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Adaptive learning algorithm of self-organizing teams

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ABSTRACT

In order to improve the ability of achieving good performance in self-organizing teams, this paper presents a self-adaptive learning algorithm for team members. Members of the self-organizing teams are simulated by agents. In the virtual self-organizing team, agents adapt their knowledge according to cooperative principles. The self-adaptive learning algorithm is approached to learn from other agents with minimal costs and improve the performance of the self-organizing team. In the algorithm, agents learn how to behave (choose different game strategies) and how much to think about how to behave (choose the learning radius). The virtual team is self-adaptively improved according to the strategies' ability of generating better quality solutions in the past generations. Six basic experiments are manipulated to prove the validity of the adaptive learning algorithm. It is found that the adaptive learning algorithm often causes agents to converge to optimal actions, based on agents' continually updated cognitive maps of how actions influence the performance of the virtual self-organizing team. This paper considered the influence of relationships in self-organizing teams over existing works. It is illustrated that the adaptive learning algorithm is beneficial to both the development of self-organizing teams and the performance of the individual agent.

1. Introduction

In many researches of self-organizing teams, team members need to adopt knowledge to improve teams' performances. However, this paper does not think that all learning algorithms are beneficial to self-organizing teams and its members. Based on an artificial self-organizing team, the paper finds that the performances of the team and its members have differently evolutional results with different learning algorithms. It is found that adaptive learning algorithm shows significance on the application of tracking control (Ni & et al., 2013), scheduling of batch processing machines (Noroozi & et al., 2013), rank of search engines (Torkestani, 2012), and service operations (Li & Kauffman, 2012), etc. An adaptive learning algorithm is proposed in the paper to improve the learning ability of the agents in the virtual self-organizing team. Agents with the adaptive learning algorithm can decide how to learn and learn what by themselves. After ten thousands periods of simulations, the artificial self-organizing team with the adaptive learning algorithm has the best performance compared with other learning algorithms.

The artificial self-organizing team in the paper is inspired by Gilbert and Ahrweiler's research (Ahrweiler et al., 2004; Gilbert, Ahrweiler, & Pyka, 2007; Gilbert, Pyka, & Ahrweiler, 2001). In their research, the "KENE" was used to describe the knowledge of members and the supplier and customer were generated by the computation of the KENE. Based on their research, this paper proposes an artificial self-organizing team as the experiments skeleton of the adaptive learning algorithm. Details on the artificial self-organizing team are discussed in Section 3.1. Moreover, except the expert knowledge in many fields, the agent in this paper has one of the three strategies, unilateral cooperation, unilateral defection and conditional cooperation. Hexmoor et al. (2006) worked on the urban traffic problem with multi-agent technologies. The evolution of the game strategies in his paper is beneficial to our research. Furthermore, Carmel viewed interaction as a repeated game and presented a general architecture for a model-based agent that learned models of the rival agents for exploitation in future encounters (Carmel & Markovitch, 1998). Janiak and Rudek (2011) constructed on-line scheduling algorithms to increase learning efficiency by the utilization of its learning ability. These papers are useful to our present study. The adaptive learning algorithm in this paper gives agents the ability of adjust game strategy and learning radius. Epstein presented an approach to adjust the learning radius to work on the evolution of the social norm (Epstein, 2001). Wang, Li, et al. (2011) used self-adaptive learning based mechanisms in swarm intelligence. Different parameter values were researched in a few papers (Liang, Yao, & Newton, 2001; Mallipeddi, Mallipeddi, & Suganthan, 2010). Based on these

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significant researches, this paper proposes a self-adjust mechanism in the adaptive learning algorithm.

2. Review of the related researches

The works on self-organizing team seek to understand not only how team members' behave but also how the interaction of many members leads to large-scale outcomes. Agent base simulation is well suited for this object. The learning algorithm in the agent based system is important for the success of the simulation. Vriend considered that an agent was said to employ individual-level learning (if it learned from its own past experiences) and to employ population-level learning (if it learned from other agents) (Vriend, 2000). This paper focuses on the population-level learning in the artificial self-organizing team. Many researchers have proposed many different algorithms for the population-level learning, such as reactive reinforcement learning, belief-based learning, anticipatory learning, evolutionary learning, and connectionist learning.

Reinforcement learning is learning what to do and how to map situations to actions, so as to maximize a numerical reward signal. The learner must find which actions yield the most reward by trying them in each state (Sutton & Barto, 1998). Shin, Ryu, et al. (2012) applied a reinforcement learning approach for autonomous goal-formation. Zhang, Luo, and Wang (2008) used reinforcement learning to learn optimal policies by maximizing the accumulated rewards. Dorca and et al. (2013) proposed reinforcement learning for modeling students learning styles based on. Reinforcement learning model was also used in supply chain for the ordering management (Chaharsooghi, Heydari, & Zegordi, 2008). Tuyls investigated reinforcement learning in multi-agent systems from an evolutionary dynamical perspective (Tuyls, Hoen, & Vanschoenwinkel, 2006). The incremental method for learning in a multi-agent system was proposed with reinforcement learning (Buffet, Dutech, & Charpillet, 2007). Masoumi and Meybodi (2011) proposed a multi-agent reinforcement learning algorithm to speed up the learning process.

The basic belief based learning process was the fictitious play proposed by Brown, 1951. This approach was used in many field (Berger, 2005; Sela, 2000). Q-learning (Watkins, 1989) was a simple way for agents to learn how to act optimally in controlled Markovian domains. It was a famous anticipatory learning approach. Watkins presented and proved in detail a convergence theorem for Q-learning based on the outlined in 1989 (Watkins, 1992). Based on Watkin's Q-learning algorithm, a multi-agent learning model was proposed to control routing within the Internet (Tillotson, Wu, & Hughes, 2004). Genetic algorithm and artificial neutral network were used as evolutionary algorithms. The evolutionary algorithm was applied to behavior learning of an individual agent in multi-agent robots (Maedo, 1998). Hwang et al. applied Q-learning to develop a tree-construction method (Hwang, et al., 2012). In order to improve the performance of cooperative teams, Li and et al. (2011) built a multi-goal Q-learning algorithm simulated by an agent-based model.

Adaptive learning shows significance on the learning in self-organizing team since the complex interaction among agents. Many adaptive learning algorithms were helpful to our study. Based on particle swarm optimization and support vector regression model Li and et al. (2013), used a hybrid adaptive algorithm to estimate grades. Zhang et al. (2008) used the dynamic stochastic selection within the framework of multimember differential evolution. In Zhu's paper, a self-organizing learning array system was implemented in software. It was an information theory based learning machine capable of handling a wide variety of classification problems (Zhu, He, Starzyk, & Tseng, 2007). Frank developed a quantitative dynamical systems approach to differential learning. Accordingly, differential learning was regarded as a self-organized process that resulted in the emergence of subject- and context-dependent attractors (Frank, Michelbrink, Beckmann, & Schöllhorn, 2008). Dressler contributed to the networking community by providing a better understanding of self-organization mechanisms focusing especially on the applicability in ad hoc and sensor networks (Dressler, 2008). Li and Kauffman (2012) proposed an adaptive learning algorithm in the refinement of service operations. Agent-based simulation was used to illustrate the application of their approach to the operations of a public rail transportation firm in a European urban setting. The research method of Li and Kauffman is similar with our paper.

Based on the learning algorithms described above, the paper proposes an adaptive learning algorithm which is implemented in an artificial self-organizing team. In the algorithm, agents can adjust their learning radius and learning knowledge adaptively. Section 3 proposes the model of the artificial self-organizing team and the adaptive learning algorithm. Section 4 describes the six experiments used to test the availability of our algorithm and the results obtained. Future directions and conclusive remarks end the paper in Section 5.

3. Adaptive learning algorithm

An artificial self-organizing team is built for experiments of the adaptive learning algorithm. The architecture of the artificial team is proposed at Section 3.1. The adaptive learning algorithm is suggested at Section 3.2.

3.1. Building up an artificial self-organizing team

The self-organizing team consists of several team members who meet some others' demands. All team members cooperate to accomplish some work with their knowledge. Each team member is simulated by an agent in the NetLogo 4.0.2. The artificial team G ($G = \langle V, E\rangle$) consists of N agents, $V = \{v_1, v_2, v_3, \ldots, v_N\}$, where each agent can be considered as a unique node in a self-organizing team. The relation in the self-organizing team is modeled by an adjacency matrix E, where an element of the adjacency matrix $e_{ij} = 1$ if the agent v_i uses his knowledge to support v_j to accomplish its task (M_{v_j}) and $e_{ij} = 0$ otherwise. The relation among the agents are directed, so $e_{ij} \neq e_{ji}$. The relation between v_i and v_j is shown in Fig. 1 with an arrow. In the model, if v_i supports v_j to do something, v_i is called as the follower in the relation of v_i and v_j. Meanwhile, v_j is called as the leader.

(1) Agent state

The state of v_i is defined as $S_{v_i} = \{g_{v_i}, k_{v_i}, r_{v_i} f_{v_i}\}$, where g_{v_i} is the game strategy, k_{v_i} is the knowledge of the agent, r_{v_i} is the learning radius and f_{v_i} is the fitness of the agent. If $f_{v_i} \leqslant 0$, v_i will be deleted from the artificial self-organizing team. If the agent v_i gets the biggest reward in last period and the reward $f_{v_i}^{last-reward}$ is more than

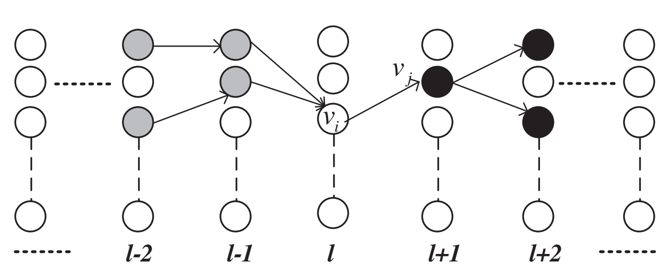

Fig. 1. The learning targets ($r_{v_i} = 2$).