知能と複雑系　127－7
(2002.　1.　9)

Modeling Agent-Based Coevolution with Learning Classifier System

NorikoETANI

Faculty of Science and Engineering, Ritsumeikan University
1-1-1 Noji-Higashi, Kusatsu, Shiga 525-8577 Japan
Email: netani@acm.org

Abstract This paper approaches the model of the agent-based coevolution with learning classifier system(LCS) so that competitive or cooperative agents could achieve a better solution of a problem. The peculiarity of this approach is that it does not assume any knowledge on learning classifier system but try to develop any shared knowledge among agents with LCS. A case that two agents compete or cooperate to reach each opposite side with crossing and avoiding collision each other in a grid environment is discussed. Based on a formal framework to define a general purpose rule-based representation of LCS, the model of coevolution is analyzed and argued.

Key words agent-based coevolution, multi-agent, learning classifier system

分類子システムを用いたエージェントベース共進化のモデル化

江谷 典子

立命館大学理工学部
〒525-8577 滋賀県草津市野路東 1-1-1

1. Introduction

This paper proposes the model of a coevolutionary architecture for solving decomposable problems and apply it to the evolution of multi-agents, although this work is an preliminary step. The coevolutionary approaches utilizes a divide-and-conquer technique in which agents representing simpler subtasks are evolved in separate instances of learning classifier system. Collaboration among agents are formed representing complete solutions. Agents are created dynamically as needed. Results are presented in which the coevolutionary architecture produces higher quality solutions in fewer evolutionary trials on the problem of evolving agents in a grid world.

In this approach, each GA(a genetic algorithm) instance evolves a agent of individuals representing competing solutions to a subtask. Rather than evaluating solutions to these subtasks independently, the GA instances communicate with each other for the purpose of forming collaborations. This is accomplished by selecting representatives from each of the GA populations, and combining them into a single composite structures flows back to the individual subcomponents reflecting how well they collaborate with the other subcomponents to achieve the top level goal. This credit is then used by the local GAs to evolve better subcomponents.

This coevolutionary architecture is tested in the domain of learning rule sets for multi-agents under the problem of evolving agents in a grid world. This problem is a type of cooperative learning in a complex and undescriptive environment.

In the next section, basic framework for coevolution is described in more detail. Section 3 describes how that framework is applied to the problem of evolving agents in a grid world. Section 4 presents simulation results. The paper concludes with a discussion of the results and ideas for future research.

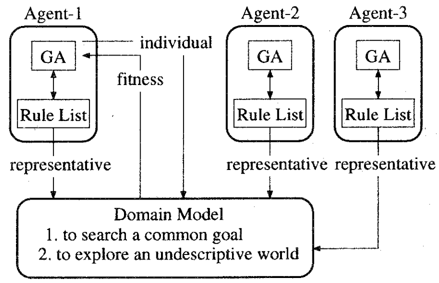

Figure1 Model of Cooperative Evolutionary Architecture

2. Basic Framework

The hypothesis underlying the idea presented here is that, in order to evolve solutions to more and more complex problems, explicit notions of modularity need to be introduced in order to provide reasonable opportunities for complex solutions to evolve in the form of interacting co-adaptived subcomponents. The difficulty comes in finding reasonable computational extensions to our current evolutionary paradigms in which such subcomponents emerge. At issue here is how to represent such subcomponents and how to apportion credit to them for their contributions to the problem solving activity such that the evolution of a solution to the top level goal proceeds without a human in the loop. Learning classifier system attempt to accomplish this through a single population of interacting rules whose individual fitness are determined by their interactions with other rules through a simulated micro-economy.

As shown Figure 1, a cooperative coevolutionary architecture consists of a collection of GA, each attempting to evolve subcomponents(agents) which are useful as modules for achieving higher level goals. Complete solutions are obtained by assembling representative members of each of the agents present. Credit assignment at the agents level is defined in terms of the fitness of the complete solutions in which the agents members participate. This provides evo-

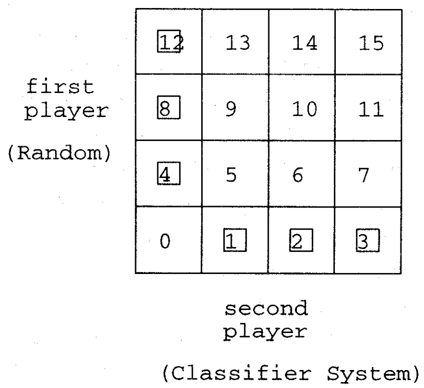

Figure2 A Number of 16 Partitions and An Initial Position of 6 Cells in a Grid

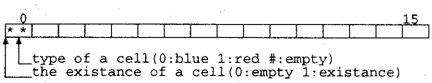

Figure3 Encode Format

lutionary pressure for agents to cooperate rather than compete. However, competition still exists among individuals within the same subpopulation. In the system used in this paper, this model of a cooperative coevolutionary architecture is implemented with learning classifier, and the evolution of each agent was handled by a standard GA.

The use of multiple interacting subpopulations has also been explored as an alternate mechanism for coevolving using island model [7]. In the island model, a fixed number of subpopulations evolve competing rather than cooperating solutions. In addition, individuals occasionally migrate from one subpopulation(island) to another, so there is a mixing of genetic materials. Based on this idea, each agent evolves one subpopulation and each agent shares each subpopulation.

3. Simulating Agent-Based Coevolution

The agent-based coevolution with learning classifier system is simulated based on the cooperative coevolutionary architecture. Two agents compete or cooperate to reach each opposite side with crossing and avoiding collision each other in an unlinked grid environment. As shown Figure 2, a simulated environment is constrained as follows:

(1) A grid is unlinked and composed of 16 partitions.

(2) There are 6 cells which move on a grid. 6 cells is divided into 2 groups. First player group(blue) has a random strategy. Second player group(red) has a strategy with learning classifier which evolves agents among first player group and a grid.

(3) One group can move one cell in one step of one trial. One cell can select one among four behaviors which are "forward,""left,""right," and "stop." And one cell can move one partition which no cell exists in a grid.

(4) One trial is finished when all cells in one group can reach an opposite side.

In this environmental model, an existence of a cell and a classification of first player group(blue) and second player group(red) are encoded into an environmental message as shown Figure 3.

4. Simulation Results

The cooperative coevolutionary approach is evaluated by comparing its performance in the number of win trials, the max value of strength and the winning ratio through 6000 trials. The vertical line incidates each figure and the horizontal line indicates the number of trials in the below three figures.

(1) the number of winning trials as shown Figure 4

Over 2000 trials, the number of the winning trials reaches more than half of trials.

(2) the max value of strength as shown Figure 5

The strength value is increased when payoff from the environment is received. A point near the zero strength is coincided with a point near the highest average number of cycle. This indicates that the number of cycle is increased in order to find a rule according to an environmental mes-

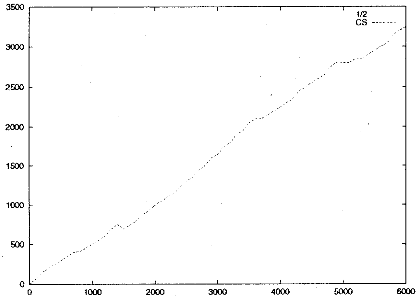

Figure4 The Number of Winning Trials

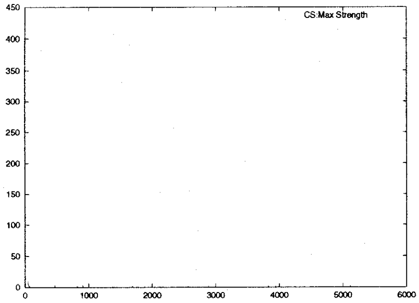

Figure5 The Max Value of Strength

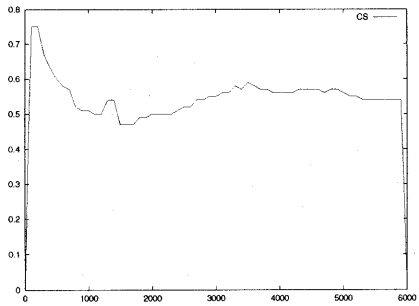

Figure6 The Winning Ratio

sage and rule list is renewed with new rules.

(3) then winning ratio as shown Figure 6

A dropping point of the winning ratio is coincided with a point in the max number of cycle and a point in the highest average of cycle. It indicates that the strongest classifier remains and causes its dropping point.

5. Conclusion

A basic framework for agent-based coevolution has been presented in which a collection of GA running in evolving subcomponents which are combined into a composite structure capable of being evaluated on a top level goal. Because credit assignment at the agent level is defined in terms of the fitness of the complete solutions in which the agent members participate, there is evolutionary pressure for individuals to collaborate rather than compete with other individuals in coevolving agents.

This model of agent-based coevolution is applied to multi-agents in a grid world. Results have been presented in which the coevolutionary architecture produces higher quality solutions in fewer evolutionary trials. Although we have achieved considerable performance improvements, our primary motivation has been a better understanding of issues related to the evolution of interacting co-adapted subcomponents.

Future research will focus on agent-based coevolution including people. There are two main difficulties introduced when one attempts this type of coevolution against people for more efficiency:

(1) Interactions with humans are a poor resource.

(2) Opponents are random and known techniques for coevolution become impossible.

The first problem is common to all applications that wish to learn from a real environment: interactions are slow and costly. We address this problem by nesting an extra loop of coevolution: while the system is waiting for human opponents, it runs more and more generations of agent-agent coevolution. The second problem led us to develop a new evaluation strategy, based on the paired comparisons statistics. It decides when each agent shares each subpopulation in trials. With it, we have been able to prove that the system has been learning through interaction with people. The paired comparisons model also gives us the possibility for a fitness function that could solve the problems of the first one.

References

[1] Noriko Etani, "Using A Classifier System to Learn Adaptive Strategies for Collision Avoidance" Master's Thesis, Department of Information Processing, Graduate School of Information Science, Nara Institute of Science and Technology, NAIST-IS-MT9651016, 1998.

[2] Sevan G. Ficici and Jordan B. Pollack, "A Game-Theoretic Approach to the Simple Coevolutionary Algorithm" Parallel Problem Solving from Nature VI, M. Schoenauer, et al, (eds.), Springer Verlag, 2000.

[3] Sevan G. Ficici and Jordan B. Pollack, "Game Theory and the Simple Coevolutionary Algorithm: Some Preliminary Results on Fitness Sharing" GECCO2001 Workshop on Coevolution: Turning Adaptive Algorithms upon Themselves, 2001.

[4] John H. Holland, "ADAPTATION IN NATURAL AND ARTIFICIAL SYSTEMS" MIT Press, 1995.

[5] Hugues Juille and Jordan B. Pollack, "Dynamics of Co-evolutionary Learning" In Proceedings of the Fifth Annual Conference on Evolutionary Programming, 461-468, MIT Press, 1996.

[6] Jordan B. Pollack and Alan D. Blair, "Co-Evolution in the Successful Learning of Backgammon Strategy" Machine Learning 32(3):225-240, September 1998.

[7] D. Whitley and T. Starkweather, "Genitor II: a distributed genetic algorithm" Journal of Experimental and Theoretical Artificial Intelligence 2, 189-214, 1990.