A Knowledge Engineering Approach to Understanding MSL Team Behavior [V2.0]

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Abstract

This second draft departs from the first one by taking a different approach. As a result of discussions with the expert Max Tjaden it became clear that finding explanations for given game situations is not always possible and in those cases also not very useful. Instead we were offered insights into what should have been done, with an explanation why. Those insights have been included in this new version.

The behavior of RoboCup MSL robots is mostly reactive. When playing against humans in the future, the behavior should become more anticipatory. That requires a deeper understanding of the opponent's actions. By analyzing the actions of the robots, we build models that provide insight into their behavior. Current approaches in Deep Learning tend to learn by exploration, in which the learned knowledge is hidden in layers of a neural network. We must have access to that learned knowledge and understand how game situations are handled. Human coaches and analysts have dealt with this problem for a long time and use visual techniques like set-pieces to explain game situations. Our work concentrates on using a similar approach to create an understanding of team- and individual robot behaviors by creating models, that are based on patterns, familiar to Futsal soccer analysts, like formations and roles. Models, based on real-world symbols serve as ground truth for a Deep Learning system, in which the strengths of the symbolic and sub-symbolic systems are combined. This work concentrates on the synbolic part first and serves as the basis for a subsequent Deep Learning part.

I. Introduction

Recent developments in Neural Networks and Deep Learning have achieved impressive results, based on self-play, like Alpha-Zero (Silver2018 [34]) and Alpha-Star (Arulkumaran2019 [1]). These approaches mostly concentrate on exploring different possibilities and in many cases outperform other methods. Unfortunately they offer little insight into what these networks have discovered and do not provide an explanation of what they have learned. Most systems that recognize or classify situations do so, based on learned features or correlations, but do not take into account what the detected features represent.

In the past, Good Old-Fashioned AI (GoFai) mostly concentrated on symbols and reasoning about them, but offered very little in terms of learning (Levesque2017 [25]). Our work aims at combining both approaches by using Knowledge Engineering principles to analyze action sequences of robotic soccer competitions and thus providing explainable game situations, that can be successfully learned by a neural network. Basing the input on symbols, both the symbolic concepts from the analysis and the sub-symbolic features of the neural network may be combined to provide a learning environment, capable of explaining what the actions mean.

The goal of analyzing team behavior is to learn a descriptive model of the actions of a team's field players. We analyze these models, to find strong- and weak points in our strategy and that of our competitors. With such models we will be able to better anticipate opponent actions.

The source data is formed by the log-files, recorded by our TURTLE robots during international competitions. These log-files have recorded the locations of all robots and the ball. For our robots, roles, actions and targets are logged as well.

The project is in an early stage and concentrates on ball passes and defensive moves of just a few competitions as a proof-of-concept.

II. Backgrounds of Our Approach

Say a bit more about using the analysis to find weak spots in our plays and ways to correct them.
Playing robot soccer in the MSL league currently is mostly reactive and deterministic. Because the number of game situations is very large and implementations generally also contain randomizers, team behavior is not easy to predict. When playing against humans, the team behavior is far from optimal, but because other robot teams take the same approach, competitions between robots are more interesting and show progress every year. When we want to start playing against humans however, some things must change:

1. Robots are dangerous to play against and we need to make changes to the design of the robots to safely play against humans.
2. The robot behavior must become more anticipatory. This means that we must take the expected actions of our competitors into account.
3. We want to learn from human coaches, how our play needs to change to make competitions more interesting.

Our approach consists of two parts: 1) analyzing existing games in order to develop a method that predicts team behaviors and 2) taking advice from Futsal coaches to make our play more human. The first part is done by using the same analysis methods that Futsal coaches are using; building a model based on set-pieces. The second part is done by taking game situations from past competitions and have these analyzed by an expert Futsal coach, using Knowledge Engineering principles. The expert analysis delivers valuable insights into which situations our robots should avoid related to the actions that were take in given game situations.

Several attempts have been made in the past to build models of RoboCup Soccer. The main problem is to design a useful representation for such a model, to interpret used strategies as well as for a later self-learning capability. In our case an explicit model is only useful if it helps explaining what an agent does. In order to be understandable and to explain their behavior, such systems need to be grounded on real-world symbols and therefore we need to find a representation that facilitates this requirement.

We propose to use hand-crafted symbols, derived from Futsal which is a 5 against 5 soccer-playing competition. We use the coaching manuals of FIFA and UEFA [10, 40], as well as the one from the Dutch National Futsal team, developed by Max Tjaden from KNVB [39]. These contain a rich collection of game situations, called set-pieces and are documented in the form of small action diagrams, that are used to classify game situations (See Figure 1).

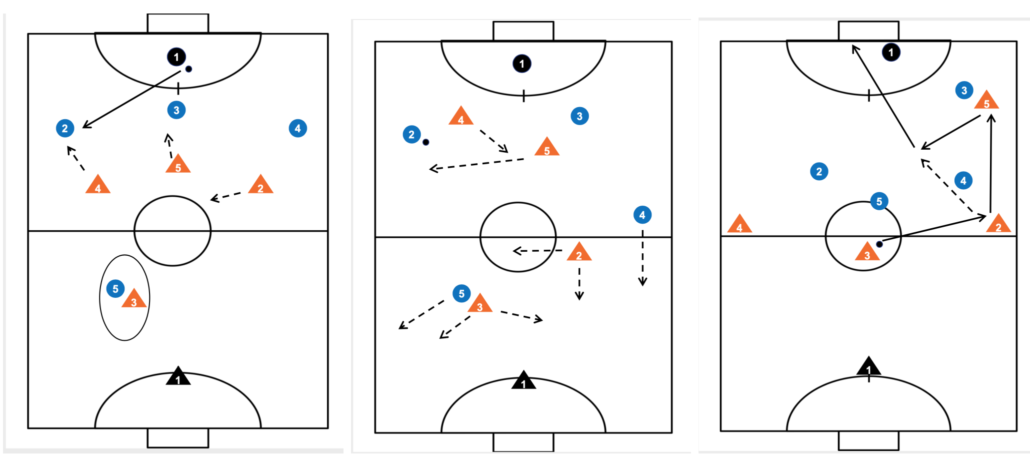


Figure 1: *Example of a defending set-piece, one where a team switches from defense to attack and an attack set-piece. Set-Pieces are represented graphically in the Futsal coaching manuals, depicting the steps taken by each player for a given game situation.*

The second source is formed by the way that our soccer-playing software is organized. In 2019 we implemented the STP framework [3], based on earlier work done by the CMUDragons SSL team. This approach consists of three parts; Skills, Tactics and Plays. The game situation, encoded in team player positions, ball position and possession is used to select a Tactic. From this an appropriate Play is selected. A Play or Set-Play (which is equivalent to the Futsal Set-Pieces) is selected and based on the skills of the robots, a role is negotiated between the robots. The STP framework consists of a declarative structure in which these Skills, Tactics and Plays are defined and serves as the grounding symbols of our approach, along with the Futsal Set-Pieces.

That has an implicit risk, that other teams may operate with different interpretations of the game situation and utilize features or grounding symbols that differ from ours. This may result in interpretation differences. but as a first approach it should be a good attempt.

III. Related Work

i. Opportent Modeling and Action Prediction

Earlier work on predicting opponent behavior was done by one of our team members, van 't Klooster (2018) [41]. In this work, traces of game situations were created in occupancy grids, representing the movements of opponents in various game situations. A Convolutional Neural Network was used to learn to recognize these traces and predict the action of an opponent. (See Figure 2)

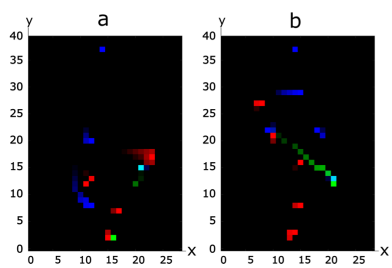


Figure 2: *Example of a trace of two game situations: a) a Pass, b) a Shot at Goal. Represented in 15 and 12 time steps*

Learning to play soccer is the subject of many earlier studies, that inspired our work. The German Brainstormers Tribot Team [14] was one of the first to try such an approach (RiedMiller [31, 32]). In the RoboCup Simulation league several approaches have been tried (Stone2005 [37]). Several teams from other leagues also have made attempts at this (Hafner2002 [14], Kurek2015 [21], Celemin2017 [4], Yoon2017 [43], Schouten2018 [33] and Cooksey2018 [5])

Several efforts on Opponent Modeling were made in the RoboCup Coach Competitions, which were held from 2001 through 2006. This sub-league of the Simulation League was specifically aimed at finding ways to analyze opponent behaviors and allowed the coach software to formulate strategic advice to the team. A more recent summary of work on Opponent Modeling in relation with more modern Deep Learning approaches is given in the work of Hernandez-Leal2018 [16]. Different strategies are described in Pourmehr2010 [28], like Team Strategy Classification, Agent Action Classification, Formation Analysis, Offense/Defense Strategy and Pass Graphs. It ranges from recognizing simple behaviors like `Intercept, Pass, Dribble`, where the special Viena Pattern Editor was used, and a language (CLang) to describe the action patterns that are being used. (Iglesias2006 [20]). More complicated are so-called Trie structures (Iglesias2009 [19]), where sequences of actions are used to model agent behaviors (`pass1to2->dribble2->pass2to10->goal10`). Case Based Reasoning is also used in some cases (Steffens2004 [36]).

ii. Formation Analysis

Formation analysis has been done, based on team tracking data before, like in Visser2001 [42] and in Felsen2018 [9]. More recently Sports Analytics STATS have described formation analysis methods in Le2017 [24, 23, 22] and Hobbs2020 [17].

Analyzing what a team does as a whole is recorded in team strategy, where team formation is often used to define cooperation patterns like 1-2-2 (the most popular Futsal formation) as used in Strategy/Formation approach. (Pourmehr2010 [28]).

Another approach is to determine a team's goals, based on the beliefs of individual team members about their intentions. Like the team wants to move to the opponent half, the intention of player X is to pass the ball to player Y. This is done in the Belief/Desire/Intention (BDI) approach, described in (Haddadi1995 [13]). All these approaches use instances of a form of Action Recognition, which has been the subject of study for the past 10 years and has seen many new ideas. In the comprehensive review of recent developments of Zhang2019 [44], most of the recent ideas are described. Another good overview of recent developments is given in (Ghosh2018 [12]), where the most influential contributions are listed.

iii. Symbolic vs SubSymbolic

Rabinowitz1802 [30] developed a Theory of Mind approach for robots in order to explain behavior in a simple grid-world. Several other researchers have developed approaches to build Neural Network systems that are capable of learning symbols, like in Garnelo1609 [11], Zhang1707 [45] and Garcez1905 [8]. Other approaches attempt to create systems, that combine reasoning about symbols with Deep Neural Networks (Hohenecker1808 [18], Mao2019 [27] and Bennetot1909 [2]). One particularly interesting approach is found in Object Oriented Deep Learning, where the layers of a neural network are formed by representations of symbols instead of weight matrices (Liao2017 [26]).

iv. Expert Analysis

Human experts in Soccer and Futsal have dealt with explaining team- and player behavior for a long time. More recently some professional teams have employed AI technology to better understand actions and formations, like in the work of the Sports Analysis Company STATS, which has developed a method to predict agent actions in the game of basketball, based on Conditional Variational AutoEncoders (Disney2017 [38], Felsen2018 [9]).

IV. Contribution of this Work

This section needs to be worked out more extensively.
Here we will list our contribution. The list underneath is a first attempt.

1. Explicit Opponent Modeling as an analysis method
2. Team Formation Analysis
3. Agent Action Prediction and Intention analysis
4. Using STP as an analysis and synthesis model
5. Using Set-Pieces as a visual model to explain strategies
6. Analysis on a symbolic level
7. Integration of Symbolic and Sub-symbolic systems

V. Formations

We take our inspiration from Futsal coaching and analysis techniques. Our objective is to classify behavior patterns on a symbolic level, expressed in the form of set-piece scenarios for a single agent. Afterwards, these scenarios form input to a neural network that will first learn the behavior of all robots of our team and later that of our opponents.

To analyze game siituations we devise a notation, related to the apparent formation, a team is playing in, which is not the strategic formation, but a description of the relative positions of the field players. We take the farthest positions of the players in the front, back, left and right and split the distances over front, central and back players as attackers, midfielders and defenders. In addition we calculate the average distance and the center of the formation, to determine the spread of the team and the half of the field where the players are concentrated.

We describe this formation with a six-position code, like AOW202 (Attack on Our half in a Wide formation with 2 attackers, 0 midfielders and 2 defenders). A similar coding scheme is used for the game situations of single agents (See Table 1).

The information is visualized in a generated set-piece with the movements of all players during an episode and is used to explain the behavior of a single agent as shown in Figure 4. Such a set-piece description can be compared to a short story, summarized like: "Our team attacks in a tight 202 formation on our half. The opponent is defending in a 211 formation. Our agent in position Attacker Left (AL) is moving towards the ball and intends to capture the ball." When we string together all encoded actions, the intentions and remarks, we get such a description as an annotation to the set-pieces and together they form the symbolic description of an entire episode. In a later phase we will use this information as input for a neural network, which then will learn to associate game situations with actions and their consequences.

Table 1: *Game Situation Codes*

Team Formations					
Type	Name	Phase	A	M	D
112	Pyramid	Defense	1	1	2
103	Wall	Defense	1	0	3
202	Square	Neutral	2	0	2
121	Diamond	Neutral	1	2	1
211	Y	Attack	2	1	1
301	AllOrNone	Attack	3	0	1

(a) *The most commonly used formations in Futsal. The last columns show the number of Attackers, Midfielders and Defenders.*

Team Game Sit		
T	C	Phase
X–	A	Attack
	D	Defense
-Y-	O	Our Half
	T	Their Half
–Z	W	Wide play
	S	Small play

(b) *Indication of the phase, location and dimension of the formations.*

Agent Formations				
Type	Name	A	B	D
211	Most common	2	1	1
212	examples	2	1	2
111	of formations	1	1	1
X1X		X	1	X
X2X	Close to Ball	X	2	X
X3X	Owns the Ball	X	3	X

(c) *Code for agent formations. It lists the number of close opponents in front and behind the agent. The number in the middle describes the relative position of the ball.*

VI. Describing Game Situations in Episodes

To analyze a competition, we designed an hierarchical description of game state aspects, called episodes, that lead to unique descriptors for the four field players in all possible game situations. Episodes are game situations in which a certain aspect remains stable. This hierarchy ranges from the level of a referee decision, called a RefBox situation in MSL terms, to an individual agent action (See Table 2b).

Set-Pieces are generated at the this level and are split into episodes that start or end with Ball Possession Turnovers (BPT - changes in ball possession). Agent actions are at the lowest level and are analyzed in the context of the BPT episode in which it occurs (see Figure 3a).

The analysis starts with selecting game episodes and determine the team formations. For example, an Episode starts or ends with a BPT event. Within each episode, agents are given a unique role and position identifier that is based on the formation the team is playing in (See Table 2a). It's role is coded as Attacker, Midfielder or Defender in a Central, Left or Right position.

Using this identifier we can refer to a player by it's role in the current formation and facilitates generalizing game situations. Additionally, an agent's game situation is encoded in a similar way as the team formation, like AT-211

Table 2: *Formation Roles and Game States*

Agent Role in Formation		
T	C	Role/Position
X-	A	Attacker
	M	Midfielder
	D	Defender
-Y	L	Left
	C	Center
	R	Right

(a) *Agent Formation Roles allow an agent to be addressed independently of its identity, relative to the current team formation.*

Game State Aspects		
Lvl	Aspect	Example
8	RefBox Situation	ThrowIn Cyan
7	Game Turnover	OurBall
6	Ball Poss. Turnover (BPT)	Agent 3[DR]
5	Our Formation	AOW202
4	Opp Formation	DOS211
3	Agent Formation	AO-211
2	Agent Intent	MaskAL[C1]
1	Remarks	PassBallLost
0	Agent Action	ShootAtGoal

(b) *Different Game States defined as episodes and their explanation*

(Attack on Their half, 2 opponents in front and 1 opponent in the back) (See Table 1b+c). With these codes we can then search for all similar game situations, and compare the actions that agents take, when in that game situation.

VII. The Intentional Stance

Given the large number of possible game situations, finding explanations is very difficult. Therefore we try to find logical explanations of the observed behavior, by attributing intentions to agents, which is taking the Intentional Stance (Dennet1971 [7]). Building a model that includes a robot's beliefs and intentions creates a semiotic network (Steels2005 [35]), that forms the basis for communication between the robot and the user and provides the basis for explanatory capabilities of a system. Because we are looking for ways to offer explanations of the observed behavior, it is important that the elements of the model are symbols that are grounded in the robotic soccer-playing world. Important work on Symbol Grounding has been done by Steels2005 [35] and Harnad1993 [15].

Therefore we need to classify sequences of actions into known behaviors like `Mark, Block, Pass` and determine for every agent the intentions that agent has. In the soccer-playing domain intentions have been investigate in the work of Rabinowitz1802 [30] and the BDI approach of Haddadi1995 [13].

We will be using actions as described in the STP implementation of our software (Browning2004 [3], Koning2017 [6]) and also in the Set-Pieces of the Futsal Coaching Manuals of FIFA, UEFA and KNVB [10, 40, 39].

VIII. The Analysis

This section needs to be rewritten to make the whole process more concrete.

During analysis all game situations are checked against two sets of rules; one describing agent movements and the possible intention an agent may have by taking this action, the second one describing situations to avoid, expressed as remarks. The Intent and Remark codes are the main result of the analysis and describe the reaction of a team to given game situations. These rules are described in Tables 3 and 4 The analysis is performed on two levels, the first one related to Ball Possession Turnovers, where the ball possession is changed according to the state diagram in Figure 3b, the second one related to the game situation of a single agent, as described in Table 1c. The other levels are used to search an entire game for similar game situations,

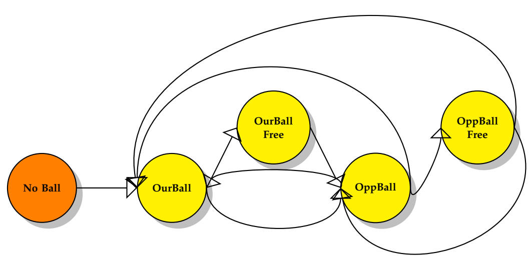
i. Creating Set-Pieces

We take information from the logfiles of past competitions and convert these into graphical representations in the form of set-pieces. To start with, we concentrate on the movements of defending agents, while the opponent is in possession of the ball and of passes from our team. We discussed set-pieces of these game situations with an expert Futsal coach to find explanations of the observed behaviors.

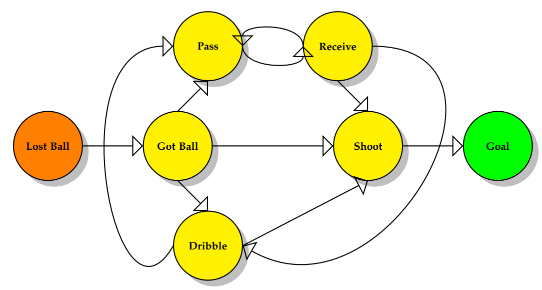
The actual analysis is done at the Ball Possession Turnover (BPT) level (See Figure 3b), which is a refinement of the Game Turnover (See Figure 3a). For each episode in the RefBox situation, an analysis is performed for each robot. This is done by comparing the start- and end conditions of the step and determining the main action of this step (like `Move` or `Intercept`) as well as the distance and direction of travel. When a step also includes shooting or dribbling actions or a change of ball possession, these take preference over moves. Based on the main action, the intention of that action is determined by using a set of simple rules, similar to those used by human analysts (See Table 3).

After that we compare the new situation against the expert rules and check if any of the moves violate these rules. If so, a warning is issued, which can be used to find an alternative action that does not violate the rules (See Table 4).

Figure 3: *Game Turnover States*



(a) *Game Turnover State Transition Diagram. NoBall means that ball is not seen. BallFree means that the ball is in between players*



(b) *Player Ball Possession Turnover (BPT) State Transition Diagram. Lost Ball means that ball is lost to the opponent. It is a subset of the states on the left.*

Each episode in a scene represents a possible state transition in the PBT state space (see Figure 3b), or the prevention of it. Preventions are found by threat analysis, which is based on assertions made by STP as recorded in the logfile. The resulting intention is the explanation how the threat is handled.

When analyzing a single agent's behavior, we need a mechanism to provide a context for this behavior. Therefore we also look at the events preceding the current game state and those following it, within the higher level episode. These are represented as successive set-pieces (See Figure 4)

ii. Passes and Defender Moves

To investigate passes we find game situations where one player kicks the ball and another player of the same team receives it. When the ball is received by the same player or when the ball is lost or ends up outside the field, we have a failed pass. In the case of a successful pass, we draw further conclusions about it's value and risk, based on what happens next. As explained in the work of Power2017 [29] the value of a pass depends on whether it results in a shot at the goal within a reasonable time. We therefore search in the succeeding episodes to see if the pass results in a shot at the goal. The risk of a pass depends on how likely it is that the opponent can capture the ball. This too is checked in the episodes, following the pass.

Defender moves are a bit more complicated. When a defender moves, we first need to establish the distance traveled. When only a small distance is crossed, this is ignored. The direction of travel is analyzed and we determine where the agent is heading. Is this towards an opponent and the agent stays close, than it is probably a `Marking` action. When it moves as a result of an attempt to intercept and a receive is the result, this is classified as an `Intercept`. When the agent travels to a location between opponents, but not close to one, it may be a `Blocking` attempt. Our log-files keep a list of opponents to defend and when an agent is moving towards one of these robots, it is Marking the opponent. Although we initially attempted to find explanations for all moves, interviewing the expert made clear that we needed to concentrate more on the risks, certain moves represented. Therefore we not only include an Intent field, but added a Remark field, in which we warned about possible dangerous moves, based on the expert's opinions, expressed in the rules in Table 4.

iii. Two Examples

Underneath we provide a simple example of a Defender Move while the opponent has the ball and another one of a Pass of our team. In both cases we show the analyzed intention and warning signals, when the move is not a good one.

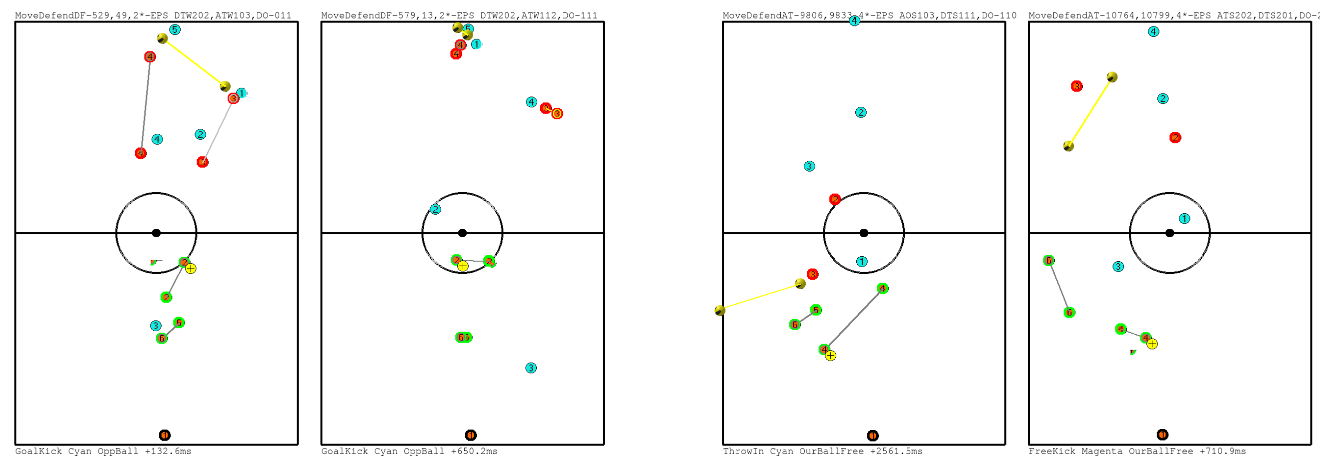


Figure 4: *Example of generated set-pieces. On the left a move in front of the ball, apparently awaiting some opportunity. On the right two defenders competing for the same opponent. (Later we will show the warnings. These are not yet the intended examples.) Also we need to include the penalty area on the field and the Intent and Remarks, associated with the examples.*

iv. Sessions With the Futsal Coach

Using printed set-pieces from previous competitions, we asked the Futsal Coach to comment on the actions, taken by the defending robots. First to see if we could find good explanations of the intention of the robots in those game situations. Secondly we were interested in his comments on those actions. However, finding good explanations proved difficult in many cases. Instead we received many comments on what would have been a better action. So finding explanations of the observed behavior did not seem so obvious as we anticipated, probably because of the way robots behave in comparison with human players. It proved simpler and much more insightful to signal erroneous or dangerous moves and to offer alternative actions. Several themes seemed to re-occur and so we compiled a set of rules (see Table 4), to extend the analysis rules, we already had created (see Table 3).

As a result of these findings we first perform an analysis to see if the robot adheres the aforementioned rules. If they do, this is taken as the explanation of their behavior. If not, a warning is issued, showing the expected action in

Action Type Analysis Rules			
Type	Action	Intent	Analysis Rule
Idle		Still	Do nothing
Move	No movement	Still	No movement detected
	MoveDef	MarkX	Moving close to opp defender
		BlockX	Block passage of opponent
Move	MoveBall	Intercept	Ball is captured
Intercept	Intercept	Received	Ball received
Shoot	Shoot	PassFail	Ball not received by peer
		PassTo	Ball received by peer
	ShootAtGoal	ShootAtGoal	Target is keeper
		GoalFail	Target is not keeper

Table 3: *Different action types and the rules, applied to determine their probable intention. Generic actions and rules are used to determine intention.*

the set-piece and the action is described as moving towards closest opponent or an opponent with a given role. When looking at the behavior of the opponent, these warnings identify weak spots, of which we must take advantage.

IX. Discussion

This section needs to be written, summarizing what has been done and explaining the results and plans we have with that. The tables underneath must be adopted to the examples and show the intents and remarks. The second table should show a collection of game situations that did lead to the same or similar actions, intents and remarks.

X. Future Work

Describe here our intention to work out more aspects and analyze more games. Then also describe how the information will be used in a neural network. Maybe make a reference to Attention Networks (and Universal Tranformers) where the game situations and intentions serve as the focal points of the attention, which is an important aspect of this new type of network.

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Expert Remark Rules		
Situation	Code	Action
Always	NoBallGoalCent	Our robots must be between our goal and the ball No robots in front of the ball, awaiting oportunities
OurBall	 NoPass, CanPass, Dribble PassShot, PassLoss	All robots move forward All robots are attackers Pass if you can, dribble if you must Determine the risk and value of a successful pass Have a rest-defender on your own half Play wide in length and width Think deep, play deep
OppBall	 CloserToOppBall NoCloseDef + NoDefs WideOppNoBall + Dist Dominance Our:Opp	All robots are defenders Put pressure on robot with the ball Around the ball play close to the opponents (small) Check if all opponents are marked Away from the ball, Mark and create space in the back (wide) Create dominance, 2:1 or 3:2, ball central Results in scrum situations

Table 4: *Situations that, according to the expert, should be avoided. They are shown in the analyzed set-pieces when violations of these rules are detected as remarks.*

Set-Piece Scenario													
St	Rw	Action	Start	Stop	Steps	Agent	BU	BT	Our	Opp	Agt	Intent	Dist
2	5	Intercept	9112	9115	4	2			AOW202	DTW301	AT-310,AT-310		0.01
	6	Idle				3					DO-010,AO-010		
	7	Pass				4	4				AT-230,DT-130	PassTo2	0.02
	8	Idle				6					DO-010,DO-010		
3	9	Intercept	9116	9123	8	2			AOW202	DTW211	AT-310,AT-330		0.14
	10	Idle				3					AO-010,DO-010		
	11	Intercept				4					DT-130,DT-110		0.07
	12	Idle				5					DO-010,AO-010		
4	13	Received	9124	9125	2	2,4	2		AOW202	DTW121	AT-330,AT-330	Received	0.02
	14	Idle				3					AO-010,DO-010		
	15	Intercept				4					DT-110,AT-110		0.01
	16	Idle				6					DO-010,DO-010		
	–	—-									——		
6	21	Move	9113	9134	2	2			AOW202	DOS001	AT-110,AT-110	MoveAt	0.05
	22	Idle				3					DO-010,DO-010		
	23	ShootGoal				4	4				AT-130,AT-130	ShootGoal	0.02
	24					6					DO-010,DO-010		

Table 5: *Example of a Set-Piece Scenario, consisting of 6 episodes, along with their analysis. This is a description of the set-piece in Figure 4.*

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Steps	RefBox	OurGS	AgtGSS	AgtGSE	Robot	STP Intent	Role	ActTyp	STP Action
2	KickOff Cyan	AOS301	DO-210	DO-210	2	Mark-AR[C2] +(2.31m)	Defend_Assist_1	Move	MoveTarget
4	KickOff Cyan	AOS301	DO-210	DO-210	2	Mark-AR[C2] +(1.97m)	Defend_Assist_1	Move	MoveTarget
2	KickOff Cyan	AOS301	DO-210	DO-210	4	Mark-AL[C1] +(1.96m)	Defend_Main	Move	MoveTarget
4	KickOff Cyan	AOS301	DO-210	DO-210	4	Move-AL[C1] +(4.65m)	Defend_Main	Move	MoveTarget
2	ThrowIn Magenta	AOW112	DO-210	DT-210	3	Mark-AR[C2] +(1.0m)	Defend_Main	Move	MoveTarget
12	ThrowIn Cyan	AOW112	DO-210	DO-210	6	Move-MC[C2] +(3.61m)	Defend_Assist_1	Move	MoveTarget
11	KickOff Cyan	ATS102	DO-210	DO-210	3	Move-AC[C3] +(4.0m)	Defend_Main	Move	MoveTarget
3	KickOff Cyan	ATS111	DO-210	DO-210	3	Move-AC[C3] +(4.0m)	Defend_Main	Move	MoveTarget
8	ThrowIn Cyan	ATS112	DO-210	DO-210	6	Move-MC[C2] +(3.61m)	Defend_Assist_1	Move	MoveTarget
3	KickOff Cyan	ATS121	DO-210	DO-210	2	Mark-MC[C2] +(0.95m)	Defend_Main	Move	MoveTarget
8	ThrowIn Cyan	ATS121	DO-210	DO-210	4	Move-DC[C2] +(5.51m)	Defend_Assist_1	Move	MoveTarget
9	ThrowIn Cyan	ATS121	DO-210	DO-210	6	Move-MC[C2] +(3.61m)	Defend_Assist_1	Move	MoveTarget
26	KickOff Cyan	ATS201	DO-210	DO-111	3	Move-MC[C1] +(3.56m)	Defend_Main	Move	MoveTarget
2	FreeKick Magenta	ATS202	DO-210	DO-111	6	Move-AL[C2] +(4.31m)	Defend_Assist_1	Move	MoveTarget
3	KickOff Cyan	ATS211	DO-210	DO-110	2	Mark-AR[C2] +(2.31m)	Defend_Assist_1	Move	MoveTarget

Table 6: *Result Table shows a grouping of team- and agent start- and end formations. The Intent column shows the analyzed intentions.*

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