Chapter 44
Decision Making Under Multi Task Based on Priority for Each Task

Takuya Masaki
Muroran Institute of Technology, Japan

Kentarou Kurashige
Muroran Institute of Technology, Japan

ABSTRACT

In recent years, autonomous robots become to be desired to treat multi-task. A robot must decide a concrete action for plural objectives. Major researches try to realize this by weighted rewards. Weighted rewards can represent a human's intention easily. But weight of each task must change dynamically by a change of surrounding situation or of a robot status. Authors consider an independent learning for each task and selection of one concrete action from candidates of each learning. Authors propose a priority function to calculate priority for each task corresponding to surrounding situation or a robot status and propose a system which do decision making by using the priority function. Authors confirmed the usefulness of proposed method with simulation.

1. INTRODUCTION

In recent years, practical use of robots in human living space is underway by some researchers. Robots are requested complicated and flexible behavior in human living space (Connell and Mahadevan, 1993). For example, a cleaning robot has cleaning task and power supply management task. And a cleaning robot focuses either task. For this demand, researches to a robot with learning function (Sutton and Barto, 1998; Kaelbling et al., 1996) for multi task has been conducted. In this study, authors focus on reinforcement learning. In reinforcement learning, a robot has been given a single task from human. But, a robot is demanded to accomplish the multitask for complicated and flexible behavior in various environments. A robot must decide a concrete action for plural objectives. Major researches try to realize this by weighted rewards (Tanaka and Yamamura, 1997; Aoki et al., 2005; Tanaka and Yamamura, 2003;

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2001). These methods add weighted rewards for each task and make a single reward function. Using this reward function, an agent does action learning in single learning space. If a relationship between tasks are changed, weights for each task are changed. If weights for each task are changed, reward that calculated by a reward function is changed and Q values that should converge by learning are changed. There is a problem that needs to relearning when reward function and Q values that should converge are changed. Moreover, if adding new tasks or deleting unnecessary tasks, there is a problem that needs to relearning.

Therefore, if a human gives various tasks to an agent in various environments, an agent takes a long time to adapt. Moreover, when number of tasks is increased, authors set weight of all tasks in advance and considering all tasks at the same time is difficult. When every time task is increased, time that until a robot outputs action becomes long.

Authors propose a method of action learning and action selection method in a robot, then if that is given multitask. Thereby, even if the relationship between each task is changed and each task priorities are changed, a robot can do action selection corresponding its change.

2. APPROACH

If a robot has multi task, importance for each task is changed by a situation. If a robot does action learning by using one reward function, a robot needs to relearn every time to change importance of each task. In order to solve the problem, proposal technique designs individual reward functions for each task and configures learning space for each task. An action value for one task is accumulated in one learning space by configures learning space for each task. Therefore, if adding a new task or deleting an unnecessary task, adding or deleting its reward function and learning space. However, if a proposal system configures learning space for each task, there are action candidates that is selected for each task.

Authors focus on importance of each task, because the system must specify one action from plural action candidates. Importance for task is changed according to changing the situation. Therefore, the system must specify one action by considering importance for each task. For example, if a task to stabilize a battery of a robot, the more decrease battery, a priority becomes higher. The priority for task that given by human are changed by human degree of hope.

In this study, a system selects conclusive action based on priority for each task. Thereby, even if a robot is given multitask, authors aim to realize a method that can do action selection from priority for each task.

3. PROPOSAL TECHNIQUE

3.1. Outline of Proposal Technique

In this paper, authors propose the action learning and the action selection method of a robot that has multi task. Proposal method is roughly divided into the action selection part and the action learning part. The system does action learning for each task in the action learning part. In the action learning part, the system does action learning and accumulate action value into learning space. Thereafter, action value that learned is passed to action selection part.

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