Rational Balancing of Planning and Communication in the Dynamic Multi-Agents World

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Abstract

This paper presents an adaptive, knowledge-based agent model that makes rational decisions in balancing the cost of planning and communication. The agent's ability to balance these factors is very important in a multi-agents world and in a dynamic environment where balancing deliberation and execution cost is crucial.

To realize this ability, we introduce two behavioral parameters, namely, the *projection level* and the *commitment level*. It is difficult to design these parameters because there exists the tradeoff between the plan's optimality and the agent's adaptability which, in turn, affects the balance between deliberation and reaction. In our earlier work, we gave fixed parameter values to the agents[2]). In this case, parameter tuning was the major task to make the agents robust. And now in this paper, as the second stage, we have designed a type of meta-knowledge which is based on the previous results of the agent. This meta-knowledge is given to the agent to adapt to the world by deciding the appropriate parameter values according to his own state and the world state.

We describe experimental results that show how the agent can control his time cost of planning and communication by changing these values. Furthermore, to break the limitations of the knowledge-based control method, we show a preliminary result of using a reinforcement learning algorithm to coordinate these parameters by the autonomous agent.

Problem Domain: We consider a world consisting of the multiple agents, the objects of actions, and the bounded resources that are not always available to all agents. We have examined the problem of "Coilyard of steel manufacturing" as a good example[2]). We modeled this problem as a kind of *tileworld problem*[1] consisting of 100×2 grid. We regard a crane, including the operator, as an agent moving in the upper line, the coil in the initial address as a tile that will be taken by the certain agent, and the designated address in the yard as a hole. The tiles and holes are in the lower line. The agent regards the other two cranes as a moving barrier, because cranes are running on the same rail. The set of tasks, which indicates the addresses of tiles and holes, are given before planning, and a new set of tasks can be added but never removed during plan execution.

Agent Rationality: We have defined the *rationality* of the agent as the balance between the plan's optimality and the adaptability to the change. To realize the rational agent, we introduce the two control parameters. **(1)Projection Level** decides how far the agent projects his future situation. If the agent has sufficient time, he is able to communicate completely and plan carefully. But if he is in a critical situation, he approximately plans his actions, and he reacts with primitive actions without doing a full-scale simulation. **(2)Commitment Level** decides the extent to which the agent adheres to his current plan. If the agent is unable to execute his plan, delay will accumulate as time passes. There are three replanning options, *interleaving* actions, *rescheduling* the current plan with no change of his goal, and *reallocation* to change his goal.

Reinforcement Learning: There is a limitation of the knowledge-based control method because of a lot of unforeseenable situations will be happened. To break this limitation , we have applied a reinforcement learning algorithm to coordinate these parameters by the autonomous agent. Each agent reinforces his alternatives, task allocation, scheduling, execution and communication, based on his experience according to a framework of the profit sharing[3].

Conclusion: The parameters to control the projection and the commitment level strongly influence the plan's optimality and the agent's adaptability. We have designed these parameters by using a knowledge-based approach as the top-down method and a reinforcement learning approach as the bottom-up method. As a result of using these two approaches, the agent can construct a good plan as well as adapt to changes in the world.

References

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