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KIRC Team

KIRC

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Abstract. *Our robot perceives environment with a single CCD camera, and it moves that two motors controlled independently. All robots are "complete autonomous". Therefore, we do not use a host computer.*

The robot has a Note PC for "image processing" , "object recognition" and "select an action." In "image processing" and "object recognition" program, it is easy setting with GUI to correspond to a change of environment that extracts color of objects and establish a threshold. "Select an action" is applying reinforcement learning(see section "Reinforcement learning").

The robot has the circuit board to control the motor. This board was connected to the parallel port in the Note PC. It is composed of a motor control unit and an interface unit by CPLD (Complex Programmable Logic Device). The personal computer can control right and left motors independently by this board in five states each backward and forward.

A specific role such as Goal-keeper, Defender and Attacker is given to each robot, because the robot is completely autonomy. The robot works cooperatively by the allotment of the role like this.

1 Reinforcement learning

Reinforcement Learning has been receiving attention as a method that an autonomous robot could select an appropriate action in each state automatically with little or no premise knowledge. The result of the robot learning activity creates a policy that maps states to actions to maximize some functions of the reinforcement signal. Q-learning [1], a well-known reinforcement learning, try to learn an action-value function to find optimal policy with respect to some object functions. Informally, this means that it tries to associate a value to each state or to each state-action pair so that such value can be used to implement a control policy.

Typically, even if an autonomous robot has continuous sensor values, they are quantized to reduce learning time. This quantization makes the action-value function a function defined on discrete sensor space. As a result, learning algorithms working on the discrete space are easily designed and analyzed from a point of optimal control. However, reinforcement learning algorithms including Q-learning suffer from lack of robustness and lack of generalization.

To overcome the above, we propose a Stochastic Field Model (SFM [2]) which is the reinforcement learning based on Q-learning and creates mapping that maps a state to an appropriate action(s) for autonomous robots. In SFM, the action-value function is represented by a summation of weighted base functions. The autonomous robot adjusts weights of base functions through interactions with a given environment. Other parameters (center coordinates, variance and so on) are calculated automatically by unification of two similar base functions.

The behavior of the soccer is so complicated that it is not easy for application of simple robot learning. Thus, we think that hierarchical control structures is useful for this problem. We constitute a hierarchical control structure which consists of modules called a subtask and rely on the programmer(who are we in this paper) to design a hierarchy of modules. We train the robot to carry out each subtask by reinforcement learning in SFM so that the robot learns the behavior of the soccer. We design the hierarchical control structure to do the soccer and train the robot from the bottom of the hierarchy.

2 Conclusion

For the **RoboCup**, we try to train real robot to learn a behavior of the soccer through the reinforcement learning in SFM. The robot is shown in Figure 1. It has one video camera in order to identify and track colored objects (ball, goal, and other robots).

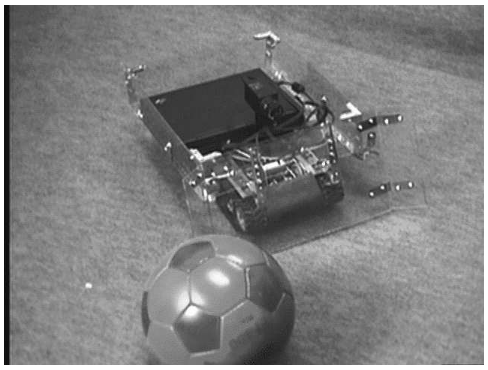

Figure 1: Real soccer robot which has one video camera

The behavior of the soccer is so complicated that it is not easy for application of simple robot learning in SFM. Thus, we think that hierarchical control structures shown in Figure 2 is useful for this problem. We constitute hierarchical control structures which consists of modules called a subtask and rely on the programmer(who are we in this paper) to design a hierarchy of modules. We train the robot to carry out each subtask by reinforcement learning in SFM so that the robot learns the behavior of the soccer. We design the hierarchical control structures so as to do the soccer and train the robot from the below of hierarchy[3].

References

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