KTH Computer Science
and Communication

Robocup Soccer

An evaluation of artificial intelligence about the differences and similarities between real and simulated football teams on the field

En studie i artificiell intelligens om skillnader mellan verkliga och simulerande fotbollslag

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Abstract

There have been an increasing interest in combining artifical intelligence with sports in the last decade. In the Robocup Simulation League soccer is simulated and a championship is held annually where several multi agent systems compete. What similarities and differences can be found between simulated soccer and real soccer? How is an effective team created? This essay examines methods of improvement by analyzing previous research and suggest new possible solutions.

The results of these litterary studies, identified similarities in the importance of role distributions on the field and the need for efficient tactics. The most significant difference found is that localization is a task that requires more effort in a simulation environment.

Several methods implemented in successful teams were identified and findings from this essay made several contributions to the current litterature.

Referat

En studie i artificiell intelligens om skillnader och likheter mellan verkliga och simulerade fotbollslag

Intresset att kombinera artificiell intelligens med sport har ökat under det senaste decenniet. I Robocup Simulation League simuleras fotboll och ett mästerskap hålls årligen där flera multi-agent system tävlar. Vilka likheter och skillnader finns mellan simulerad fotboll och verklig fotboll? Hur skapas ett effektivt lag? Denna uppsats undersöker metoder för förbättring genom att analysera tidigare forskning och föreslå nya möjliga lösningar.

Resultaten av dessa litterär studier identifierade likheter i vikten av rolldistributioner på fältet och behovet av en effektiv taktik. Den viktigaste skillnaden som identifierades är att lokalisering är en uppgift som kräver mer ansträngning i en simuleringsmiljö.

Flera metoder som implementerats i framgångsrika team identifierades och resultaten från denna uppsats gjorde flera bidrag till den aktuella litteraturen.

Foreword

This essay is part of the bachelor's degree at CSC, KTH. Before continue reading we would like to thank some poeple that contributed one way or another. Thanks to Johannes Linder for helping us with formulations. Special thanks to Simon Haque for a meeting and a discussion of references, football and proofreading. The last thanks goes to Krishan Johansson Haque for helping us understand references.

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Chapter 1

Introduction

Soccer, or as we say in Europe; football, is one of the biggest sports in the world. According to Forbes magazine the top ten list of the highest-paying sporting event of the world is occupied by four different football tournaments[1]. In recent years, there has been an increasing interest of combining football with computer science. Developments in the field of artificial intelligence in computer science have led to a renewed interest in simulation environments[2].

1.1 Problem statement

Implementing flawless artificial intelligence for digital football players is a complex task. The problem lies in creating a cooperating football team with players that are aware of the importance of different roles on the field. This essay will argue for this importance by analyzing how a real football team behaves. Are there differences or similarities between real and simulated football teams that can be exploited to enhance performance? If so, how can this be done?

1.1.1 Methodology

The questions raised in the problem statement are to be concluded by conducting a literature study of related research and theory in the field of artificial intelligence as well as football theory. By analyse and discussion of the aforementioned material the essay will present independent conclusions on the subject of integrating state of the art artificial intelligence models and real-world sport theory for optimizing the simulated play in Robocup, in order to find the link between artificial intelligence models and real world optimization problems.

1.2 Purpose

The past decade has seen the rapid development of artificial intelligence in many emerged areas such as video games and computational models. Further this concept has been encouraged to become combined and used in simulation environments[2]. These environments evolved into a competitive thinking and in the late 90's an initiative to a contest was made. The contest was an immediate success and over 5000 spectators attended the event[2]. This formed an annual competition called Robocup Soccer.

One of the most significant purposes of this essay is conveying that methods involving artificial intelligence is not only applicable for problem solving and optimization based on computations or statistical analysis, but may also be used to enhance performance in interdisciplinary areas such as sports. When a real soccer game is modelled in a simulation environment there are specific factors which have to be considered that deviates from the real soccer environment. For some specific situations there are no predefined regulations that would result in penalty in an actual soccer game.

Another objective of this degree essay is to examine and pinpoint the differences between real and simulated environments as well as analyzing distinct behaviors of a football team. However, since the analyzing is primarily focused on one team, the essay's content will partially reflect on their behavior.

1.3 Statement of collaboration

The concept of the collaboration has been divided into three different phases. The first two phases were made individual, and Marcus was responsible for the creative segment. The creative segment included observing a real team and determine efficient tactics for Robocup soccer. Daniel's liability was the analytic section. This section was to partially understand the source code of Robocup soccer as well as find various methods to implement solutions or to tune a given solvent. In response to both these sections, the third phase was to create a compilation of developed work as well as contribute with new solutions, which have been a shared task.

1.4 Overview of the document

This document is written in accordance with the Royal Institute of Technology bachelor essay template. This essay is part of the course DD143x and has been organised in the following way.

- Chapter 2 - Begins by laying out the theoretical dimensions of the research.
- Chapter 3 - Describes the design, characterization and evaluation.
- Chapter 4 - Introduce a generalized summary of findings
- Chapter 5 - Defines conclusion and describes the future work.

1.5 Definitions

1.5.1 Terms

High Pressure	Is a style of playing football. Pressure the opponents ball possessor
Agent	Simulated player on the field
Target	A specific area on the field
Box	Goalkeepers area

1.5.2 Abbreviations

GK	Goalkeeper; is the position rearmost of everyone on the pitch
CD	Central defender; is two positions just in front of the goalkeeper
LD	Left defender; is located to the left of the central defenders
RD	Right defender; equal to left defender, but to the right side instead
DM	Defensive midfielder; should always be centralized on the pitch
CM	Central midfielder; behind the forward and should also be centralized on the field
LW	Left winger; is right between forward and central midfielder
RW	Right winger; equal to left winger
FW	Forward; is in front of all fellow players
VO	Vector offset

Chapter 2

Background

2.1 Robocup overview

2.1.1 Server

The server in Robocup Soccer simulation league allows for autonomous soccer players written in various programming languages to connect to the server and play a simulated soccer game. This is a client/server architecture where communication is done through UDP sockets. The server sends strings of information on what each player sees, hears and their respective body data such as stamina[3]. Each client must then parse these strings to understandable and useful information objects. Controlling players is done by generating and sending action command strings to the server that updates the environment[3]. However, commands must be sent in specific time intervals for them to be executed since the server operates in cycles with different time durations[3]. This constraint leads to the need of efficient and synchronized clients to avoid missing important actions.

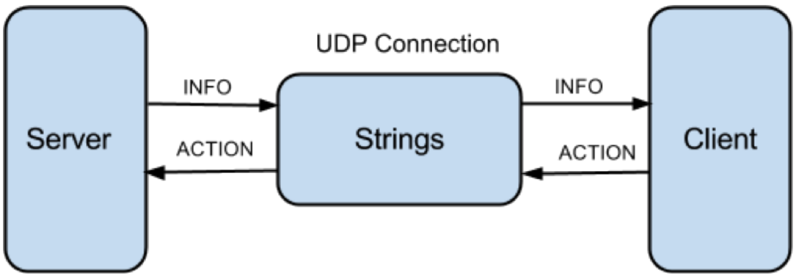

Figure 2.1. Server to client communication in Robocup Soccer Simulation League.

2.1.2 Monitor

The monitor is used to visualize a game but may also be used to judge a game by issuing yellow/red cards or perhaps assign a free kick. However using a monitor is not essential to play a game, but it is a good feature. All communication is handled between the server and the monitor which means that there is no interference with the clients.

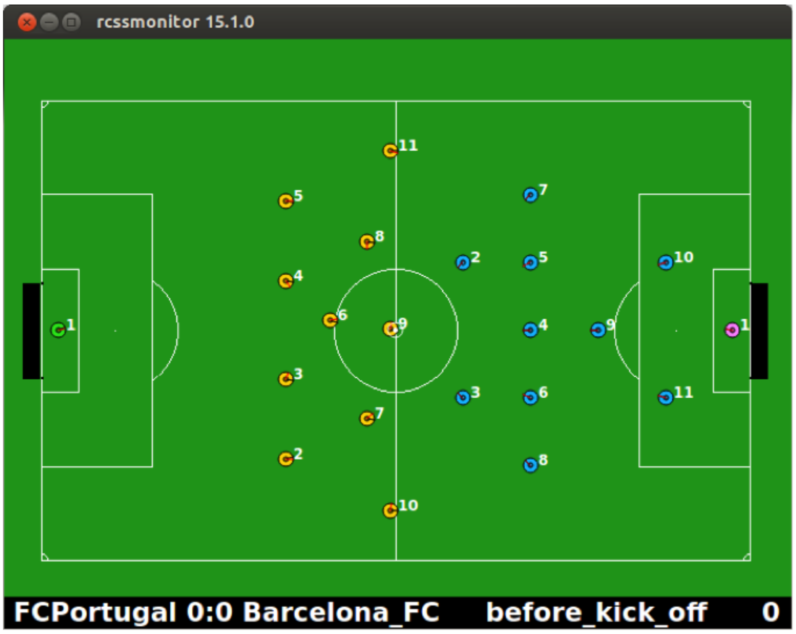

Figure 2.2. Visualization of a game in Robocup Soccer Simulation League.

2.1.3 Parsing using Atan Interface

Atan is an interface to the 2D Soccer Server of Robocup's simulation league[4]. This interface provides clear and understandable information by interpreting the server-to-client information. Implementing this interface relieves a client from performing the parse tasks mentioned in section 2.1.1, allowing the programmer to focus on controlling the players. Atan is a free software released under the MIT License[4].

2.2 Improving player performance

Improving player actions are vital in creating a successful team. One area of improvement in achieving effective actions is providing player localization on the field. Several methods to do this have emerged in recent years[5]. The estimation of a player's location is based on analysis of visual information and actions performed. One method to achieve localization based on Markov process theory is reviewed in section 2.2.1. Another area of improvement is creating learning players and one method based on machine learning is reviewed in section 2.2.2.

2.2.1 Markov localization

In a research paper from the institute for systems and robotics in Lisboa Portugal, an approach of player localization based on Markov processes is examined[5]. The approach is that a player location is expressed by a random variable L_t providing the position and orientation at time t, and this variable can be expressed as every location on the field. The probability that a player is at location l at time t is expressed by $Bel(L_t = l)$, and every location is updated with an according probability. To continuously update and calculate that belief, the task is to estimate a probability distribution according to given sensor data. With this distribution it is possible to calculate the conditional probability using equation (2.1)[5], where d_n is the set of all available sensor data.

$$Bel(L_t = l) = P(L_t = l | d_{1,\ldots,t}) \tag{2.1}$$

Details regarding computing the probability P is left out in this essay but is calculated using normal distributions with sensor data collected from each player[5].

The implementation of this Markov localization approach uses a divided representation of the field to represent the location of a player. Each possible location is divided into a grid where the location l is defined by a coordinate (x, y, θ) which represents the player coordinates and orientation. This grid approach is illustrated in figure 2.3.

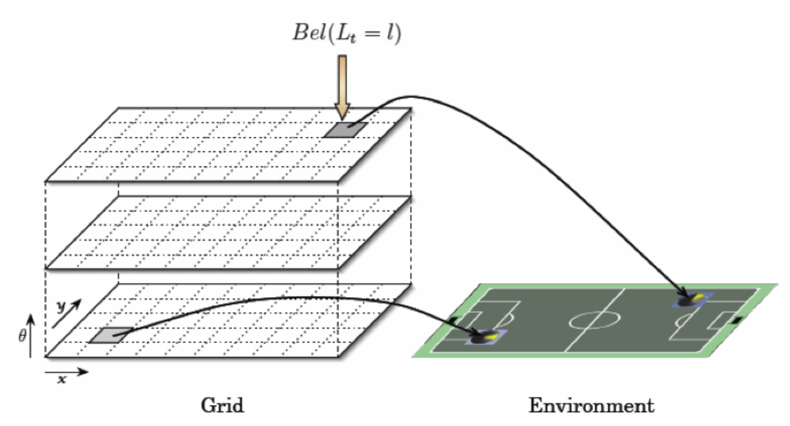

Figure 2.3. Transformation of grid coordinates into field coordinates. From [5].

Figure 2.3 illustrates that the belief $Bel(L_t = l)$ locates the player to some grid in this structure and each layer determines the current orientation of the player from all orientations possible.

2.2.2 Reinforcement learning

Reinforcement learning is a form of machine learning focused on maximizing some reward function according to actions performed by an agent in a specific environment. The environment that the agent operates in is usually defined as a markov decision process. In 2005, Stone et al. published a paper in which they described a method on implementing reinforcement learning for a subtask in robocup soccer called keepaway[6]. Keepaway is a task of maintaining possession of the ball in a limited region for as long as possible. Player actions are defined by the variable a_i to denote one action in the set of all actions. Following an action performed is the transition to a new state s_{i+1} with the reward r_{i+1}. The ultimate goal of keepaway is to maximize ball possession which means that the reward r_i is the number of server time cycles elapsed while following the previous action a_{i-1}. Thus maximizing the total reward is done by choosing action sequences that keeps the ball in possession for as long as possible. The task of choosing actions is handled by following different policies which in reinforcement learning is defined as a mapping from sets of states to sets of actions.

2.3 Integrating tactics knowledge

Integrating a formal tactic in digital players may be perceived as an abstract task focused only on the ball possessor, but recent studies have shown that several other areas need to be considered. In 2013, MacAlpine et al. published a paper in which they identified the importance of other agents positions in relations to the ball possessor[7]. To determine these positions in the most effective way, MacAlpine et al. introduced three steps. First step is to compute the team formation which will be precalculated for the best performance of a first formation between agents. Further they observed the formation by considering the ball position on the field, which means that agents positions relative to the ball position is represented by vector offsets. By using a predefined area, the vector offsets operates as boundaries between two different groups, with two separate assignations. The role positions are definite to these boundaries and by adding the vector offsets to the ball each agent is mapped to one of the groups which represent the formation[7].

The second step in MacAlpine's et al. theorem is to assign optimal role positions of agents compatible with the current formation[7]. The comparative study concluded that for a given team formation, each player (agent) needs to be mapped to a specific role, pursuant to MacAlpine's et al. definition; target positions on the field. Further the theorem argues that three properties must be fulfilled for a role assignment function to be valid[7].
A role assignment function is valid when:

1. Minimizing the distance an agent needs to travel.
2. The calculated path guarantee no collision when an agent might cross another agent's path.
3. When an approved role assignment function maps the agents, it will retain to it until amendment in the target position is formed.

The third step is to process incoming communication between agents and compute the best proposed position[7]. MacAlpine's et al. uses the ability to communicate and send messages between agents. These messages defines the mapping prefered by the individual agents. The most frequent mapping found is the one utilized[7].

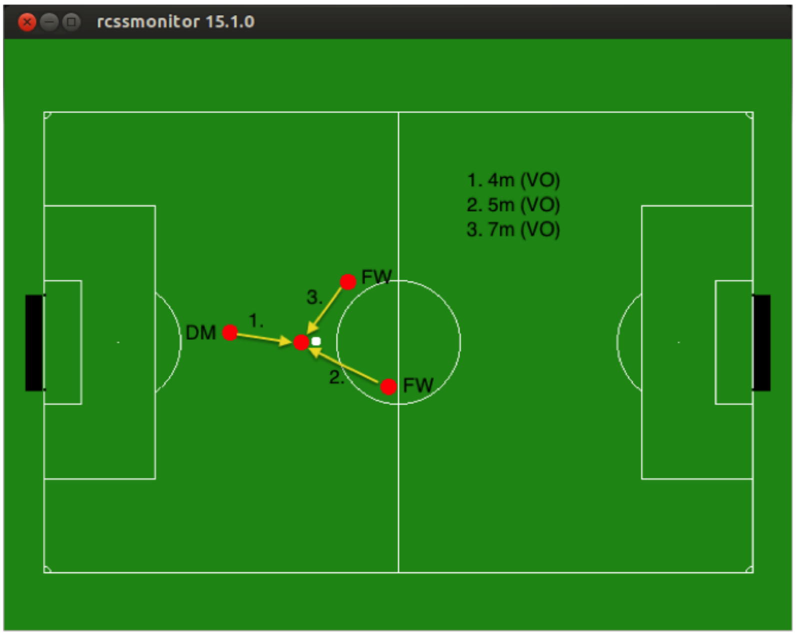

Figure 2.4. A demonstration of vector offsets.

2.4 Related work

This section describes characteristics of succesfully implemented teams in the Robocup Simulation League. FC Portugal and WrightEagle have both managed to win the Robocup Simulation League several times.

2.4.1 FC Portugal

FC Portugal is a team that resulted from research on multi-agent systems in a collaboration project between two universities and won the robocup 2000 simulation league[8]. The need for a set of roles and tactics to be distributed amongst players was identified, which enabled players to be assigned different positions and behaviours at any location on the field. A dynamic role exchange function was implemented enabling players to switch roles dynamically, and experiments showed that this function significantly increased performance[8]. Agents communicates when useful for the team, sharing world perceptions and information. To achieve successful team play, an algorithm to calculate optimal kicks was implemented. The algorithm samples random kick data and then fine tunes the outcome to achieve the best combination.

2.4.2 WrightEagle

WrightEagle is a team that have won the robocup simulation league championship three times since 1998[9]. A dynamic formation detection system was implemented to detect what formation an opponent team is using, which is used to position own players accordingly. To overcome the noisy sensor data a localization method called Monte Carlo localization was implemented. Localization is done by sampling sensor data and updating a belief on player positions. The team uses a heuristic search tree to find a potential future attack process in which a player is positioned to receive a future pass.

Chapter 3

Analysis

This chapter outlines different approaches that may be utilized to create a team in robocup soccer that behaves and acts like effective soccer players. They were formed by own observations and from analyzing the literature referred to in the background section.

3.1 Tactics - Pras model

The design of a team can be divided into two different groups. These groups have two separate workspace and they have been developed and modified after analysing the movement patterns of a real team.

3.1.1 Defense

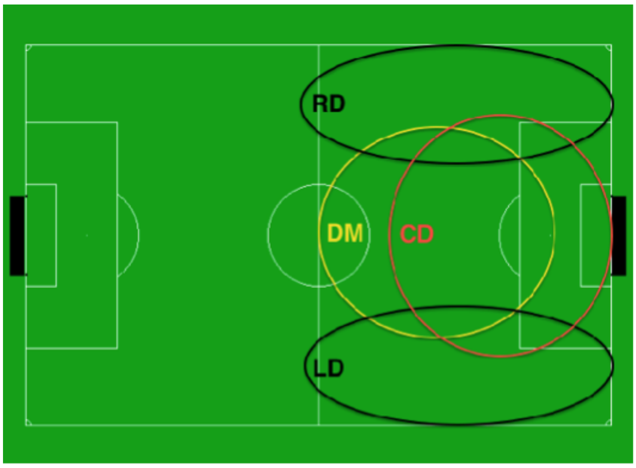

Figure 3.1. A visualization of the defense group workspaces.

The initial basis of defending is comprised of four individual player workspaces. These are central defenders, left defender, right defender, and one defensive midfielder.

An eligibility criteria requires central defenders to be at the rear most than the remainder of the team. Difficulties arise, however, when central defenders have to equal the rest of the defenders to enable a possible offside trap[10]. Central defenders expects to possess agility, speed and understand the game mechanics more thoroughly.

The criteria for left and right defender is endurance since they possess the highest workload amongst all. They should be able to play with high pressure as well as give support to the attacking group. The players are expected to possess speed, technique and persistent stamina.

The defensive midfielder has an essential part of the pressure. This role will give assistance to defenders through the middle of the pitch and put pressure on the possessive player. Defensive midfielder expects to possess persistent stamina, technique and understand the game mechanics.

3.1.2 Offense

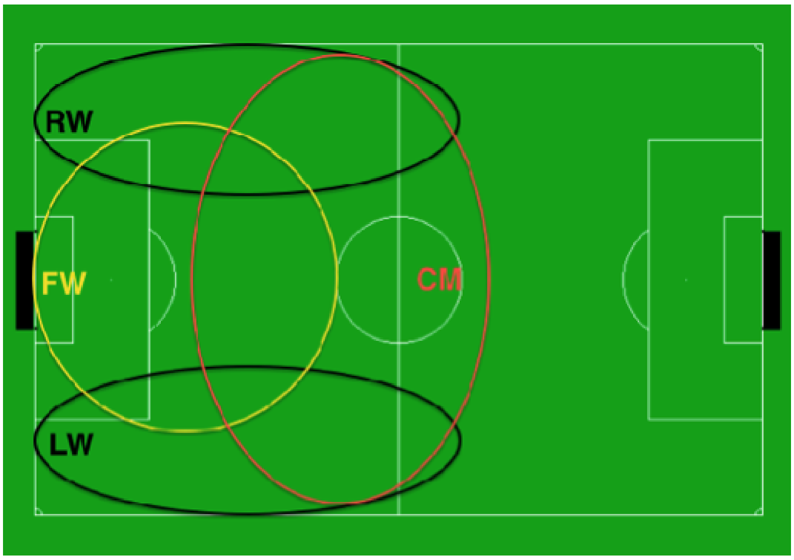

Figure 3.2. A visualization of the offense group workspaces.

The offense is comprised of four diverse player workspaces. These are central midfielder, left wing, right wing and two forwards.

A significant criteria of the central midfielder role is the accession between the separated groups. Another vital part of this role is the assistance to other players, since they will form a vaguely triangular positioning around the ball possessor.

Central midfielder expects to possess understanding of game mechanics and have persistent stamina.

The left and right wing provides an additional depth for the strategy. These roles should increase the game's pace and always be a threat for opponents defenders. They are expected to possess persistent stamina, pace and a good technique.

The characteristics of forwards are the mission to score a goal. They will always take the minimizing path to the goal, and always try to shoot in the box. Forwards should possess a good technique, good shot, and always be powerful.

3.1.3 Mentality

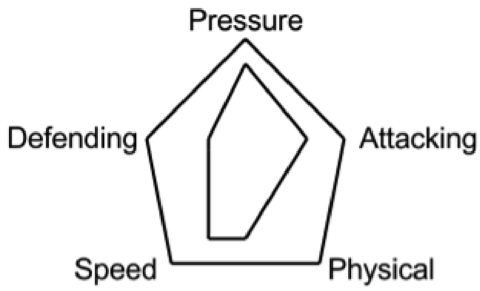

Figure 3.3. The pentagon represents the concept of the evaluated and determined tactics.

The purpose of a team's mentality is to formally define a foundation and give a team their characteristics. The mentality will act as basis to bring all individuals united and to ensure that the ultimate mission are fulfilled, to win the game. The importance to have this compound is to achieve appropriate tradeoffs, and provide an overview on the mentality overall.

To play with high pressure has its disadvantages such as minimal defensive thinking and physical approach. However, the advantage is more beneficial overall since the high pressure gains a recovery of a lost ball more rapidly as well as pace of the players.

In order to determine the mentality in RoboCup Soccer a criteria was prepared for enabling implementation. The criteria was to originate an eligibility from an abstract real world team orientation which provides guidance for how to implement this in a simulated team.

3.1.4 Use case

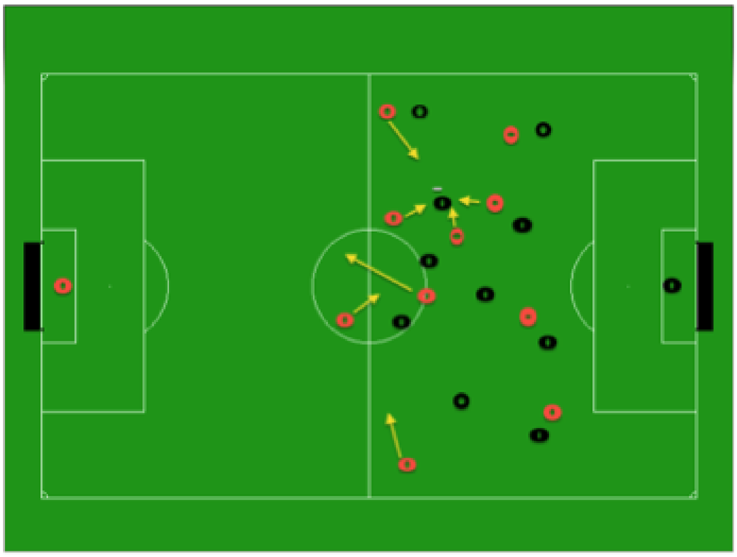

Figure 3.4. An event from a real game where arrows represents pressure on the opponents ball possessor.

If the offense group loses a ball, both groups has a crucial turning point to recover it. A criteria for the high pressure to work is that almost the entire team needs to be placed at the offensive half of the field. Through this the groups gain the possibility to recover the ball within seconds. Figure 3.4 demonstrates a possible outcome where pressure is placed on the ball possessor. Three different players are able to pressure current ball possessor from three separate positions in close distance. As a clear beneficial of a high pressure is the ability of baiting, which means that margins of error in a bad pass is probably more feasible to end where defenders or midfielders can absorb the ball. The main objective of this tactics is to make the field tighter and provide a falseness of teammates for the opponents ball possessor.

3.2 Key methods

3.2.1 Localization

One method of localization is recognised in this essay and is based on triangulation. This method of localization is less complicated than the approach based on markov theory examined in section 2.2.1. Perhaps the most serious disadvantage of this method is that it fails to take sensor noise into account. Another problem with this approach is that the player have to continuously alternate the view 90 degrees to update the location, according to figure 3.5.

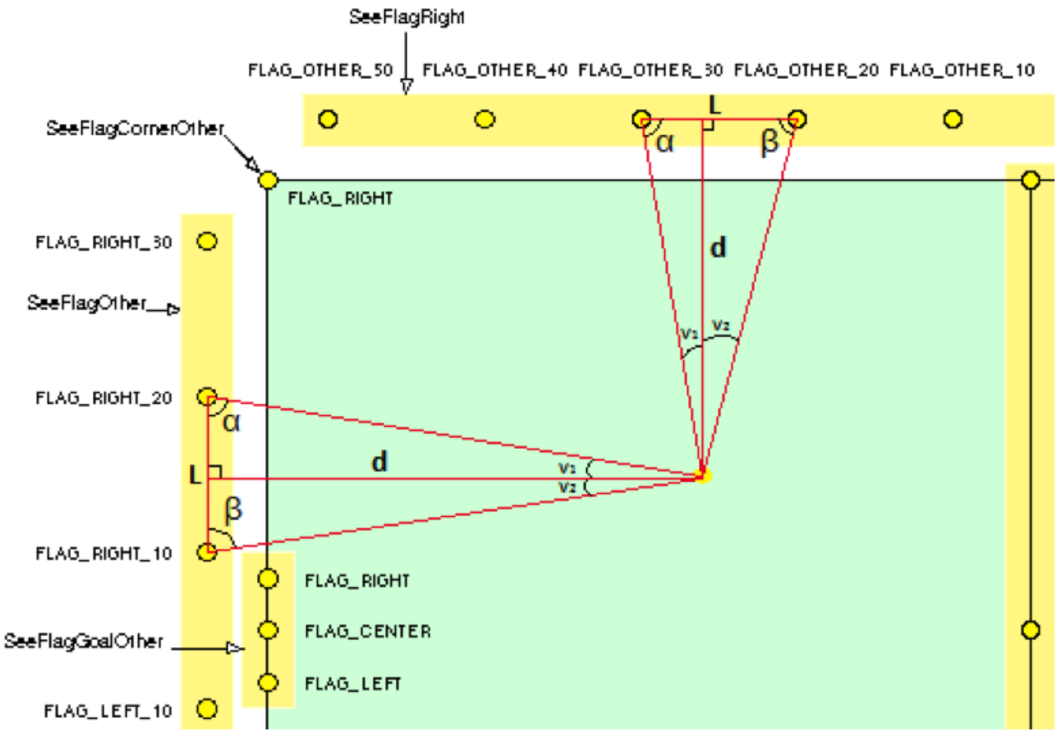

Figure 3.5. Top left part of a soccer field with possible visual information used for localization. Modified image from [4].

$$\alpha = 90 - v_1 \tag{3.1}$$

$$\beta = 90 - v_2 \tag{3.2}$$

$$d = \frac{L \times sin(\alpha) \times sin(\beta)}{sin(\alpha + \beta)} \tag{3.3}$$

Flags are visual objects placed at fixed locations around the field. When a player sees a flag it is provided with an angle and a distance to the flag. However this is not sufficient to determine a location, hence additional calculations must be done. Triangulation is a mathematical method of calculating the distance to an object by measuring angles to the object from two known points and their relative distance. Since a player is provided with angles to different flags, the angles used for triangulation can be calculated using equation 3.1 and 3.2. The distance is computed by utilizing the definition of triangulation, equation 3.3. Location is now provided since the field is a Cartesian coordinate plane and the distance is therefore equivalent to x and y-coordinates.

3.2.2 Integrating tactics

The correlation between Pras model (from section 3.1) and integrating tactics knowledge are subtle due to the theorem developed by MacAlpine et al. Furthermore the Pras model are based on two separate groups, with different preferences and division of labor. This view is supported by MacAlpine et al. (2011) who advocates two various groups with two different assignments[7]. Further these groups assign roles to each player depending on where they appear on the field. Each role assignment are based on MacAlpine's et al. theorem, role assignment function examined in section 2.3. Nevertheless, this strategy only takes two groups in consideration, and an extension in the Pras model has been made to further resemble a real team and improve from MacAlpine's et al. algorithm. In addition to dividing into two separate groups the Pras model splits one of the groups into subgroups of roles. The idea of dividing into subgroups of roles is to incorporate the high pressure and flexible transitions between roles. The mean score for the flexible transitions is to give a multivariate of role assignments, for example a central defender could hold an offensive position if necessary.

3.2.3 Machine learning

One area in which machine learning could be applied is the task of ball interception. This is a typical task in which reinforcement learning would be ideal. Intercepting the ball is done by a series of actions that turns the player towards the ball, dash and finally catch the ball. A reward function is needed to find optimal actions in each state. This means that when a ball intercepting sequence have started the player should tabulate the turn and dash data with the action chosen. Each state in the table should be updated with a reward representing which order the associated action had in this sequence. This means that the action performed in the state transitioning to the final state of catching the ball will have the highest reward. When the player is trained with several intercepting sequences it learns to choose the optimal action with the highest reward in each state, enabling the player to catch the ball in the minimal amount of steps.

Chapter 4

Discussion

This section will connect to the questions raised in section 1.1.

4.1 Role awareness

For players in an actual soccer game it is apparent that awareness of positions creates a dynamic team with alternating formations. An alternating formation establish an efficient method of mutable assignments of roles between players. The efficiency of a role assignment is measured in the severeness of defending against it. An eligible criteria for this is an increasing amount of work required by a defending player. This applies to Robocup Simulation League as well as the importance of dynamic role assignments is vital. Detailed examination of dynamic role assignments by MacAlpine et al (2011) argues that a static role assignment is less efficient due to the unpredictability of a game[7]. Pras model was prepared according to the theorem used by MacAlpine et al. (2011) and further developed as discussed in section 3.1. This combination of findings provides some support for the conceptual premise of the natural flow that appear in an actual game. Hence, it could conceivably be hypothesised that the similarity of the Pras model is reminiscent to characteristics of dynamic actual games.

4.2 Simulator characteristics

In the Robocup Simulation League noise is added to senses and actions to simulate unexpected events. Noise provides an element of realism since perceptions and actions are rarely accurate in real soccer environments. Previous research have shown that noise is a feature that should not be neglected since it will influence the accuracy in localization methods.

Another feature of the simulator that add to realism is a limitation of the number of actions executable at once, which implies that players should optimize action sequences. Disregarding this limitation causes the server to reject actions which impacts performance.

4.3 The digital player

Several similarities between actual soccer players and digital players have been identified in this essay. Learning from experience in actual soccer has proven to be just as important in simulated soccer. Methods utilizing reinforcement learning to learn from experiences is frequently implemented in successful Robocup teams. Subtasks like keep away and ball interception are distinctive tasks where reinforcement learning could be applied to increase performance.

Localization is an area where more effort is required in simulation environments to restrict players to field boundaries and possible dynamic boundaries. Another simulation restriction is the unawareness of other players physical locations. Observing other players is not sufficient to determine a location. Consequently locations must be shared amongst players through communication, which require every player to have the ability to self-localize.

4.4 Contributions

The present essay confirms the applicability of previous findings and contributes additional evidence that suggests how artificial intelligence could be implemented in simulated soccer. However, this essay has been unable to demonstrate the concepts through implementation. Instead a proof of concept was demonstrated by describing different approaches on machine learning, localization and tactics as they emerged as reliable predictors of an efficient team.

Chapter 5

Conclusions

The study have shown that there is a substantial amount of research done on the subject and several contributions have been made to the current literature from these findings. There is no definite solution in creating flawless artificial intelligence. However, a consistent theme in many successful teams is implementations on localization and machine learning. Hence these subjects have been a focus in this essay. Since there is such a substantial amount of research available there might be other implementations where focus is put on other areas not mentioned in this essay. This means that it is not possible to state that localization and machine learning is the best approach, even though it is common.

Efficient tactics is another area reviewed in this essay. Research have shown that by applying tactics to digital teams it is possible to significantly improve performance. Tactics is a subject often discussed in real soccer and is just as important in simulated soccer. This essay focused on tactics derived from a real team which means that they might not be suitable for simulated soccer even though there are many similarities between real and simulated soccer. However, the tactics model were combined with a well performing model, and thus the tactics should be applicable to this model.

The importance of role awareness mentioned in the introduction have been demonstrated in this essay and a role assignment function have been extended from an existing role assignment function. The findings of this study shows that there is several well performing teams that implements a role assignment function.

5.1 Future work

A future study on this subject could include implementations of the methods developed in this essay to assess performance. Comparing the implemented team with a well performing team would add another dimension to the measurements. Further previous research should be reviewed to either confirm or dismiss the proposal that localization and machine learning are the most important functions of an efficient team.

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