid double assignments. Best results are achieved by a zonal marking defensive strategy [13].

Implementation	Goal difference	Ball possession
NearestEnemyAssignment	-3,99	56,85 %
TeamCostEnemyAssignment	-3,25	57,82 %
ZonalMarkingEnemyAssignment	-2,71	57,86 %

Table 2. Comparison of different opponent assignment implementations.

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