A Swarm Based Approach for Task Allocation in Dynamic Agents Organizations

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Abstract

One of the well-studied issues in multi-agent systems is the standard action-selection and sequencing problem where a goal task can be performed in different ways, by different agents. Tasks have constraints while agents have different characteristics such as capacity, access to resources, motivations, etc. This class of problems has been tackled under different approaches. Moreover, in open, dynamic environments, agents must be able to adapt to the changing organizational goals, available resources, their relationships to another agents, and so on. This problem is a key one in multi-agent systems and relates to models of learning and adaptation, such as those observed among social insects. The present paper tackles the process of generating, adapting, and changing multi-agent organization dynamically at system runtime, using a swarm inspired approach. This approach is used here mainly for task allocation with low need of pre-planning and specification, and no need of explicit coordination. The results of our approach and another quantitative one are compared here and it is shown that in dynamic domains, the agents adapt to changes in the organization, just as social insects do.

1. Introduction

Multiagent systems (MAS) need to manage the issues appearing in dynamic environments such as variation in the number of agents, system's goals, etc. The question is how to derive specific organizational structures given particular situations. Most of the works in this area focus on adapting some specific aspects of the organization or on structure generation. Issues related to organizational adaptation in MAS are still open. Similar problems can also be found among social insects. These show evidences of ecological success due to their *organization* which is observed in division of labor, specialization, collective regulation, etc. [1]. The needs of the colony organization change over time and are associated with temporal and environmental conditions. Despite drastic variations in these conditions, social insects do have ecological success.

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2. Organization in MAS and Social Insects

Although many approaches to organization in MAS exist, this paper focuses only on organizational representation, planning and scheduling (TÆMS/GPGP/DTC framework), and on the swarm based model necessary to explain our approach. The former has been used as a domain-independent language for description of tasks associated with agents, planning and scheduling of agent's tasks. By using these tools, it is possible to construct the task structure of a problem-solving situation. As for the latter, There is a model for self-organization inspired on the plasticity of division of labor in colonies of social insects [1]. Interactions among members of the colony and the individual perception of local needs result in a dynamic distribution of tasks. This model describes the colony task distribution using the stimulus produced by tasks that need to be performed and an individual response threshold related to each task. Each individual insect has a response threshold to each task to be performed. That means, at individual level, each task has an associated stimulus.

Henceforward, let us assume that there are M tasks to be performed, each denoted by j, and that each of these tasks are associated with a stimulus s_j. Also as-

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sume that there are N individuals, each denoted by i, with response thresholds θ_{ij} associated with task j stimulus. An individual i engages in task j with probability $T_{\theta_{ij}}(s_j) = \frac{s_j^2}{s_j^2+\theta_{ij}^2}$ where s_j is the stimulus associated with task j, and θ_{ij} is the response threshold of individual i to task j.

Each response threshold θ_{ij} is associated with a time interval Δt. These thresholds are computed by: $\theta_{ij} = \theta_{ij} \pm \xi \Delta t_{ij}$ where ξ is the learning coefficient and Δt is the time interval. Thresholds increase when not performing tasks, and decrease otherwise.

3. A Swarm Based Approach for Task Allocation

We use the swarm-based model to allocate insects-like agents to perform specific tasks when the structure of this tasks change on the fly. All tasks available for an insect have probability distributions of quality, cost, and duration (TÆMS-like way). These values describe the possible results of the method execution. The intensity of this stimulus is associated with the results of the task execution. Each task j have one stimulus s_j given by: $s_j = \varphi * (\alpha * \hat{q_j} - \beta * \hat{c_j} - \gamma * \hat{d_j} + \beta + \gamma) + (1-\varphi) * x_j$ where $\hat{q_j}$ is the normalized expected quality of task j, $\hat{c_j}$ is the normalized expected cost of task j, $\hat{d_j}$ is the normalized expected duration of task j, x_j is the stimulus associated with the quality accumulation function related to the task j, and α, β, γ, φ are constants employed to set different priorities to the quality, cost and duration values.

In some social insects, temporal polyethism is the main form of division of labor. To calculate the response thresholds with polyethism, we modify the specialization model proposed in the literature to employ two variables as coefficients of learning and forgetting based on temporal polyethism. The response threshold θ_{ij} of i when *not* performing j is $\theta_{ij} = \theta_{ij} + \frac{a_i}{A_i} * \frac{m_j}{\mathcal{A}}$. When a task is performed by an agent, the response threshold changes. For the agent to specialize in selecting a specific method, it is necessary that it selects this method some times. Thus, it is necessary to run the model for several rounds. In each round our approach produces a task allocation for the given task structure (TS).

4. Experiments

Two scenarios were simulated. In the first the TS relates to a typical problem of job scheduling among multi-purpose machines. Task T_1 is the first stage of production. Jobs of type a, b, or c can arrive. If it is of type a, for example, then m_{1a} is allocated to an agent. This enables method m_{2a} and so on. For this static situation, DTC produces a schedule with the quality of 14.35, cost of 0.6, and the duration of 17.0. Since our approach is probabilistic, we have run the task allocation for 1000 times. The most frequent schedule is produced 32.7% of the time and has quality of 14.4, cost 0.6, and duration of 17.0. That means that our more frequent output is the one which resembles the output of DTC. However, our approach is intended not for static environments but for dynamically evolving ones. This means that our agents can adapt to changes in the environment with no need of commitments and communication.

In such a dynamic scenario, 4 different TSs appear randomly with the same probability. The first TS is the one described above. The other three are variants of it: one has no enable relationships between the tasks and the other has one task less plus one task with a longer deadline. Of course, we can only compare individual tasks structures to the DTC outputs. In our simulation, the 4 outputs appear 48% of the 1000 repetitions, which is a good result considering that agents have to adapt to the changes in TSs appearing randomly. In summary, one notices that modifying the TS on the fly disturbs only slightly the performance of the agents.

5. Conclusion

The approach presented here deals with the action-selection and sequencing problem. It aims at situations when the environment changes and so demands different organizations of tasks and agents. In other approaches, this adaptation requires a learning component normally based on explicit coordination and/or communication. We focus on a paradigm based on colonies of social insects, where there are plenty of evidences of ecological success, despite the apparent lack of explicit coordination. The key issues are the learning/forgetting specialization and the plasticity in division of labor. In summary, there is a tradeoff between explicit coordination leading to highly accurate outputs *versus* implicit coordination via learning and adaptation leading to more relaxed ones. Our approach is certainly not the best in static situations, while it is effective in dynamic ones. The efficiency is an issue related to the specific scenarios.

References

[1] Bonabeau, E., Theraulaz, G., and Dorigo, M. *Swarm Intelligence: From Natural to Artificial Systems.* Oxford Univ Press, 1999.

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