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Cooperation Algorithms in Multi-Agent Systems for Dynamic Task Allocation: A Brief Overview

Bing Xie, Jing Chen, Lincheng Shen
College of Mechatronics and Automation,
National University of Defense Technology,
Changsha, 410073, China

Abstract: Since the dynamic task allocation problem has gradually become one of the key points in the research of multi-agent systems (MASs), a booming development of agent cooperation methods reaches a point of warranting a survey. This paper firstly introduces the dynamic task problem and gives some analysis on multi-agent cooperation. Then, we introduce some popular multi-agent cooperation algorithms for dynamic task allocation in MASs, the cooperation rules on this issue. Also, this paper reviews the cooperation goals in literature. Finally, we give our analysis on benefits and future challenges in multi-agent cooperation.

Key Words: cooperation; multi-agent systems; dynamic task allocation

1 Introduction

As multi-agent systems (MASs) have been increasingly employed in dynamic circumstance, like emergency rescues [1,2], sensor surveillance [3,4,5,6], cloud service [7], machine scheduling [8,9,10,11] and even army assignments [12,13,14,15,16], dynamic task allocation problems have grabbed high attention in research. For a group of agents to effectively perform on dynamic task flows, the research on agent cooperation needs to address the question of which and when agents should cooperate on a dynamically emerging task. The process of assigning agents to a certain task emerging timely is called task allocation. As tasks become increasingly complicated that a single agent cannot complete on its own, the need of cooperation methods for dynamic task allocation in MASs has become increasingly highlighted.

Specifically, since dynamic tasks in MASs become heterogeneous on resource requirement, cooperation has turned to be essential in dynamic task allocation. That is, agents in MASs need to cooperate with other agents for completing tasks. Obviously, cooperation helps agents be aware of the entire circumstance more exactly and promote the global efficiency of a system, like high task completion rate, high quality solutions and increased robustness on solution [17]. Moreover, when complex applications are gradually involved with agent cooperation, cooperation game theory and agent preferences need to be taken into consideration to fit the applications. For example, personal profit policy of agents would be adopted in commercial multi-agent problems, heterogenous resource requirements of tasks, agent personal preferences in tasks, e.g., tasks in and intelligence transportation [18], health care management [19,20,21], information transmission [22,23]. Dynamic task allocation is a class of task allocation problems in which the assignment of agents to tasks is a dynamic process and may need to be continuously adjusted in response to changes in the task environment or group performance. The dynamic task allocation problem in a distributed MASs is further compounded by the fact that how distributed agents negotiate to reach a solution. Apparently, based on the considerations above, the computational complexity grows exponentially along with those considerations.

Historically, the most general approaches aim at central coordination to deal with cooperation [21]. And there are numbers of cooperation algorithms for dynamic task allocation. In those algorithms, a central task coordinator coordinate agents' assignments to achieve task allocation. Due to communication issues, such approaches are mainly used in MASs with fully connected communication networks. When communication is constrained, task allocation through intentional coordination remains the preferred approach because it is better understood, easier to design and implement, and more amenable to formal analysis.

However, as task complexity grows, the complexity of designing negotiation approaches increases due to increased size of DASs. Furthermore, complexity that is introduced by increased robot interactions makes such systems much more difficult to analyze and design. Utilizing personal policy as a new feature of agents enables them more intelligent, and makes applying scenarios more close to the real-world problems. But it also brings many challenges to dynamic task allocation problems, such as the system lost caused by competitions among them, untruth of information agents might report, etc. Therefore, more sophisticated coordination methods are desired for solving those attacks. Some researchers attempted to import market-based approaches [25,26,27,28,29] and game theory [30,31,32,33,34,35] in MASs to handle the obstacles mentioned above. and they have made lots of achievements in this field.

In this paper, we firstly introduce the background on agent cooperation in MASs in section 2; then we present some cooperation approaches for dynamic task allocation in MASs in section 3. In section 4, we give out our views about future challenges in this area. Finally, the paper concludes with a summary of the survey and potential research points in this research area. Moreover, this review principally considers approaches that actively reason about cooperative

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agent determination policies when coordinating the entire system, and that avoid selfish agents from violate the total social welfare.

2 Background on Cooperation Algorithms in MASs

In this section, the necessary background on agent cooperation is introduced. Identified from the ways of calculation, cooperation algorithms are generally classed into centralized algorithms and decentralized algorithms. Since the two kinds of cooperation algorithms are different in design, the main considerations of each algorithm are different. Here, we analyze main considerations in centralized cooperation algorithms and decentralized cooperation algorithms respectively, and give out their individually general employments.

Generally, a cooperation problem in dynamic task allocation is defined as a tuple $D = \ < A, T, u >$, where A is a set of agents, T is a set of dynamic tasks and u is a utility function that reflects a utility of a certain group of agents completing a certain task.

Specifically, for task $t_i \in T$, it remains unknown till it emerges in a MAS. Usually, t_i can be described as a tuple t_i=<start_time, requirement, deadline, status> :

- Start_time. It describes dynamic task t_i's entering time, which is unknown until agents emerge in systems.
- Requirement. It describes task t_i's resource demand. Complex tasks often come with requirements on heterogeneous resources, which demands agent cooperation in need.
- Deadline. It is task t_i's completing requirement on time. Tasks always comes with deadline for execution, which is normal in general employments.
- Status. It describes task t_i's status, like unhandled, or completed.

And for agent $a_i \in A$, we can define it as a tuple a_i=<resource, preference, status> :

- Resource. It describes resources obtained by agent a_i. Agents can own heterogenous resource for task requirements.
- Preference. It describes agent a_i's personal preference on tasks. And taking preference into designing agent utility function can calculate optimal solution with more effective.
- Status. It describes agent a_i's availability on cooperation. There are two status of agent a_i on cooperation, idle and busy. A status of agent a_i indicates is whether it can join a cooperation or not.

And the definitions of utility function are differently defined in different calculation methods. Generally, the definitions of utility functions are defined in two forms. Like in centralized cooperation algorithms, since there is a central allocator being responsible for gathering all information in the system and assigning agents tasks, designers often define a global utility function for optimization; while in decentralized cooperation algorithms, there is no central task allocator and agents need to make decisions based on its local information, designers often define an agent individual utility function for optimization. Therefore, negotiation mechanisms for solution optimization calculation in those two kinds of cooperation algorithms differ.

2.1 Centralized cooperation algorithms

In centralized cooperation algorithms, there is supposed to have a central allocator that calculate agent cooperation solutions and assign agents with certain tasks, via gathering system information.

The central allocator is usually settled with full connection with all agents for information and task assignments. It collects all information of agents for task assignment optimization calculation, and inform agents with calculated optimal allocation solution. Since the central allocator assigns tasks to all agents, the negotiation on task allocation is also done by the central allocator. In addition, a global utility function is defined in centralized cooperation algorithms to assist the solution calculation. With complete information, it is easy for a central allocator to calculate an optimal solution. Therefore, the main work of centralized cooperation algorithms is to design a most appropriate utility function to get an optimal solution with unknown dynamic tasks.

However, robust of centralized cooperation algorithms relies on efficiency and robust of employed communications. Once communication breaks down, the algorithm would not work robustly as expected. Thus, centralized cooperative algorithms are generally employed in applications with steady communication, e.g., clouding service, cloud computation. Besides, any breakdown of the central allocator also effect the performance of the whole system.

2.2 Decentralized cooperation algorithms

Generally, because communication in distributed MASs is infeasible to keep in steady, decentralized cooperation algorithms are usually employed for dynamic tasks allocation in those systems. unlike centralized cooperation algorithms, there is no central allocator, who is responsible for assigning tasks to agents, in decentralized cooperation algorithms.

Since being distributed agent, each agent can only perceive its local information and there is no central processor gathering and distributing all information. Thus, each agent collects its local information for making task participating decisions, negotiates with other agents to achieve a task allocation plan. Thus, decentralized cooperation algorithm designers usually define an agent individual utility function for assisting agent making decisions. And obviously, the key point of decentralized cooperation algorithms is negotiation mechanism designing.

Evidently, local information is incomplete for making optimal decision, and it is not feasible for agents in distributed MASs to form a global optimal solution. They also find methods to approximate a global utility with agent individual utility. Generally, a sub-optimal allocation is a solution of decentralized cooperation algorithms.

3 Coordination Algorithms in MASs

In this section, we introduce some well employed cooperation algorithms, including a centralized cooperation algorithm and some decentralized cooperation algorithms, of which we give brief introduction on the working framework and on calculation process.

3.1 Centralized Cooperation Algorithm based on Coalition Formation Games

The centralized cooperation algorithm based on coalition formation games(CCACFG) [27] we introduce deals with tasks with heterogeneous resource requirement by utilizing coalition formation theory. In this approach, there has a task coordinator that is responsible for dynamic task response. It is supposed to form coalitions to response tasks based on coalition game theory. The novelty of this approach is that its designers model the process of assigning agents as a coalition formation game where groups of agents are evaluated with respect to resources and cost. When new tasks emerge in the system, the task coordinator calls to form responding coalitions for executing tasks based on tasks requirements.

Since tasks and agents are heterogenous on resource, designers propose a coalition utility function via encoding resource sufficiency, resource excessiveness and waiting time to start executing tasks. And the process of the algorithm is given in figure 1.

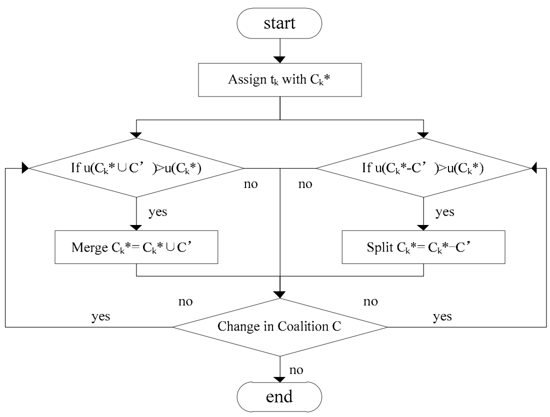

Figure 1. Process of CCACFG

Based on the Pareto order given by the preference of agents, the task coordinator form coalitions by two phrases, merge and split. The coordinator uses merge and split operations on the existing coalitions. Through the two operations, an optimal coalition will be formed for a certain task.

3.2 A decentralized belief propagation-based algorithm

The decentralized belief propagation-based algorithm [7] is proposed for multi-agent task allocation in open and dynamic grid and cloud environments where both the sets of agents and tasks constantly change. This approach is designed to accelerate the online response, improve the resilience from the unpredicted changing in the environments, and reduce the burden of information passing for task allocation. The pruning phase focuses on reducing the search space through pruning the resource providers, and the decomposition addresses decomposing the network into multiple independent parts where belief propagation can be operated in parallel.

In cloud environments, many tasks with deadlines require resources from multiple providers with independent resource. Considering the dynamism and openness of the environments where both resource providers and consumers can come and leave freely, in-time online response and reduction on communication burden are urgent concerns.

Moreover, a task in cloud service generally consists of more than one subtask that have dependent constraints. Thus, the goal of the corresponding task allocation is to find an optimal configuration to maximize the system utility. And agents do optimizing calculation via two steps, pruning and decomposition. Tasks are designed to have a reserved cost, which can be used to do pruning. And agents need to do belief propagation on others' states to find the optimal task executor.

3.3 Max-sum Algorithm based on DCOP

In [1], researchers propose an agent-based decentralized cooperation algorithm based on distributed constraint optimization problem (DCOP) formulation [33]. The algorithm is based on a factor graph representation of agents' interactions, as shown in figure 2.

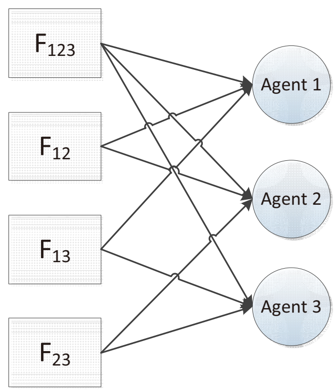

Figure 2. Factor graph in DCOP

As shown in figure 2, F is a factor, representing constrains among agents. For example, F123 is a factor among agent 1, agent 2 and agent 3, and it is defined by constraints among the three agents. So as the other Fs in figure 2. By factor graph, we can have a relation network on constrains of the whole system.

Based on the factor graph, the max-sum algorithm, a specific instance of a general message passing algorithm that exploits the generalized distributive law to decompose a complex calculation by factorizing it, is adopted for optimization and negotiation. Also, since max-sum algorithm is an approximate solution technique for decentralized cooperation that has been successfully deployed on low-power devices, it can be employed in dynamic circumstance for dynamic task allocation calculation.

3.4 Asynchronous Consensus-Based Bundle Algorithm

The asynchronous consensus-based bundle algorithm (ACBBA) [9] is proposed to solve real time implementation issues of decentralized planners. This algorithm utilizes a new implementation that allows further insight into the consensus and message passing structures of ACBBA. And asynchronous re-planning is introduced to ACBBA's functionality that enables efficient updates to large changes in local situational awareness.

This algorithm is agent-based with each agent bidding on dynamic tasks. Since being in a distributed system, each agent keeps a list of its bids and a list of winning bids of all emerged tasks as well. Though there is no auctioneer in the system, an auction method is adopted to solve the bids. Thus, agents need to transmit messages about winning bids to achieve a consensus for a task allocation. The main feature enabled by ACBBA is the ability for each agent to build bundles and perform consensus on their own schedule.

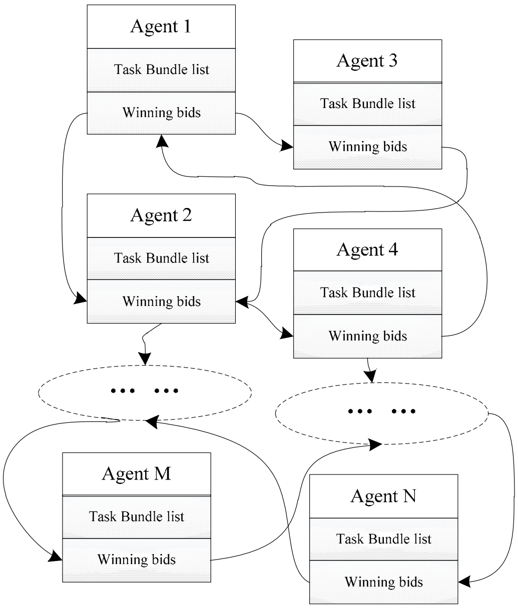

Figure 3. Negotiation process in ACBBA

As illustrated in figure 3, each agent transmits messages on its belief about winning bids. Agents transmit messages to their neighbors with its belief about winning bids, and solve the local conflicts on winning bids with proposed local deconflict rules. And the ACBBA deconfliction protocol is that, not only does it specify how the receiver should update its winning agents and winning bids lists, but it also specifies what messages to rebroadcast.

3.5 A Self-Adaptation-Based Dynamic Coalition Formation Algorithm

The self-adaptation based dynamic coalition formation algorithm [34] is proposed for dynamic sensor networks, illustrated in figure 4. This approach is designed based on coalition game theory. Considering the existence of a distributed working circumstance, it is infeasible for sensors to directly interact with all other agents. Thus, designers employ a social network for agent communication in this situation. With this communication network, agents transmit information via their neighbors.

Based on the adopted social network, the proposed distributed algorithm incorporated a self-adaptation concept, which enables agents to dynamically adjust their degrees of involvement in current coalitions or join new coalitions. The process of self-adaptation in a large-scale and distributed system is of key importance to the performance of a distributed MAS. And it can be employed in agent networks to improve the cooperative behaviors of agents.

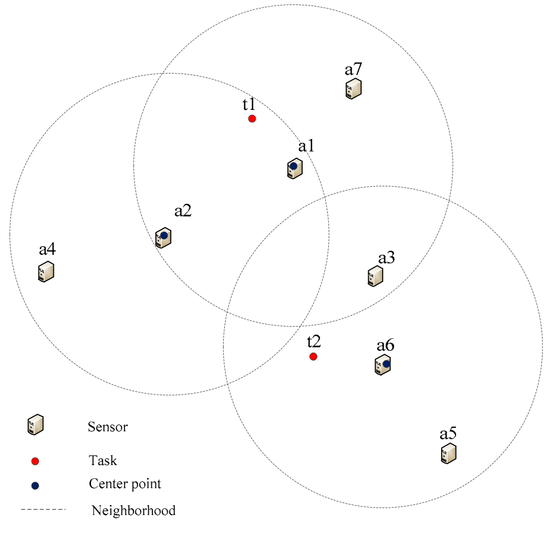

Figure 4. Dynamic sensor networks

In this algorithm, the auction method is employed to do the optimization. idle agents generate offers to their neighbors when they detect tasks. The agents those receive offers make their choice on its own situation. When an agent accepts an offer, that means it agrees with a temporary contract with the task announcer. Once it finds an offer unsatisfied, it can send back a counter-offer for its available resource. And in this algorithm, agents could partly join a task based on the available resource it has. And the negotiation process can be described as figure 5.

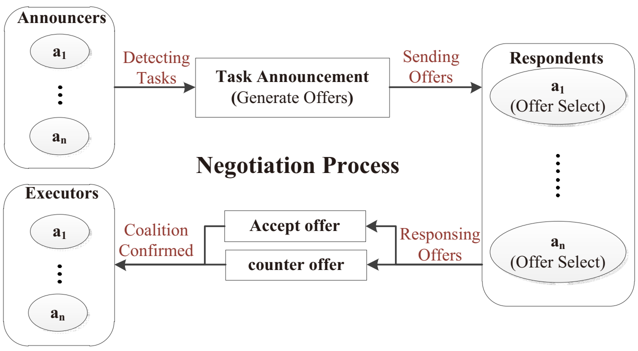

Figure 5. Process of the self-adaptation-based dynamic coalition formation algorithm

4 Benefits and Challenges

The popularity of cooperation algorithms is mainly derived from the gradually growing applications of MASs. With cooperation, agents are enabled to cooper with more complicated tasks, e.g., heterogeneous requirements on resource and unpredictable emerging time of tasks. In all, cooperation helps to enhance the practical ability of MASs on executing tasks.

Meanwhile, as practical problems turn out to be more complex, agents are supposed to be with more individual features to adapt to situations in those applications, which demands gradually growing self-organization and intelligence of individual agents. Thus, more challenges come. Here, we give out our own consideration on future challenge in this field.

- Sophisticated model. As tasks become more complicated with unpredictable dynamics and heterogenous resource requirements, a sophisticated model is demanded urgently for the problem formulation. Evidently, the model will be more practical when its considers more details.

- Decomposition of tasks. Complex tasks often have complicated requirements which can be decomposed of several sub-tasks, or tasks are not independent. To deal with this, task decomposition is in need to simplify the problem.

- Intelligent agents. As distributed MASs are employed more widely, the scale of the problem increases hugely. Considering practical communication, intelligent agents are needed for distributed cooperation. Agents are assumed to have enough intelligence to do its own decision with little local information.

- Negotiation mechanism design. In distributed MASs, agents need to negotiate with its neighbors for more information or agreement on cooperation solutions. With large scale of cooperation in MASs, well designed negotiation mechanisms are demanded for reducing the communication burden.

5 Conclusion

Agent cooperation for dynamic task allocation in MASs is an active and rapidly expanding field in research, and aims to provide an effective and flexible response with intelligence on dynamic task allocation. To this end, agent cooperation needs to integrate system performance, task requirements and agent preference.

This paper has provided a brief overview on agent cooperation in MASs. We firstly present the main benefits and challenges of agent cooperation. Then, we give the background of agent cooperation and analyze the main factors. Additionally, we present some agent cooperation algorithms in dynamic task allocation, including central cooperation algorithms and decentral cooperation algorithms. And we also give out advantages and applied situation of the two kinds of cooperation algorithms. finally, we give our views on agent cooperation and analyze its future challenges based on its future employments.

As a boosting issue in artificial intelligence research, agent cooperation owns outstanding benefits in MASs, especially in distributed MASs. Along with those benefits, there also comes challenges in agent cooperation, like task decomposition, negotiation in agent individual decision and decision making on local information.

In our view, magnificent progress in this area can be achieved by a more intelligent cross between the fields of system control and game theory.

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