Case Based Game Play in the RoboCup Four-Legged League Part I The Theoretical Model

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Abstract. Robot Soccer involves planning at many levels, and in this paper we develop high level planning strategies for robots playing in the RoboCup Four-Legged League using case based reasoning. We develop a framework for developing and choosing game plays. Game plays are widely used in many team sports e.g. soccer, hockey, polo, and rugby. One of the current challenges for robots playing in the RoboCup Four-Legged League is choosing the right behaviour in any game situation. We argue that a flexible theoretical model for using case based reasoning for game plays will prove useful in robot soccer. Our model supports game play selection in key game situations which should in turn significantly advantage the team.

1 Introduction

Robot Soccer involves planning at many levels. In this paper we are concerned with developing high level planning strategies for robots playing in the RoboCup Four-Legged League. We develop a framework for developing and choosing game plays. Game plays are widely used in many team sports e.g. soccer, hockey, polo, basketball and rugby. There are several important differences between robot soccer in the Four-Legged League and human soccer, e.g. all the players on a team have the same physical capability so specialisation cannot exploit individuals physical talents. This is in contrast to the simulated league where it is possible for the players to have different attributes and physical capabilities. In addition because of their poor sensors, relative to humans, the AIBO robots possess a limited capability to predict detailed actions of others and hence there is little advantage to be gained from certain moves, e.g. *disguising a kick*.

Robot Soccer is a relatively new research initiative and in terms of its development it is in its infancy. One of the current challenges for robots playing in the RoboCup Four-Legged League is choosing the right behaviour, e.g. *the best kick*, in any game situation. Soccer is all about positioning; being in the right place at the right time. If a robot implements a kick then it needs to be in the best position to obtain maximum power and control.

We argue that a flexible theoretical model for using case based reasoning [8] for game plays will prove useful in the Four-Legged League. Our model will support game

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play selection in key game situations which should, in turn, significantly advantage the team. Case based reasoning has been used in other robot soccer leagues for various purposes. Most of the focus in strategy development has been in the *Simulated League*. The Simulated League lends itself to cased based techniques and to machine learning approaches because of the speed and flexibility of developing virtual robots as well as the ease and practicality of data collection during actual games.

In 1999 Wendler *et al* [10] developed a case based reasoning approach to action selection in the Simulation League, whilst Wendler, Kaminka and Veloso [11] provided a general theoretical case based reasoning model for robot coordination between team members. More recently, Gabel and Veloso [3] described a highly sophisticated case based approach to enhance the performance of the online coach in the Simulated League. Their system allows knowledge about previous match performances to be incorporated into the online coach's decision making process.

In this paper we propose a simple and robust cased based reasoning model for the RoboCup Four-Legged League that can be customised and enhanced. In a companion paper we will describe some experimental results that evaluate the model's performance using the UTS Unleashed Robot Soccer System (http://magic.it.uts.edu.au/unleashed).

2 Robot Soccer Game Play

A major benefit of developing a case base for robot soccer game plays is that it will result in a powerful knowledge base containing important knowledge about the game. A case base of game plays can capture creative genius and enduring principles of how to play the game for the purpose of teaching robots to play soccer more effectively.

Cases can describe set situations, like *kickoffs*, as well as running and passing game plays, attacking moves, and defensive formations. For any game situation, in our model, game plays are chosen based on the similarity between the current state of play and a collection of cases in the knowledge base. As our robot soccer multiagent system evolves, more ambitious new game play cases can be added, for example, as the robots become better at passing we can develop cases for *pass blocking*.

The game play strategies embedded in the cases can blend the lessons of the past with best guesses for future matches, and as such they incorporate some key elements for a winning game. The game play cases in the knowledge base can be selected depending on the type of game required. For example, if it is known that a particular opposition plays a certain style of game then the case base used could reflect specific tactics and strategies to counter that style.

Game play cases allow teams to string several plays together that take advantage of a teams' strengths. In other words, game play cases can form the building blocks of larger plans. Set game plays could prove critical for the success of team. In human games the difference between winning and losing is often the successful execution of set game plays in both offense and defense. In human soccer it has been calculated that as many as 40% of all goals scored are from set game play situations.

3 Case Based Reasoning in Conceptual Spaces

Categorisation of information helps robots reduce the complexity of the information they need to acquire and manage during their lifetime. In addition, the ability to categorise gives rise to broad powers of explanation. For example, without the ability to categorise, robots would not be capable of representing visual information beyond the pixel level, and as a result would not develop a world model that could support even simple forms of object recognition and reasoning. The ability to form and manipulate categories enhances robots capacity for problem solving, communication, collaboration etc. We expect robots to respond appropriately to information acquired through their sensory systems. The ability to categorise new sensory information and to anchor it to objects in the real world allows a robot to behave *sensibly* in previously unencountered situations[6].

For the purpose of this paper we believe that categorizing game situations will assist robots play better soccer. We use the conceptual spaces approach [4, 6, 5] to categorization driven by similarity measures.

Few concepts or categories of objects can be specified using necessary and sufficient conditions: Mathematical entities like *triangles* can, but almost all everyday objects, like *chairs* for example, defy explicit definition.

A similarity based approach to categorization is more widely applicable to robot soccer than explicit rules, because soccer playing robots need to make useful generalizations about previously unencountered situations. To play soccer well robots cannot be *hardwired* they must be able to respond appropriately to situations that were not foreseen at design time.

Conceptual spaces are multidimensional spaces that can be used to describe both physical and abstract concepts and objects. In contradistinction to the use of explicit (causality) rules to describe the relationship between objects, conceptual spaces adopt a similarity-based approach to categorization.

The main idea is that objects are categorized according to how similar they are to a prototype or (cluster of) exemplar(s). For instance, the colour *yellow* is more similar to *green* than it is to *blue*. For the purpose of robot soccer strategies we are interested in identifying prototypical or important game states and measuring the similarity across different game states.

Conceptual spaces are geometrical structures based on quality dimensions. Quality dimensions correspond to the ways in which stimuli/features are judged to be similar or different. Judgments of similarity and difference typically generate an ordering relation of stimuli/features, e.g. judgments of *level of control of the ball* generate a natural ordering from “weak” to “strong” [4]. There have been extensive studies conducted over the years that have explored psychological similarity judgments by exposing human subjects to various physical stimuli.

Objects are characterized by a set of qualities or features $\{\mathbf{q_1}, \mathbf{q_2}, ..., \mathbf{q_n}\}$. Each feature $\mathbf{q_i}$ takes values in a domain $\mathbf{Q_i}$. For example, the distance from a robot to the goal can take values in the domain of positive real numbers. Objects are identified with points in the conceptual space $\mathbf{C} = \mathbf{Q_1}$ x $\mathbf{Q_2}$ x $\ldots \mathbf{Q_n}$, and concepts/categories are regions in conceptual space.

For the purpose of problem solving, learning and communication, robots can adopt a range of conceptualizations using different conceptual spaces depending on the cognitive task at hand. For this reason we develop various meta-level strategies that determine the cases to consider and a number of pertinent similarity measures for our application in robot soccer.

For our current purpose, and without loss of generality, we often identify a conceptual space $\mathbf{C}$ with $\mathbf{R^n}$, but hasten to note that conceptual spaces do not require the full richness of $\mathbf{R^n}$. For example, in two of our similarity measure given in Section 4 we measure the distance between two objects on the soccer field using Euclidean distance, however we also develop a third qualitative similarity measure based on a partitioning of the field into strategic regions where each region can be given a weighting that represents its strategic importance (see Figure 1).

Similarity relations are fundamental to conceptual spaces [7]. They capture information about similarity judgments. In order to model some similarity relations we can endow a conceptual space with a distance measure; A distance measure d is a function from $\mathbf{C}$ x $\mathbf{C}$ into $\mathbf{T}$ where $\mathbf{C}$ is a conceptual space and $\mathbf{T}$ is a totally ordered set. Distance measures lead to a natural model of similarity; the smaller the distance between two objects in conceptual space, the more similar they are. The relationship between distance and similarity need not be linear, e.g. similarity may decay exponentially with distance.

A categorization results in a partitioning of a conceptual space into (meaningful) subregions. The geometrical nature of conceptual spaces coupled with representations for prototypes, and the ability to manipulate dimensions independently of one another ensures that they provide a highly flexible and practical representation of context-sensitive case-based reasoning.

Our cases consist of *prototypical situations* and *important situations* that are encountered during a soccer match. For example: kick off, a single attacking player in the goal penalty area, a player with the ball in a goal-end corner, or a player with the ball on the field border.

The cases have been developed over the last year through observation of the NUbot [1] team in practice matches and in competition matches at RoboCup 2002, and more recently during the practice matches of UTS Unleashed!. In Part II, the sequel to this paper, the cases will be refined and tested using experimentation. During the experiments robots will be placed in preselected positions and their behaviour monitored. Successful sequences of actions that lead to positive results will be adopted and incorporated into the cases.

Our aim is to develop a collection of cases to create a conceptual space for the purpose of providing strategic decision making assistance to robots. To that end we must define the appropriate quality dimensions, i.e. features, which will prove crucial for the similarity measure, and then the similarity measure itself. In addition, we identify some meta-level features which can be used to determine the set of cases that should be considered during a game.

Each of our cases consists of a set:

$$\text{Case} = \{\text{Field}, \text{Possession}\}$$

The State of the Field is described in terms of absolute coordinates with the center of the field prescribed as the origin of the coordinate system. The positive y-axis is directed along the opponents goal. In such a system we can then denote the position of the players by an ordered pair (x, y).

The state of the field is defined by the position of the players. We denote the set of our players by P and the opponents by the set P', where

$$P = \{p_1, p_2, p_3, p_4\} \text{ and } P' = \{p'_1, p'_2, p'_3, p'_4\}$$

Here $p_i = (x_i, y_i)$ and $p'_i = (x'_i, y'_i)$ are the absolute x and y coordinates of the ith player.

The Degree of Possession is another important dimension in our case. The degree of possession is a measure of which team possesses the ball and what the nature of that possession is.

Table 1. Degree of Possession

Possession	degree
no possession	0
no possession but in a scrum	1
possession but in a scrum	2
possession and clear	3
possession by the opponent team in the scrum	-2
possession by the opponent team and clear	-3

This numerical degree given to an otherwise qualitative characteristic will allow us to use it effectively in calculating a similarity between a current situation and our case-base.

In addition to the object level features we also use several meta-level features (or global parameters) that can aid in the selection of the appropriate strategy. For example, these meta-level features can help us identify a subset of the possible cases that should be considered in a given situation. Furthermore, they can also be used to resolve conflicts when two or more cases are "equally" similar.

The Situation involves a numerical evaluation that represents the context of the player with a high degree of possession. If the player with control of the ball has no obstacles between herself and the goal, then the team's situation is said to be "wide open" and is given a degree of 2. If the player with control of the ball has obstacles between herself and the goal, then the team's context is *clear* and assigned a degree of 1 and if the player is in a scrum then the situation is given a degree of 0. Negative numerical values are attributed to the above situations if the ball is in possession of the opponent team. A player's *situation* differs to a player's *degree of possession* in that the situation is determined by the global state of the field, whilst degree of possession only concerns the immediate vicinity of the robot.

The Score and the Time to Game Completion are two important meta-level parameters that can be used to determine the set of cases that should be considered. In this way the score and the time left in the game can influence the strategy. For example, an unfavourable score and a short time remaining might induce the robots to take more adventurous actions. In contrast a favourable score and a short time remaining could induce a more defensive behaviour.

Countering Opponent Team Strategies. This parameter can be advantageous in the case where reliable information about the opponent teams strategies can be obtained. For example if the other team is known to play a strong attacking game, then it would be in the interests of a team to ensure that they maintained possession of the ball at the cost of pushing the ball forward.

4 Measure of Similarity and Action

As mentioned earlier an appropriate measure of similarity is essential for developing strategies based upon past experiences. The performance of case based reasoning is strictly dependent on the quality of the similarity measure adopted. We intend to verify our similarity measures' effectiveness via experiment and for that reason we have developed several measures of similarity; two quantitative measures and one qualitative measure.

The quantitative similarity measures that we chose to make a correlation with a prototypical case and the current situation on the field are calculated by minimising the Euclidean norm.

Let N be the number of cases. Then the field in the j_{th} case can be represented as:

$$C_j = \{P_{ij}, P'_{ij}\}$$

We let the current field situation be represented by $C = \{Q_i, Q'_i\}$. If we now want to determine the similarity between a case C_j and the current situation, we have to come up with a pairing between the players in the case and the current situation. We will use a permutation π for this purpose.

For any given case C_j and given permutation π, we find the distance between the players

$$P_{ij}Q_{\pi(i)} = \sqrt{(x_{P_{ij}} - x_{Q_{\pi(i)}})^2 + (y_{P_{ij}} - y_{Q_{\pi(i)}})^2}$$

We construct a 4×4 matrix as follows

$$\begin{bmatrix} P_{1j}Q_{\pi(1)} & P_{1j}Q_{\pi(2)} & P_{1j}Q_{\pi(3)} & P_{1j}Q_{\pi(4)} \\ P_{2j}Q_{\pi(1)} & P_{2j}Q_{\pi(2)} & P_{2j}Q_{\pi(3)} & P_{2j}Q_{\pi(4)} \\ P_{3j}Q_{\pi(1)} & P_{3j}Q_{\pi(2)} & P_{3j}Q_{\pi(3)} & P_{3j}Q_{\pi(4)} \\ P_{4j}Q_{\pi(1)} & P_{4j}Q_{\pi(2)} & P_{4j}Q_{\pi(3)} & P_{4j}Q_{\pi(4)} \end{bmatrix}$$

A corresponding matrix can be constructed for the opponent team as well. We now look at two different methods of defining a quantitative similarity measure. Both of these methods can be easily extended to include a weighting given to the position of the players.

Method 1. The similarity measure is achieved by calculating the following:

$$\min_{k,\pi}\left(\sum_i\sum_k P_{i1}Q_{\pi(k)},\cdots,\sum_i\sum_k P_{ij}Q_{\pi(k)}),\cdots,\sum_i\sum_k P_{iN}Q_{\pi(k)}\right)$$

If the minimum is found for C_l and π, then we say that in terms of the field configuration the l^{th} case with player pairing π is the most similar to the current situation.

Method 2. In this method we first find the maximum distance between any two players:

$$d_j \text{ max } = \text{ max } \left(P_{ij}Q_{\pi(k)}\right) \qquad i,k = 1,\cdots 4.$$

The rationale behind this is that the similarity between two cases should be based on the time required to move all robots into the positions from one case to the other. Since each robot can move independently it can be done in parallel, hence it is enough if we look for the maximum distance.

The similarity measure is then found by: $\min\limits_{k,\pi}(d_1,\cdots,d_j,\cdots,d_N)$

Since we have to consider all pairings between our own players and between the opponent players, we have to compare all in all $N \times (4! + 4!)$ (sub-) cases with our current situation, i.e., we have to look at $48 \times N$ (sub-)cases. If we want to apply this method to larger teams, e.g., with 11 players, one clearly needs to employ different methods because we would have to consider approx. $(11! + 11!) \times N$ cases which is approximately equal to $8.0 \times 10^7 \times N$ cases. However, fortunately, one could use *minimal-weight perfect matching* [2] techniques at this point, which are polynomial in the number of players.

However it is important to note that our case actions are based solely upon the position of our team's players since we have no control over the movement of the opponent team's players. So in order to have a more comprehensive strategy we include in our analysis a subset of similar cases. Suppose that the similarity measure for the state of the field gives us a minimum distance D from a particular case. Instead of simply considering the best matched case, we could also consider cases which satisfy $D + \epsilon$ where ϵ is small. The best case can then be selected from this subset by taking a meta-feature such as the *situation* into account.

The qualitative measure of similarity is based upon the minimum number of moves that the players have to make to go from a particular situation to one of the situations in our case-base. To achieve this numerical value we divide the field into 30 strategic regions. For simplicity we assume that the various regions are rectangular regions. The sectors are created by dividing the field into three vertical regions and then each region is subdivided into four smaller regions (along the horizontal direction). The four corners thus generated are further subdivided into four regions. Each region or sector of the field is given a number to uniquely identify the region. The diagram of the field is shown in Figure (1).

We can then classify the regions by assigning them a number. Our *goal region* is given the number 0 and then starting from the field on our side we number the regions left to right. Each player is then given a corresponding number which is equal to the number of the region it is found in. We define our similarity measure by calculating the

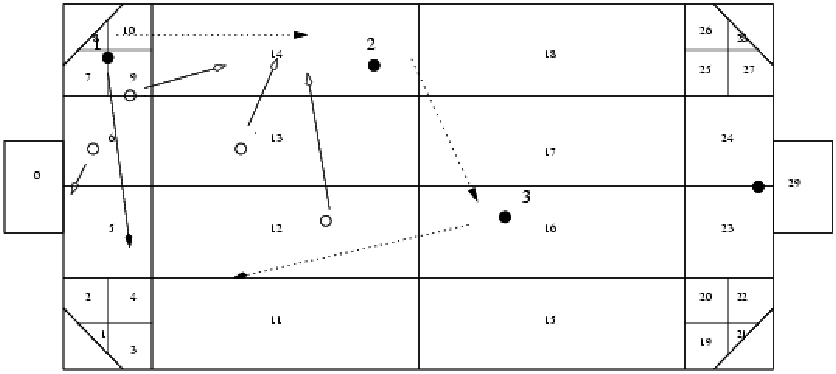

Fig. 1. The soccer field divided into 30 strategic regions and an example of game play scenario

minimum number of moves our players have to make to be in the same position as the case being compared with. We weight the moves as: a move towards the opponents goal is given a weight of $+2$, a move backward towards our goal is given a weight of -2 and a move to the left or the right is given a weight of $+1$.

5 Example

Let us consider a prototypical case in a soccer match; the player and the ball are stuck in a corner with the player facing away from the field and obstructed by an opponent player. The situation is represented in Figure (1) which illustrates the motion of the ball and the movement of the players. Our team players are represented by fully shaded circles while the opponent team players are represented by hollow circles. Dotted arrows indicate the motion of the ball and the arrows with a shaded head show the movement of our team players. The unshaded arrows indicate the motion of the opponent team players.

In this particular example, the strategy is to kick the ball backwards. As a result of the motion of the ball the opponent players move along the direction of the moving ball. The receiving player (Player 2) then kicks the ball back to Player 3. This motion leaves the situation wide open and without any obstructions and allows Player 1 to position itself in front of the opponents goal.

6 Discussion

Robot Soccer involves planning at many levels, and in this paper we developed a theoretical case based reasoning model for robot soccer strategies for the RoboCup Four-Legged League.

We argued that a flexible theoretical model for using case based reasoning for game plays will prove useful in robot soccer. Our model will support game play selection in common and key game situations which should in turn significantly advantage the team.

One of the current challenges for robots playing in the RoboCup Four-Legged League is choosing the right behaviour in any game situation. Our model allows robots to develop and choose game plays for any game situation.

We adopted the conceptual spaces framework which relies on the determination of prototypical situations and a measure of similarity across all situations. We developed three similarity measures for our model; two quantitative and a strategically oriented qualitative measure.

Having developed a theoretical model we intend putting it to the test using experimental evaluations, and have begun to develop our experimental framework using the UTS Unleashed! Robot Soccer Multiagent System.

One of the challenges for our future work is to extend our model to handle incompleteness and uncertainty. Throughout our discussion we have assumed that the robots world model is reasonably, but not perfectly, accurate, however in reality much of the information required to choose the best matching case may be simply *unknown* even in the case where robots can communicate. We expect our experimentation to reveal the best way to design for high level incompleteness and uncertainty and plan to address it using techniques given in Liu and Williams[9].

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