Soccer Robot Strategy for FIRA SimuroSot

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Abstract

Based on a new particle optimization method, a robust and flexible soccer robot control system, which could prepare simultaneously for several tasks and select the best one to execute, is proposed. Experiments and FIRA SimuroSot games show that, the soccer robot strategy is suitable and efficient.

1 Introduction

Robot soccer is entertaining game and challenging platform for robot control and Artificial Intelligence [1]. Situate in a highly dynamic and uncertain probabilistic environment facing a team of adversary agents which must be beaten, soccer robots must have the abilities of action planning and learning. Robot soccer games had been popular with educational institutions around the world since the inauguration of the FIRA competition in 1996 and the RoboCup competition in 1997. These initiatives provide a good platform for Artificial Intelligence domain research, dealing with issues such as co-operation by distributed control, real-time image processing, real-time robot path planning and obstacle avoidance.

Particle Swarm Optimization (PSO) is a stochastic global optimization approach introduced by Kennedy and Eberhart [2]. PSO is population-based optimization algorithm modeled after the simulation of social behavior of bird flocks. It includes aspects of genetic algorithms and evolutionary programming. Each potential solution is assigned a randomized velocity vector and the potential solutions called particles which can "fly" through the space in search of the function optima. Each particle keeps track of its coordinates in multi-dimensional space that are associated with the best solution (pbest) it has observed so far. A global best parameter (gbest) is used to store the best location among all particles. The velocity of each particle is then changed towards pbest and gbest in a probabilistic way.

In this paper, an action search strategy based on particle swarm option is proposed and implemented for a five-a-side robot soccer game. For soccer robots to perform like human beings, we build a task set for soccer robots and a hierarchical planning method. The robot control system works very well on FIRA soccer games.

2 Soccer Robot Strategy

Strategy is the soul of robot soccer system. In robot soccer games, images of objects on the field are processed by a vision system. Analysis of this raw data will yield information such as identification of objects including ball, player, and opponents. Other information such as object identity, opponent, position, orientation and velocity can also be computed [3]. Then, based on this information, soccer robot strategy controls robots to choose the appropriate behavior at each point in time given the overall goal of winning the soccer game.

A strategy is a set of mappings from situations to actions and can be defined as: f: S→A, in which, S means situations set and A means the action set. A good strategy must perform many complex information processing tasks in real time.

The usual approach to building a soccer robot strategy is the system based on knowledge and decision tree [3-5]. Figure.1. shows a typical paradigm of soccer robot strategy.

There are some disadvantages in the strategy based on decision tree. Firstly, some knowledge and preconditions are very difficult to acquire. Althought lots of methods, such as knowledge mapping, q-learning, and reinforcement learning (RL) methods have been used, flexible and effective knowledge and veracious preconditions often fail to meet the requirements. Secondly, strategy based on this architecture is inertial and could not adjust to nice change of the circumstances. Most of scenarios in the games are arranged by the strategy designer. In the mean time, it is very rigid when the top policy changed from one to another. Thirdly, and the most important is, this method didn't take account of the interactive relation between the layers. Infact, it is not reasonable make the top policy without calculating of advance action layer and basic action layer, especially when the related information is deficient.

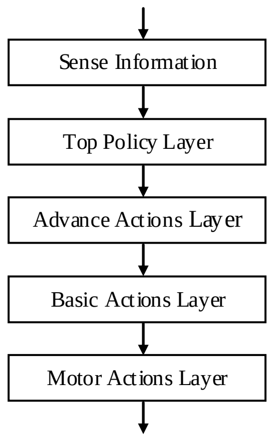

Figure 1: A traditional soccer robot strategy

3 Strategy Based on PSO

3.1 Strategy Layers

To match decision making paradigms of human and to use some knowledge derived from real soccer games, we keep down the hierarchical planning architecture as Figure 1. shows.

Top Policy Layer makes decision such as a) *Shooting*, b) *Dribbling*, c) *Passing*, d) *intercepting*, e) *Goalie*, and the desire direction of the ball in the future. Fig.2. is a *Passing*, a typical case of the top policy layer.

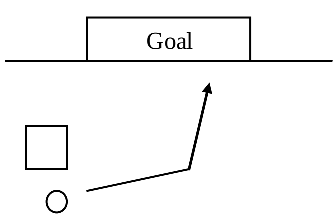

Figure 2: A typical case of the top policy layer: planning of passing.

Advance Actions Layer makes decision such as the ways to a certain task. Three cases in the advance actions layer planning shows as Figure 3.

Basic Actions Layer make decision terminal location, time cost, terminal pose and velocity of agents and so on.

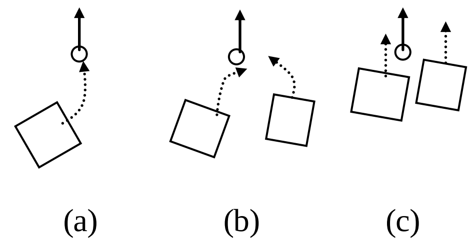

Figure 3: Three cases in the advance actions layer planning. (a) soloist, (b) converging attack, and (c) coopering.

3.2 A New PSO

We integrate planning layers with each other in the particles, which means, different planning layers be valued as a whole, but be initialized and evolved respectively. During valuating, some knowledge about the relationship between layers is taken into account. Fig.4. shows soccer robot strategy architecture based on PSO particle swarm.

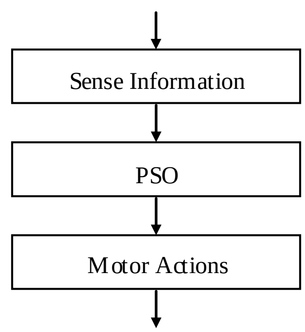

Figure 4: Soccer robot strategy based on PSO.

The structure design of PSO is very important. On the one hand, the particles should be easy to apply existing knowledge; On the one hand, they must own the powerful capacity to form knowledge. In the soccer robot strategy, we found that, without existing knowledge, it is not feasible to search solutions in real time. So we decompose the main goal into some tasks and apply related knowledge in the strategy. To make the swarm particles chase after different tasks at different situation, the structure of it is designed as Table 1. shows.

Table 1. Particle structure design.

Particle Structure
… …
applied layer no. list
particle fitness
… …
top policy layer structure_1
top policy layer structure_2
… …
advance actions layer structure_1
advance actions layer structure_2
… …
basic actions layer structure_1
basic actions layer structure_2
… …

With every *Planning Layer* structure designed as Table 2. shows:

Table 2. Planning layer structure design.

Planning Layer Structure
… …
parameters of the structure
velocity vector of the structure
position vector of the structure
… …

In the PSO, particles respected different solutions to different tasks. The structures be used, value-function, initialized and evolved methods are varied according to the situation of the game.

4 Simulation Study and Conclusion

We implement the soccer robot strategy based on PSO on FIRA SimuroSot 5vs5 platform. The simulation experiments show that, it is a robust and flexible soccer robot control method.

Statistics of instantaneous working particles kinds show as Table 3. Results show that, there are always more than one tasks being prepared simultaneously, but only the best one be selected and executed. The turning from one task to another is smooth and efficient.

Table 3. Working particles frequency.

Kinds	Frequency
1	3
2	10
3	21
4	41
5	25

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