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Behavior Acquisition in RoboCup Middle Size League Domain

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1. Introduction

The RoboCup middle size league is one of the leagues that have the longest histories in RoboCup. This league has unique features, for example, bigger robots (around 45cm square) plays on the largest field (say, 18m×12m in 2007), any global sensory system is not allowed to use, all robots have on-board vision systems and controllers. Each robot plays based on its own sensory information, and it can share some information with teammates and a coach box located outside the playing field over wireless communication, then, shows some cooperative behaviors among them during the game.

This chapter briefly introduces research activities in RoboCup middle size league. A variety of research topics have been attacked in this league. Some of them are common to other real robot leagues such as small size and 4-legged leagues. For example, robust real-time on-board vision system, precise localization based on vision system, and design of cooperative behavior are actively investigated in RoboCup middle size league. On the other hand, skill and cooperative/competitive behavior acquisition/emergence based on machine learning techniques is also well-studied. The latter is focused on in this chapter.

First, a purposive behavior acquisition of a single robot based on machine learning technique is introduced. Reinforcement learning is one of machine learning techniques and extensively studied to be applied to acquisition of robot behavior like shooting a ball into a goal. It has a simple framework and algorithm to be applied to robots however some difficulties exist in practical use because of its simplicity. In order to overcome these problems, some modular learning and hierarchical systems have been proposed. Not only reinforcement learning but also evolutional methods have been investigated as well. Some examples will be shown.

Next, studies on cooperative/competitive behavior acquisition based on machine learning techniques are introduced. Application of machine learning to multi-agent system usually has some difficulties because of complex dynamics of the system. The complexity is induced by decision making by multi-players, growing amount of information to decide an action by an individual, perceptual aliasing, and so on. In order to reduce the complexity, wireless communication between teammates is commonly used. In case of unavailability of communication between players, for example, lack of communication with opponents,

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methods of situation estimation and acquisition of appropriate behavior in the estimated situation has been proposed. Finally, discussions and future work are given.

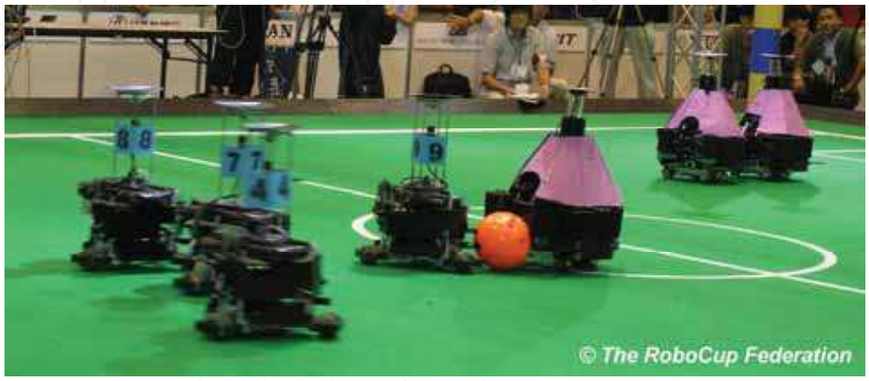


Fig. 1. A game scene of middle size league from RoboCup2005

2. RoboCup Middle Size League

Robots of no more than 50 cm square play soccer in teams of up to 6 robots with an orange soccer ball on a field whose size is 18×12 meters. Matches are divided in 15-minute halves. Overhead cameras or external sensors around a field are forbidden in this league. Almost robots have omni-directional cameras and some of them have additional ordinary cameras in order to detect a ball and localize themselves on the field. A referee box system is introduced for conveying referee decisions to robot players without interception of operators from the teams. It successfully enhances the autonomy of the game. Robots have omni-directional vehicles with 3 or 4 omni-wheels and maximum speed of robots is up to 4 m/sec, then, precise motion control and localization are necessary. All robots have ball kicking devices and speed of a kicked ball is up to 11 m/sec. The devices can kick a ball upward, therefore, fast and better image understanding and price control are required especially for a goalie to prevent a loop shoot. Because the size of the field has become larger and larger, more cooperative behaviors among teammates should be taken in a game.

3. Behavior Acquisition Through Trials and Errors

We briefly review reinforcement learning scheme for various behavior acquisition/executions first then introduce some examples of acquisition of basic skills.

3.1 Layout of Manuscript

Fig.2 shows a basic framework of reinforcement learning. An agent can discriminate a set S of distinct world states. The world is modeled as a Markov process, making stochastic transitions based on its current state and the action taken by the agent based on a policy π.

The agent receives reward r_t at each step t. State value V^{π}, the discounted sum of the reward received over time under execution of policy π, will be calculated as follows:

$$V^{\pi} = \sum_{t=0}^{\infty} \gamma^t r_t \tag{1}$$

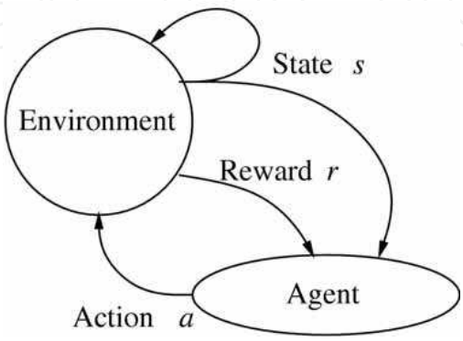


Fig. 2. Agent-environment interaction

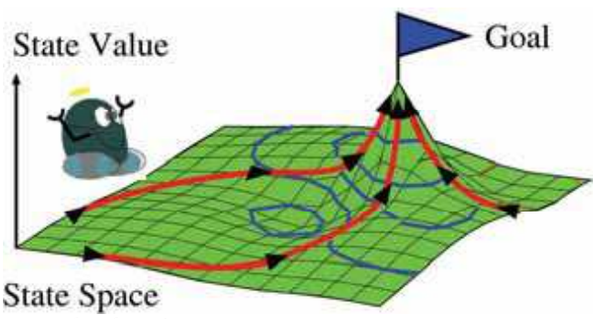


Fig. 3. Sketch of state value function

Fig.3 shows a sketch of a state value function where a robot receives a positive reward when it stays at a specified goal while zero reward else. The state value becomes highest at the state where the agent receives a reward and discounted value is propagated backward to the most recent states.

The state value increases if the agent follows a good policy π. The agent updates its policy through the interaction with the environment in order to receive higher positive rewards in future. Analogously, as animals get closer to former action sequences that led to goals, they are more likely to retry it. For further details, please refer to the textbook of Sutton and Barto(Sutton and Barto, 1998) or a survey of robot learning(Connell and Mahadevan, 1993).

3.2 Basic Behavior Acquisition

As an early study of applications of reinforcement learning techniques to a real soccer robot, acquisition of shooting behavior is investigated (for example, (Asada et al., 1996)). Recent investigation has been continued by teams. For example, Brainstormer-Tribot team has

applied reinforcement learning to dribbling behavior of a real robot without any computer simulation based on physical world and robot models, and the robot acquires an appropriate motion for the behavior within reasonable time.

Asada et al.(Asada et al., 1996) presented a method of vision-based reinforcement learning by which a robot learns to shoot a ball into a goal. Several issues in applying the reinforcement learning method to a real robot with vision sensor by which the robot can obtain information about the changes in an environment were discussed. A state space was constructed in terms of size, position, and orientation of a ball and a goal in an image of an ordinary camera (shown in Fig.4) and an action space is designed in terms of the action commands to be sent to the left and right motors of a vehicle. In order to speed up the learning time, a mechanism of Learning from Easy Missions (or LEM) is implemented.

LEM reduces the learning time from exponential to almost linear order in the size of the state space. At this moment, the behavior was acquired in a soccer simulator on a workstation and the acquired behavior is implemented on a real robot.

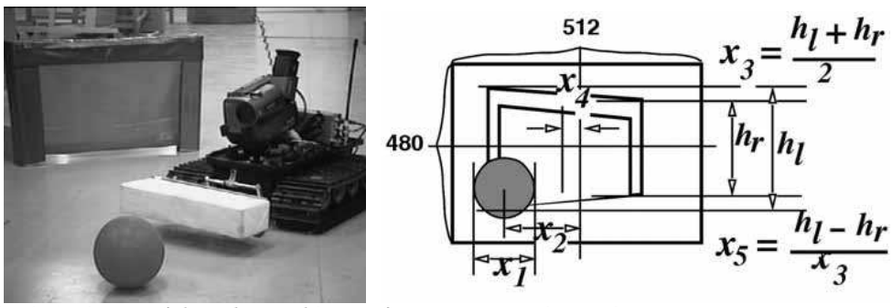


Fig. 4. A picture of the robot and image features composing an input vector

3.3 State Space Construction

Reinforcement learning has been investigated as a method for robot learning with little or no a priori knowledge and higher capability of reactive and adaptive behaviors. However, there are two major problems in applying it to real robot tasks: how to construct a state space, and how to reduce the learning time. Robot learning such as reinforcement learning generally needs a well-defined state space in order to converge. However, to build such a state space is one of the main issues of the robot learning because of the inter-dependence between state and action spaces, which resembles to the well known "chicken and egg" problem.

Asada et al.(Asada et al., 1995) proposed a method of robot learning by which a set of pairs of a state and an action are constructed to achieve a goal. A state is defined as a cluster of input vectors[1] from which the robot can reach the goal state or the state already obtained by a sequence of one kind action primitive regardless of its length, and that this sequence is defined as one action. The input vectors are clustered as hyper ellipsoids so that the whole state space is segmented into a state transition map in terms of action from which the optimal action sequence is obtained (see Fig.4).

[1] An input vector usually consists of the sensory information. An example is shown at the right side of Fig.4.

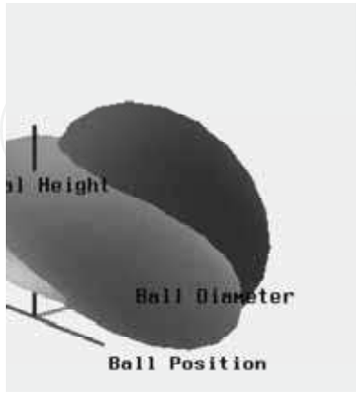


Fig. 5. An example of state space construction

Takahashi et al (Takahashi et al., 1996a,b) presented a method by which a robot learns a purposive behavior within less learning time by incrementally segmenting the sensor space based on the experiences of the robot. The incremental segmentation is performed by constructing local models in the state space, which is based on the function approximation of the sensor outputs to reduce the learning time, and on the reinforcement signal to emerge a purposive behavior. The method is applied to a soccer robot that tries to shoot a ball into a goal. The experiments with computer simulations and a real robot were carried out. As a result, a real robot has learned a shooting behavior within less than one hour training by incrementally segmenting the state space.

Uchibe et al. (Uchibe et al., 1998a,b; Asada et al., 1998, 1999) proposed a method that estimates the relationships between learner's behaviors and other agents' ones in the environment through interactions (observation and action) using the method of system identification. In order to identify the model of each agent, Akaike's Information Criterion is applied to the results of Canonical Variate Analysis for the relationship between the observed data in terms of action and future observation. Then, reinforcement learning based on the estimated state vectors is performed to obtain the optimal behavior. The proposed method is applied to a soccer playing situation, where a rolling ball and other moving agents are well modeled and the learner's behaviors are successfully acquired by the method.

3.4 Towards Complex Behavior Acquisition

A simple and straightforward application of reinforcement learning methods to complex behavior acquisition is considerably difficult due to its almost endless exploration of which time easily scales up exponentially with the size of the state/action spaces, which seems almost impossible from a practical viewpoint. One of the potential solutions might be application of so-called modular learning and multi-layered system in which a set of expert modules learn and one gating system weights the output of the each expert module for the final system output. This idea is very general and has a wide range of applications. Stone and Veloso (Stone and Veloso, 1998) has proposed to introduce layered learning system

with basic skills such as “shootGoal”, “shootAway”, “dribbleBall”, and so on. Kleiner et al (Kleiner et al., 2002) has also proposed multi-layered learning system for behavior acquisition of a soccer robot. Their experimental results show that the performance of the acquired behavior learned by lower and higher modules simultaneously is better than the one of the behavior that lower and higher modules are trained separately. However, we have to consider the following two issues to apply it to the real robot tasks:

- Task decomposition: how to find a set of simple behaviors and assign each of them to a learning module or an expert in order to achieve the given initial task. Usually, human designer carefully decomposes the long time-scale task into a sequence of simple behaviors such that the one short time-scale subtask can be accomplished by one learning module.
- Abstraction of states and/or actions for scaling up: To accomplish a complex behavior, much sensory information is taken into account and the exploration space for learning behavior based on the information easily becomes huge. In order to cope with complicated real robot tasks, more abstraction of the states and/or actions is necessary.

A basic idea to cope with the above two issues is that any learning module has a limited resource constraint and this constraint of the learning capability leads us to introduce a multi-module and multi-layered learning system. That is, one learning module has a compact state-action space and acquires a simple map from the states to the actions, and a gating system enables the robot to select one of the behavior modules depending on the situation. More generally, the higher module controls the lower modules depending on the situation. The definition of this situation depends on the capability of the lower modules because the gating module selects one of the lower modules based on their acquired behaviors. From the other viewpoint, the lower modules provide not only the rational behaviors but also the abstracted situations for the higher module; how feasible the module is, how close to its subgoal, and so on. It is reasonable to utilize such information in order to construct state/action spaces of higher modules from already abstracted situations and behaviors of lower ones. Thus, the hierarchical structure can be constructed with not only experts and gating module but also more layers with multiple homogeneous learning modules.

Takahashi and Asada (Takahashi and Asada, 2000) proposed self-construction of hierarchical structure with purely homogeneous learning modules. Since the resource (and therefore the capability, too) of one learning module is limited, the initially given task is automatically decomposed into a set of small subtasks each of which corresponds to one of the small learning modules, and also the upper layer is recursively generated to cover the whole task. In this case, the all learning modules in the one layer share the same state and action spaces although some modules need only the part of them.

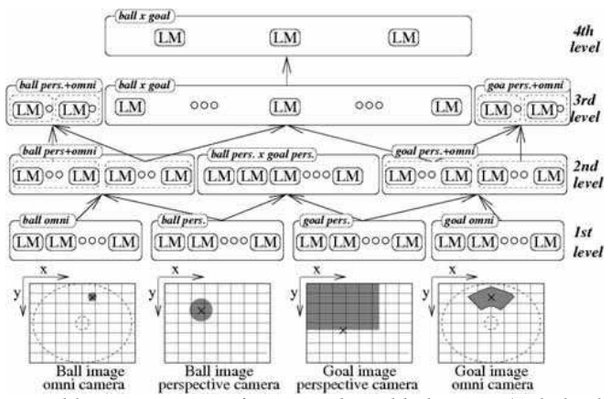


Fig. 6. A multi-layered learning system for vision based behaviors (Takahashi and Asada, 2001)

Their following work (Takahashi and Asada, 2001, 2003) focused on the state and action space decomposition according to the subtasks to make the learning much more efficient. Further, Takahashi et al, (Takahashi et al., 2003b, 2005c; Nishi et al., 2006) realized unsupervised decomposition of a long time-scale task by finding the compact state spaces, which consequently leads the subtask decomposition.

4. Cooperative/Competitive Behavior

Cooperative/competitive behavior realization is one of the most interested topics in RoboCup community. Peter stone et al.(Stone et al., 2005) proposed "keep away" task in RoboCup simulation league and many investigations have been done on the task (for example, (Kuhlmann and Stone, 2004; Taylor and Stone, 2004; Stone et al., 2005)). The topic also interests people participating in RoboCup middle size league. In this section, related works are briefly introduced.

4.1 Cooperation Via Environmental Dynamics

Cooperation is one the most important issues in multiagent systems. There is a trade-off between the centralized control and the distributed one from the performance viewpoint of cooperation. Takahashi et al.(Takahashi et al., 2001) proposed a method to emerge cooperative behaviors via environmental dynamics caused by multi robots in a hostile environment without any planning for cooperation. Each robot has its own policy to achieve the goal with/without explicit social behavior such as yielding. Co-existence of such robots in a dynamic, hostile environment produces various environmental dynamics, in which the heterogeneous robots can be seen as cooperating each other. Fig.7 shows an example of how the two robots recover each others' failures quickly. Two type robots, A and B, were prepared in this case. Type A robot is selfish, skillful and careful to shoot a ball. On the other hand, Type B is moderate and not so skillful but has a much fast shooting behavior. (1) indicates that the two different robots follow a ball. Type B robot tries to shoot a ball to the opponent goal at (2). But it failed at (3) because the ball handling skill of type B is not so good, and type A robot recovers the failure soon. Type A robot tries to shoot the ball, but the

opponent goalie defends it at (4). Type A robot tries to shoot the ball from left side of the goal at (5) and (6), but unfortunately fails again while type B robot moves its position behind type A robot. Type B robot tries to recover the failure of type A robot's shooting at (7), and it shoots the ball successfully after all at (8).

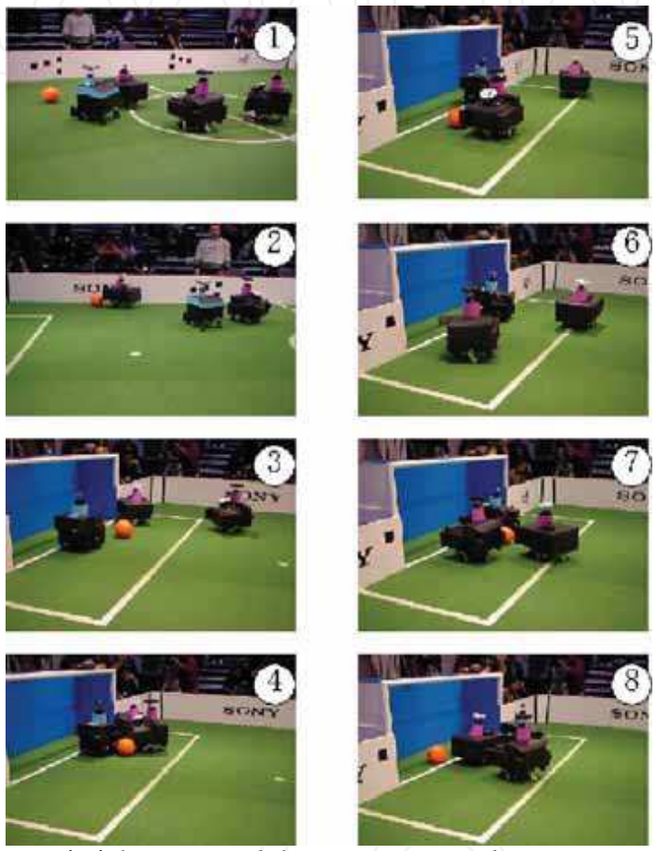


Fig. 7. A sequence of a failure recovery behavior among two robots

4.2 Strategy Learing for a Team

Team strategy acquisition is one of the most important issues of multiagent systems, especially in an adversary environment. RoboCup has been providing such an environment. A deliberative approach to the team strategy acquisition seems to be difficult for applying in such a dynamic and hostile environment. Takahashi et al.(Takahashi et al., 2002b) presented a learning method to acquire team strategy from a viewpoint of coach who can change a combination of players each of which has a fixed policy. Assuming that the opponent has the same choice for the team strategy but keeps the fixed strategy during one match, the coach estimates the opponent team strategy (player's combination) based on game progress

(obtained and lost goals) and notification of the opponent strategy just after each match. The trade-off between exploration and exploitation is handled by considering how correct the expectation in each mode is. A case of 2 to 2 match was simulated and the final result (a class of the strongest combinations) was applied to RoboCup-2000 competition.

4.3 Emergence of Cooperative Behavior Though Co-evolution

Co-evolution has been investigated as a method for multi agent simultaneous learning. Uchibe et al.(Uchibe et al., 1998c,d; Uchibe and Asada, 2006) discussed how multiple robots can emerge cooperative behaviors through co-evolutionary processes. As an example task, a simplified soccer game with three learning robots is selected and a GP (genetic programming) method is applied to individual population corresponding to each robot so as to obtain cooperative and competitive behaviors through evolutionary processes. The complexity of the problem can be explained twofold: co-evolution for cooperative behaviors needs exact synchronization of mutual evolutions, and three robot co-evolution requires well-complicated environment setups that may gradually change from simpler to more complicated situations so that they can obtain cooperative and competitive behaviors simultaneously in a wide range of search area in various kinds of aspects.

4.4 Dynamic Roll Assignment Based on Module Conflict Resolution

It is necessary to coordinate multiple tasks in order to cope with larger-scaled and more complicated tasks. However, it seems very hard to accomplish the multiple tasks at the same time. Uchibe et al.(Uchibe et al., 2001) proposed a method to resolve a conflict between task modules through the processes of their executions. Based on the proposed method, the robot can select an appropriate module according to the priority. In addition, they applied the module conflict resolution to a multiagent environment. Consequently, multiple tasks are automatically allocated to the multiple robots.

4.5 Coping with Behavior Alternation of Others

Existing reinforcement learning approaches have been suffering from policy alternation of others in multi-agent dynamic environments that may cause sudden changes in state transition probabilities of which constancy is needed for behavior learning to converge. A typical example is the case of RoboCup competitions because behaviors of other agents may change the state transition probabilities. The keys for simultaneous learning to acquire competitive behaviors in such an environment are

- a modular learning system for adaptation to the policy alternation of others; and
- an introduction of macro actions for simultaneous learning to reduce the search space.

Takahashi et al.(Takahashi et al., 2005a,b; Edazawa et al., 2004; Takahashi et al., 2003a, 2002a) presented a method of modular learning in a multi-agent environment in which the learning agents can simultaneously learn their behaviors and adapt themselves to the resultant situations by the others' behaviors.

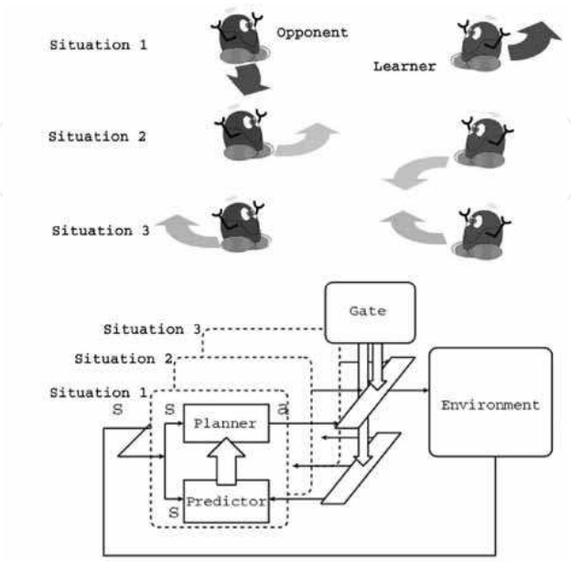


Fig. 8. A multi-module learning system in multi-agent environment

4.6 Behavior Based on Estimation of Status of Others

The existing reinforcement learning approaches have been suffering from the curse of dimension problem when they are applied to multiagent dynamic environments. The keys for learning to acquire cooperative/competitive behaviors in such an environment are as follows:

- a two-layer hierarchical system with multi learning modules is adopted to reduce the size of the sensor and action spaces. The state space of the top layer consists of the state values of the individual modules at the lower level that indicate how close to the goals, and the macro actions are used to reduce the size of the physical action space, and further,
- other's state estimation modules by observation are added in order to estimate to what extent the other agent task has been achieved and the estimated state values are used in the top layer state space to accelerate the cooperative/competitive behavior learning.

Takahashi et al. (Takahashi et al., 2006) showed a method of modular learning involving the above two issues, by which the learning agent can acquire cooperative behaviors with its team mates and competitive ones against its opponents. The method is applied to 4 on 5 passing task, and the learning agent successfully obtained the desired behaviors.

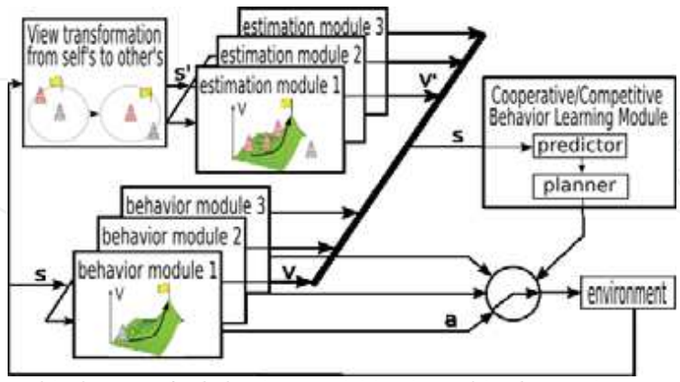


Fig. 9. A hierarchical system for behavior acquisition in multi-robot environment

5. Discussion and Future Work

This chapter briefly overviewed research activities, especially on behavior acquisition/ emergence based on machine learning techniques, in RoboCup middle size league. This research area has kept attracting people and been investigated not only in middle size league but also other ones such as simulation soccer and 4-legged leagues. Many results of applications of machine learning techniques to robots in the RoboCup domain show promising contributions to generate adaptive behaviors in real situations. On the other hand, many difficulties in practical use have also been unveiled so far. For example, selection of important features for purposeful behaviors, purposive behavior discovery through observation of others, self task decomposition and integration, rapid team strategy adaptation during a game, and so on, are to be investigated furthermore. One of the goals of RoboCup is "By the year 2050, develop a team of fully autonomous humanoid robots that can win against the human world soccer champion team."(Federation) A game of a middle size league robot team v.s. a human team was demonstrated in RoboCup2007 Atlanta USA. The human team showed much better performance than the robot team although it won the championship in the middle size league this year. Taking achievements in the past decade into consideration, however, we foresee that robots will play soccer with human players, learn many skills, cooperative/competitive behaviors, team coordination, positioning in the teams, fast adaptation of team strategy, and so on through interaction during games, and finally a robot team beats the human world soccer champion team.



Fig. 10. A demonstration game scene of robot and human teams

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Many papers in the book concern advanced research on (multi-)robot subsystems, naturally motivated by the challenges posed by robot soccer, but certainly applicable to other domains: reasoning, multi-criteria decision-making, behavior and team coordination, cooperative perception, localization, mobility systems (namely omni-directional wheeled motion, as well as quadruped and biped locomotion, all strongly developed within RoboCup), and even a couple of papers on a topic apparently solved before Soccer Robotics - color segmentation - but for which several new algorithms were introduced since the mid-nineties by researchers on the field, to solve dynamic illumination and fast color segmentation problems, among others. This book is certainly a small sample of the research activity on Soccer Robotics going on around the globe as you read it, but it surely covers a good deal of what has been done in the field recently, and as such it works as a valuable source for researchers interested in the involved subjects, whether they are currently "soccer roboticists" or not.

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