Community of Practice under Learning Classifier Systems

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ABSTRACT
This paper proposes a learning mechanism for multi-agent systems based on the concept of community of practice, implemented with Learning Classifier Systems. The learning mechanism takes place in three levels (1) individual level, (2) group level and (3) collective level. A variation of the maze problem was employed to evaluate the effectiveness of the proposed learning mechanism.

Categories and Subject Descriptors
I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence – *Intelligent Agents, and Multiagent Systems.*

General Terms
Algorithms, Experimentation, Theory

Keywords
Organizational learning, community of practice, multiagent systems, and learning classifier systems.

1. INTRODUCTION
Learning is an essential issue in the field of Multi-Agent Systems (MAS), where agents should adapt to the environment and environment's changes. Several researches on this field have proposed a set of different learning mechanisms for agents. For instance, neural networks, reinforcement learning [4], learning classifier system [1, 2, 3] and some modifications of them allow agents to learn individually. In other words, agents learn by themselves by interacting with the environment with no influence of other agents. In this case, the search space is higher as the number of agents and the complexity of the model is increased. As a consequence, even though several possibilities can be evaluated, the time required for accurate evaluation is highly increased. This mechanism is used when considering heterogeneous agents. More sophisticated implementations provide knowledge exchange capabilities. In this case all agents are homogeneous and they exchange the strongest rules they have learned. Under this circumstance, it may speed the learning time due to the fact that the search space is reduced. However, this reduction of the search space may cause the elimination of some important characteristics of the environment.

These two types of mechanisms are useful, but they fail in problems, such as rescue of lives in disasters, where the environment is highly dynamic, information is limited, immediately response is required, number of agents is considerable and agent's specialization is necessary. In this kind of situation, a sort of organizational learning is required.

For this reason, in this paper, an organizational learning mechanism for MAS is proposed. It consists on grouping agents in communities in each of which all agents share knowledge (rules), increasing the learning speed of agents in the community. Also, the creation of groups provides the capability of keeping diversity. Finally, in a certain time, common behaviors between communities are analyzed in order to obtain general behavior required for every agent. This mechanism is implemented in XCS [1].

In order to evaluate the performance of the proposed algorithm, a variation of the maze problem was considered.

The structure of this paper is as follows. Section 2 provides a brief description of the proposed algorithm. Section 3 describes the case study with its experimental results. Finally, discussions and conclusions are presented in Section 4.

2. COMMUNITY OF PRACTICE BY XCS
2.1 Concept
The community of Practice by XCS (COPXCS) was inspired by the concept of community of practice [5] in organizational theory. Community of practice consists of grouping people who share similar goals and interests. In pursuit of these goals and interests, they employ common practices, work with the same tools and express themselves in a common language. Through such common activity, they come to hold similar beliefs and value systems. In other words, they learn collectively. Members of an organization may participate in several communities according to their interests and responsibilities, improving the organizational knowledge and therefore, the performance of the organization.

Agents are grouped in communities, according to the similarity of tasks they should perform, improving learning accuracy and speed. The learning is performed in three levels as showed in Figure 1.

GECCO'06, July 8–12, 2004, Seattle, WA, USA.

1. *Individual level* (Individual Learning): Agents learn independently by using XCS as learning mechanism

2. *Group level* (Knowledge Exchange within communities): In each community, agents exchange their most valuable knowledge (rules with higher strengths). These rules are inserted in all community members with neutral strength initialization due to the fact that good rules for one agent may not be good for another.

3. *Collective level* (Knowledge Exchange between communities): Useful knowledge obtained in every community is exchanged between communities, generalizing some global knowledge that is required for every agent in the system. The reason is that necessary experience for every agent may not be learnt in some communities due to lack of learning opportunities.

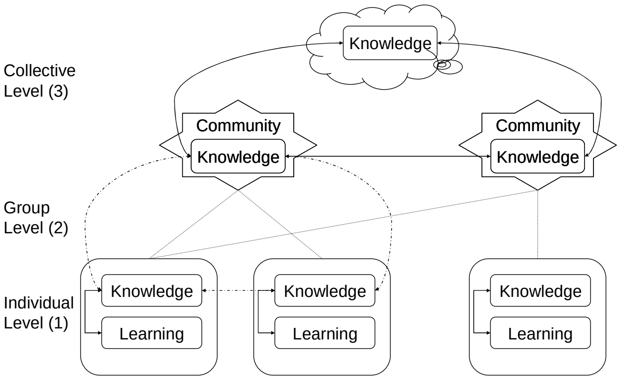

Figure 1. Learning mechanism based on community of practice. Learning takes place in three levels: individual level, group level and collective level.

3. CASE STUDY

3.1 Problem

A variation of the well known maze problem, as shown in Figure 2, was employed. Here, two agents are located in a grid and they have to move ten objects from a starting point to two goal positions (five per goal position). As opposed to common maze problems where the simulation finish when reaching the goal, agents have to return to the starting point after reaching goals, in order to move more objects. One generation is counted when all the ten objects are transported to the goal positions moved.

Agents are provided with two rules sets, one for going to the goal point and another for returning to the starting point. Agents may share the task by given the object to another available agent in order to avoid some possible bottle necks. Eight agents were employed distributing two agents in one maze. Four communities were constructed which consist of two members per group. Individual learning is performed time step. Group learning is performed every five generations in every maze. And every twenty generations the collective learning is performed.

The COPXCS were compared with results obtained when applying only XCS (individual learning) (XCS) and XCS with knowledge exchange between all agents (XCS+KX).

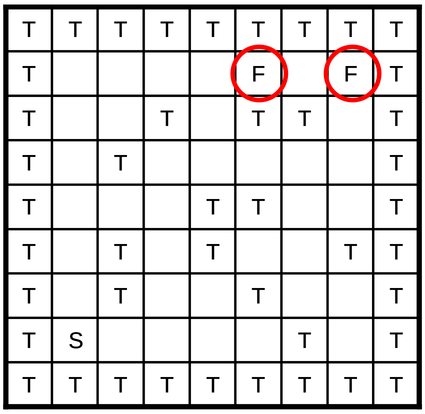

Figure 2. Maze Problem

3.2 Experimental Results

The experimental results are shown in Figure 3. This figure represents the simulation performance where *x*-axis represents learning type and *y*-axis represents the performance based on the inverse of the time required for moving all the ten objects after convergence of the results.

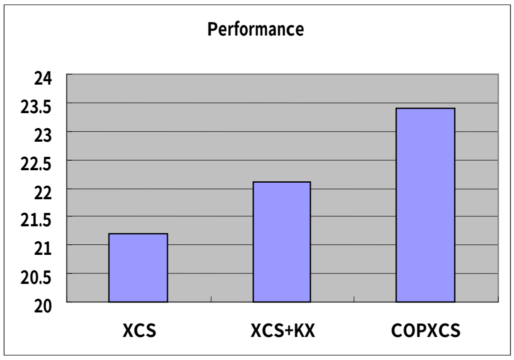

Figure 3. Type of learning vs. performance based on the inverse of the time required to move the ten objects

3.3 Discussion

The exchange of knowledge in/between communities provides better performance than only using individual learning. The reason is that some experience of one agent may be useful for another agent, avoiding learning from scratch.

Regarding the grouping criteria, agents were included in 4 groups randomly. However, one important question that may be answered by further research is to determine the conditions to establish the criteria that may assure the increase of performance.

4. CONCLUSIONS

This paper presents the COPXCS as an organizational learning algorithm for MAS based on the concept of community of practice in organizational theory. The learning takes place in three levels: (1) individual level, where agents learn individually by exploring the environment by themselves with no influence of other agents, the XCS was employed; (2) group level, agents are grouped in communities for sharing knowledge with agents with similar aims or tasks; and (3) collective level, where the knowledge between communities is analyzed and global knowledge, that is essential for any agent, is collected and provided to every agent. Experimental results shown that the proposed algorithm performs better than performing both only individual learning and performing individual learning with knowledge exchange between all agents. Further research based on more sophisticated problems will be considered. Additionally, adequate criteria for grouping agents will be analyzed.

5. ACKNOWLEDGMENTS

This research was partly conducted as the "Research on Human Communication" with funding from the Telecommunications Advancement Organization of Japan. This research also was supported in part by the Sasagawa Scientific Research Grant from the Japan Science Society. The research reported here was also supported in part by a Grant-in-Aid for Scientific Research (B, No. 16300051) of the Ministry of Education, Culture, Sports, Science and Technology (MEXT), Japan. We would like to express our thanks for all of the above support.

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