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The evolution of rules for conflicts resolution in self-organizing teams

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ABSTRACT

The purpose of the paper is to study the emergency and effects of conflict resolution rules in self-organizing teams. Intelligent agents are used to simulate team members of self-organizing teams. In the virtual self-organizing team, agents adapt the *Q*-learning algorithm to adjust their actions. Three sets of experiments are manipulated to study the evolution of rules. The results of few experiments show a new rule for conflict resolution emerged from the dynamic interactions of agents. For the other experiments, agents cannot resolve conflicts by themselves.

1. Introduction

In self-organizing teams, team members adopt knowledge to work for the team task. The team task consists of several dependent sub-tasks. Each sub-task has requirements for the member who want to accomplish it. Since there are no stronger leaders of the teams, each member chooses the sub-task whose requirements are fit with his abilities. The quality of team tasks depends on the worst quality of team members' works. Since the characteristics of self-organizing teams, the fit rule between tasks and members is "Do the fittest task". However, if the team members' ability is not perfect for the tasks, the fit rule will lead to team problems. For example, two tasks requirements are 50 (t_1) and 70 (t_2). Two members have the ability of 70 (m_1) and 90 (m_2). Based on the rule of "Do the fittest task", m_1 chooses the task of t_2. In order to accomplish the team task, m_2 have to choose t_1. Since the distance between m_2 and t_1, the quality of team task is 40 (90 – 50). This scenario is defined as assignment conflict in the paper. The paper studies the rules to resolve this kind of assignment conflicts in self-organizing teams.

For the target of high tasks' quality, the optimal assignment of this example is m_1 choose t_1 and m_2 do the task of t_2. For the optimal assignment, the quality of team task is 20 (70 – 50 or 90 – 70). In the paper, this optimal assignment rule is defined as "Do a fitter task". Team members following fixed behavioral rules can be limited in performance and efficiency. In order to emerge the rule of "Do a fitter task" from the dynamic interactions of team members, the paper uses multi-agent technology to simulate the self-organizing teams. Intelligent agents are used to simulated team members. Adaptability is key components of intelligent behavior which allow agents to improve performance in a given domain using prior experiences. The *Q*-learning algorithm is applied to improve the self-adaptive ability of agents. Three sets of experiments are manipulated to analyze the evolution of the rule in self-organizing teams. The emergency and effects of conflict resolution rules are analyzed by the experiments' results.

The rest of the paper is organized as follows. The related literature is reviewed in Section 2 and then the multi-agent model is developed in Section 3. The experiments are conducted in Section 4. A detailed result analysis is presented in Section 4. Finally, the conclusions are summarized and future work is suggested in Section 5.

2. Review of the related research

For the management of self-organizing teams, Romme built a model of self-organizing processes in top management teams and described Boolean comparison as a rigorous method for testing process theories on the basis of qualitative evidence from case studies (Romme, 1995). Levi and Slem examined professional level teams in research and development facilities at three corporations. All of these corporations were attempting to introduce self-managing teams in their R&D projects. These teams encountered similar problems, such as (1) The overall success of team work depends on corporate culture, (2) Working relationships among team members can be disrupted in a variety of ways and (3) There is not a best approach to leadership and decision-making in research and development teams (Levi & Slem, 1995). The research of self-organizing team shows significance on the management of self-managing teams.

In the self-organizing team, the conflict of mission assignment can disrupt the cooperative relationships among team members

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and there is no best approach to resolve conflicts. Researchers have proposed many approaches to resolve conflicts. Ng discussed the dynamic nature of conflicts in terms of their evolution and escalation within a project and the interaction between conflicts and dispute avoidance and resolution techniques (Ng, Peña-Mora, & Tamaki, 2007). Miller and Engemann investigated inter-group conflict and examined the impact of strategies to manage and hopefully reduce it. Based on feedback principles, a probabilistic computer simulation model was used in Engemann's work. The model examined how conflict between two groups evolved over time (Miller & Engemann, 2004).Tools of conflicts measures were introduced as a view to diagnosing problems of model fit at any point in the paper's model structure (Dahl, Gåsemyr, & Natvig, 2007). The normative organizations were designed by a three-phase iterative optimization process (Levchuk, Levchuk, Luo, et al., 2002a, 2002b). It focused on devising mission planning strategies to optimally achieve mission goals while optimally utilizing organization's resources. The paper presented a multi-objective structural optimization process of designing an organization to execute a specific mission. Our paper studies the mission assign conflicts too.

Many other approaches have been used to resolve team conflicts in other researches. Cohen proposed an expert system to resolve conflicts generated by shared robots and machines (Cohen, 1995). Tsang and Ho proposed a multi-agent model for the railway open market and demonstrated its feasibility by modeling the negotiation between an infrastructure provider and a train service operator (Tsang & Ho, 2006). The negotiation was proved as an effective approach to resolve conflicts. Kwon and Lee studied how a multi-agent-based coordination mechanism could resolve conflicts among functional units in an enterprise (Kwon & Lee, 2002). Haynes and Sen proposed a framework in which individual group members learned cases from problem-solving experiences to improve their model of other group members. Their research showed that simultaneous learning by group members could lead to significant improvement in group performance and efficiency over agent groups following static behavioral rules (Haynes & Sen, 1998). Jacak and Pröll presented a heuristic method that allowed an intelligent multi-agent system to coordinate and negotiate their actions in order to achieve a common goal (Jacak & Pröll, 2007).

Inspired by these researches, our paper proposed a multi-agent model to simulate the self-organizing team. The paper's multi-agent model depends on the development of the former artificial model based on multi-agent system. Gilbert built a multi-agent model embodying a theory of innovation networks. A number of policy-relevant conclusions were suggested through experiments with the model's parameters (Gilbert, Pyka, & Ahrweiler, 2001). Bhavnani provided a general introduction to an agent-based computational framework for studying the relationship between natural resources, ethnicity, and civil war (Bhavnani, Miodownik, & Nart, 2008). The framework in Bhavnani's work is beneficial for the building of our model. Lei discussed a distributed modeling architecture in a multi-agent-based behavioral economic landscape (MABEL) model that simulated land-use changes over time and space (Lei, Pijanowski, & Olson, 2005). Li and Zhou used the multi-agent technology to build a virtual self-organizing team in their researches (Li & Zhou, 2010). These agent-based models show significance to build the framework of our paper. The dynamic structure of the multi-agent model depends on the knowledge of agents and the characteristics of sub-tasks. The C2 architecture, which was studied to present a network (Krackhardt & Carley, 1998), inspired the structure definition of our paper. Fuller and Dennis strived to explain how the two major FAM (Fit Appropriation Model) constructs, TTF (Task-Technology Fit) and appropriation, influenced team performance (Fuller & Dennis, 2009).

In our paper, the *Q*-learning approach is used by agents to improve their actions. *Q*-learning is one of the reinforcement learning models that have been studied extensively by researchers. *Q*-learning was a simple way for agents to learn how to act optimally in controlled Markovian domains (Watkins, 1989). It was a famous anticipatory learning approach. Watkins presented and proved in detail a convergence theorem for *Q*-learning based on the outlined in 1992 (Watkins, 1992). Many researchers improved the learning model in their paper, such as Even-Dar and Mansour (2003) and Akchurina (2008).

Based on the literature review stated the above, the paper is focused on the emergency and effects of conflict resolution rules in self-organizing teams. Three sets of experiments were conducted to reveal the evolution of conflict resolution rules.

3. Conflicts resolution model of self-organizing team

The virtual self-organizing team ($V = \{v_1, v_2, v_3, \ldots, v_N\}$) is a multi-agent model containing heterogeneous agents (v_i, virtual members) which act in a virtual environment. All members cooperate to accomplish tasks with their knowledge. Each member is simulated by an agent in the model. The team task ($M = \{m_1, m_2, m_3, \ldots, m_N\}$) consists of N sub-tasks. If the member v_i has the ability which is required by sub-task m_j, v_i can do m_j with high quality and v_i can get maximal profits. If v_i does not fit the ability which is required by sub-task m_j, v_i can do m_j with low quality and v_i cannot get maximal profits. The quality of team task depends on the worst quality of sub-tasks. The team reward to each virtual member is decided by the quality of team task. If the ability of v_i does not fit the requirement of m_j and all sub-tasks except m_j have been done by other members, then m_j is the only one choice of v_i. This is the conflict of the paper researched. The algorithm of compute conflict is proposed in Section 3.2.

The team task ($M = \{m_1, m_2, m_3, \ldots, m_N\}$) is generated by the multi-agent model. Each sub-task ($m_j = \{f_j, t_j\}$) requires the member (If the member do m_j) has the special knowledge of research field f_j and has the special technology t_j in the field of f_j. Since all tasks are similar for a self-organizing team, the requirements of tasks at different period follow normal distribution. For each simulation period (all sub-tasks are accomplished), the f_j and t_j of 30% sub-tasks follow normal distribution of (μ_f^1, σ_f^1) and (μ_t^1, σ_t^1), the requirements of 25% sub-tasks follow (μ_f^2, σ_f^2) and (μ_t^2, σ_t^2), the requirements of other 25% sub-tasks follow (μ_f^3, σ_f^3) and (μ_t^3, σ_t^3), and the other sub-tasks follow (μ_f^4, σ_f^4) and (μ_t^4, σ_t^4).

3.1. Agent status

The state of v_i is defined as $S_{v_i} = \{k_{v_i}, f_{v_i}\}$, where k_{v_i} is the knowledge of the agent, and f_{v_i} is the fitness of the agent. In the virtual self-organizing team, the agent is a team member with an individual knowledge base. This knowledge of v_i is represented as $k_{v_i} = \{\{k_{v_i}^F, k_{v_i}^T\}, \{k_{v_i}^F, k_{v_i}^T\}, \ldots, \{k_{v_i}^F, k_{v_i}^T\}\}$, where $k_{v_i}^F$ ($k_{v_i}^F \in [1, 100]$) is the research field, $k_{v_i}^T$ ($k_{v_i}^T \in [1, 100]$) is the special technology in the field of $k_{v_i}^F$. The length of k_{v_i} is between $kl_{v_i}^{min}$ and $kl_{v_i}^{max}$.

The agent's performance in the model is presented as the fitness (f_{v_i}). The fitness can be explained by the sum of rewards in the all last periods. In the paper, all rewards and costs are in fitness units. Each new agent's fitness is $f_{initial}$.

3.2. Agent actions

A finite set of actions for agent v_i is defined as $A_{v_i} = \{a_{av_i}, a_{bv_i}, a_{sv_i}, a_{tv_i}\}$. a_{av_i} means the action of v_i to compute his attributes, such as fields and technologies. a_{bv_i} means the bid action of v_i (each agent need do a sub-task in a simulation period). In the paper, a