Exploiting Past Experience – Case-Based Decision Support for Soccer Agents
– Extended Abstract –

Ralf Berger and Gregor Lämmel

Humboldt University Berlin, Department of Computer Science
berger@informatik.hu-berlin.de, laemmel@vsp.tu-berlin.de
http://www.robocup.de/AT-Humboldt

Abstract. Selecting and initiating an appropriate (possibly cooperative) behavior in a given context is one of the most important and difficult tasks for soccer playing robots or software agents. Of course, this applies to other complex robot environments as well.

In this paper we present a methodology for using Case Based Reasoning techniques for this challenging problem. We will show a complete workflow from case-acquisition up to case-base maintenance. Our system uses several techniques for optimizing the case base and the retrieval step in order to be efficient enough to use it in a realtime environment.

The framework we propose could successfully be tested within the robot soccer domain where it was able to select and initiate complex game plays by using experience from previous situations. Due to space constraints we can give just a very brief overview about the most important aspects of our system here.

1 Introduction

Selecting and initiating an appropriate (long term and possibly cooperative) behavior in a given context is one of the most important tasks for autonomous robots in complex and dynamic environments. Various methods have been developed in order to determine the best action or the best behavior (in terms of action sequences).

Case Based Reasoning (CBR) is a method of problem solving and learning based on the principle of conclusion by analogy. In simple terms it means using old experiences to understand and solve new problems - a reasoner remembers a past problem/situation similar to the current one and uses this to solve the new problem.

The goal of the system we are about to introduce is to support the decision making processes of our soccer playing robots / agents with the help of experience gained by already played games. We found this particular useful on a higher behavior selection level, where the designer wants to influence the decision making processes in an easy and symbolical way. Our test scenario is the *wall pass*[1]

[1] Player one passes the ball to player two, who immediately passes it back to player one. The idea is to use the ball as a distraction for the opponent team to allow the passer to move into a position of advantage in order to receive the ball again.

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in RoboCup [1] – a typical coordination problem where a cooperative behavior has to be initialized and controlled only by individual cognition and reasoning. Although the *wall pass* is stated the simplest combination play in soccer, it is hard to achieve intentionaly for robots, especially without using communication.

Case Based Reasoning has been used in RoboCup for a long time and for very different purposes. [2] gives a very broad overview about what has been achieved so far in this field. An approach that is quite similar to ours in some aspects comes from Ros [3]. The major differences are that our system addresses the whole CBR-workflow and could already provide first results in a competitive environment.

As we already stated, we can only pick some interesting points from our work here, namely the topics of case acquisition, retrieval, case base optimization and maintenance.

2 Building Up a Case Base

The selection of a suitable case format is of vital importance for the Case Based Reasoning system. Basically the case format dictates by which features the similarity between a case from the case-base and a query situation is determined. Several spatial features are possible, like positions, velocities as well as game-based features as current score or remaining playing time. In the underlying domain, a snapshot of a situation seems to be sufficient to determine, whether a *wall pass* is possible or not. We think the possibility and utility of performing a *wall pass* most of all depends on the spatial relation between the involved players (attackers and defenders). Information about velocities are neglected here, especially since the perception of other's velocities is quite unreliable. Finally we define the similarity between cases / situations to be only dependant on the similarity of positional features. Thus, a case contains, besides the information about the class (*wall pass* possible/ impossible), the information about the players' positions on the field as quantified Euclidean coordinates.

For every CBR system the question comes up how to acquire cases for a first case base. Our test domain (RoboCup Simulation League) provides the exceptional opportunity to access a huge repository of logfiles of already played games. We exploit this pool of experience by building up our initial case-base from these matches. Our goal is, that after the primary case acquisition, the agents start to advance and extend their case-bases by own experience.
First, we have experimented with a fully automated case extraction. But because of the minor number of already played *wall passes* the automatic case acquisition was not suitable to built up the initial case base[2].

To get an initial case-base under these circumstances, we decided to extract all 'potential' *wall pass* situations automatically and to classify the situation manually afterwards. The thusly built-up case-base contains so far 1010 cases (560 cases belong to the class ***wall pass* possible**, 450 cases belong to the class ***wall pass* impossible**).

[2] However, after more teams are able to perform such game-plays intentionally, the automatic case acquisition could be again an option to acquire additional cases.

3 Retrieval

There are two key issues for the retrieval mechanism. Firstly, it should find the most similar case out of the case-base for a given query situation. Secondly, the retrieval needs to be fast, especially in the underlying domain. In spatial domains it is common to use a distance function to describe the relation between similarity and distance. In many approaches the similarity decreases with the distance according to a Gaussian function (e.g. [4]). However, in this approach the similarity is rather defined by degree of match of the quantified spatial features, then of the (spatial) distance. That means, a feature based retrieval mechanism was required. A Case Retrieval Net (CRN) [5] excellently meets those requirements. It provides an efficient and flexible way of retrieving a relatively small number of relevant cases out of a possibly huge case base. Especially, the avoidance of exhaustive memory search speeds up the retrieval. We not only show that the CRN work with a high grade of accuracy, but we also show that this kind of retrieval mechanism is very fast[3].

4 Case Base Optimization and Maintenance

It is obvious that the runtime performance of the retrieval mechanism does not only depend on the retrieval mechanisms itself, but also on the amount of information that a case in the case base describes. There are two opposed needs, on the one hand we want to reduce the information that a case describes (i.e. deletion of irrelevant players out of the cases). On the other hand we must keep the cases unambiguous, otherwise a case based retrieval is not applicable. In the underlying domain it is easy to see, that only a few players have an influence on the success of a *wall pass*. If a player can take influence depends on its spatial relation to the directly involved players. We developed a simple procedure to extract the relevant players. We could show that mostly 3-4 players are sufficient to describe a case sufficiently.

Using the procedure in 2 it's obvious that the initial case base contains some redundant cases. Thus we have to find a way to find and delete redundant cases. Competence models provide a way to identify redundant parts of knowledge-bases [6]. Smyth and McKenna introduced a competence model that select redundant cases based on their individual competence contribution [7]. We show that this model outperforms other (competence) models in the number of deleteable cases without a decrease of competence.

Maintenance in the context of CBR usually denotes the enduring adaptation, refinement and optimization of the system (mainly the case-base), as well as remedying deficiencies, in order to ensure or improve the usability and applicability of the CBR-system. It is substantial for the success of CBR in soccer programs, since the overall behavior of the teams or individual skills are subject to continuous changes. However, maintenance was often ignored for a long time

[3] For a given query situation, the retrieval of the most similar case takes not even 1 ms, although the case base is built-up of much more than 1000 cases.

[8], also in RoboCup. We have developed a framework and a tool-chain for offline maintenance of our case bases. It handles the automatic acquisition of new cases from own experience, the monitoring of consistency and redundancy within the case-base, analysis and optimization based on use- and success-histories to name only the most important things.

5 Conclusion

We have developed a methodology for using Case Based Reasoning for high-level decision making in the robot soccer domain. Our work encompasses the complete workflow of finding an appropriate case-format, the case-acquisition, defining similarity measures and an efficient retrieval, as well as providing optimization and maintenance tools. We have successfully tested the system in the RoboCup Soccer Simulation League with a first cooperative game-play (*wall pass*), where it showed very promising results. Right now we are working on applying it to other cooperative combination plays, e.g. free-kicks.

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