Negotiations in Holonic Multi-agent Systems

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Abstract Holonic multi-agent systems (HOMAS) have their own properties that make them distinct from general multi-agent systems (MAS). They are neither like competitive multi-agent systems nor cooperative, and they have features from both of these categories. There are many circumstances that holonic agents need to negotiate. Agents involved in negotiations try to maximize their utility as well as their holon's utility. In addition, holon's Head can overrule the negotiation whenever it wants. These differences make defining a specific negotiation mechanism for holonic multi-agent systems more significant. In this work, holonic systems are introduced at the beginning; and then different aspects of negotiation in these systems are studied. We especially try to introduce the idea of *holonic negotiations*. A specific negotiation mechanism for holonic multi-agent systems is proposed which is consistent with the challenges of HOMAS.

Keywords Multi-agent systems · Negotiation · Holonic

1 Introduction

Negotiation techniques are used to overcome conflicts and coalitions, and to come to an agreement among agents, instead of persuading them to accept a ready solution [13]. In fact, negotiation is the core of many agent interactions, since it is often unavoidable between different project participants with their particular tasks and

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domain knowledge whilst they interact to achieve their individual objective as well as the group goals. The importance of negotiation in MAS is likely to increase due to the growth of fast standardized communication infrastructures, which allow, separately, designed agents to interact in an open and real-time environment and carry out transactions safely [19].

Negotiations in MAS can be divided into two main categories: Negotiations in competitive and cooperative MAS. Competitive MAS refers to systems that agents are fully self-interested, and want to maximize their own pay-offs. In cooperative environments, agents usually care about their pay-off and also others' [17]. Holonic multi-agent systems are not fully competitive or cooperative. They are similar to semi-cooperative MAS [8], but there are some critical differences between these two. Few work has been done in the field of holonic multi-agent systems. In the same manner, negotiations in HOMAS are not studied as a separate phenomenon that much.

In this paper, first of all we provide a brief overview of HOMAS in Sect. 2. Then, in Sect. 3 negotiations in HOMAS are studied and the differences that make them distinct from the rest are illustrated. Section 4 is devoted to proposal of a specific negotiation mechanism for HOMAS, and in Sect. 5 the experimental results are provided. Finally, Sect. 6 includes concluding remarks.

2 Holonic Multi-agent Systems

The theory of holonic structures was proposed by Arthur Koestler in 1967. This theory implies a structure which is composed of components named "Holons". A holon is a self-similar or fractal structure that is stable and coherent and consists of several holons as sub-structures [12]. Each holon may contain several subholons, and might be part of a greater holon itself. In this manner a hierarchical structure forms. The organizational structure of a holonic society or holarchy, offers advantages that the monolithic design of most technical artifacts lacks: They are robust in the face of external and internal disturbances and damage [1, 10]. They are efficient in their use of resources, and they can adapt to environmental changes [11]. The concepts of fractal and holonic system design in manufacturing were proposed to combine top-down hierarchical organizational structure with decentralized control, which takes the bottom-up perspective [18].

Within the multi-agent systems domain, holonic multi-agent systems are a special category which are based on holonic structures introduced above. In these systems, several agents join together and make a holon. Form the external view, each holon is quite similar to a single agent. It has common properties of an agent. So, we can use the terms 'holon agent' and 'agent' interchangeably. Figure 1 shows a simple scheme of HOMAS. Each holon usually has a representative called "Head". Other agents within a holon are called "body-agents". Head can be elected by holon's members, or it can be a predefined agent. The main idea of HOMAS is to assign a task which a single agent cannot accomplish to a holon. The holon then decides how to perform

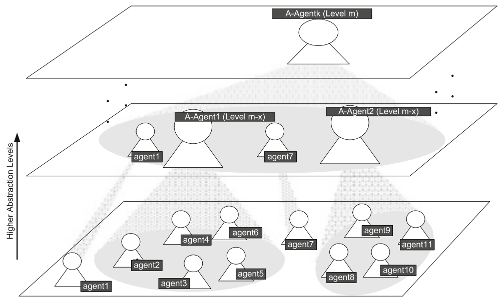

Fig. 1 Holonic multi-agent systems structure, courtesy of Botti and Giret [5]

this task. In this way a big/super goal divides to several sub-goals, and each holon is responsible for one or more sub-goals. In the same manner, these goals can be divided into several sub-goals which a holon assigns to its sub-holons. This makes HOMAS design more flexible and simple. The capability of the resulting MAS is an emergent functionality that may surpass the capabilities of each individual agent [16]. Often, problems are neither completely decomposable nor completely non-decomposable. In many hybrid cases, some aspects of the problem can be decomposed, while others cannot.

Holonic agents are structured hierarchically. They can easily realize actions of different granularity, they are autonomous to a certain degree, and they are pro-active; hence holonic agents systems can naturally deal with problems of that type [11]. Agents acting in such structures can encapsulate the complexity of subsystems (simplifying representation and design) and modularize its functionality (providing the basis for rapid development and incremental deployment) [16]. Especially, for extra large systems which contain many agents -for example, a simulator of a city's pedestrians or cars- HOMAS efficiency becomes more visible. Holonic dynamism makes these systems able to have better performance in dynamic and complex environments.

The key property of holonic agents is **bounded autonomy**. Agents in HOMAS are rational and self-interested and decide what to do based on their own preferences like general agents in MAS. But, from the time an agent joins a holon, it cannot do whatever it wants. It should obey holon's commitments after this. This does not mean that every action which the agent makes is determined by the holon's Head like fully cooperative MAS. An agent usually can decide when to join a holon, or leave the holon [4].

3 Negotiations in Holonic Multi-agent Systems

In HOMAS, agents need to coordinate or reach agreement during their activities like other MAS. Generally, there are several ways to reach an agreement in MAS. One of the most common ways is negotiation. In a negotiation process, two or more parties try to reach agreement as soon as possible. They usually want to maximize their payoff too. Negotiations in HOMAS have common properties and characteristics of MAS, but they have some differences too. If the overall problem is decomposed into sub-problems that are not partitions of original one, but there is some overlap in the sense that logical interdependencies occur, communication among the problem solvers is needed. Sub-agents of a holon are communicative and hence, holonic agents are useful in domains of this type. Furthermore, a domain often induces an asymmetric communication behavior between problem solvers in the sense that each unit does not communicate to all other units equally often, i.e., patterns in the communication behavior can be observed. These patterns indicate possible structures for holonic agents: Holons provide facilities for efficient intra-holonic communication, supporting higher frequent communication inside the holon than among different holons (inter-holonic) [11].

The connections (among the agents) in HOMAS can be within a holon or between the holons. Head is responsible for the connections between the holons. In this way, three types of negotiation can be considered in HOMAS. These three types are shown in Fig. 2. The first is among two or more Heads. The second is between a holon's Head and its body-agents, and the last is among the body-agents. The first and third types of negotiation are like general negotiations in MAS. Common mechanisms and settings of negotiations can be used in these negotiations, too. But, the second type is the type which we called *holonic negotiations*. There are a lot of circumstances that a holon's Head decides to reach agreement on something with other holon's agents. For example, in task assigning, Head can negotiate with the agents about what task each agent prefers to accomplish. The main difference of this type of negotiation with other type of negotiations is the possibility of overrule in the negotiation. In general negotiations a self-interested negotiator agent continues the negotiation while it's confident about gaining payoff, and it can also leave the negotiation process whenever it wants. In HOMAS, an agent wants to maximize its utility, but it also knows that it is possible for Head to overrule its decision. Head's overruling means that the agent is forced to do something not based on its preferences, instead because of its commitments to the holon. In this manner, all of negotiation's configurations are affected by these characteristics. Head should decide when to terminate the negotiation and other agents should always consider that if they do not compromise enough, it is possible that they do not gain any utility.

In real negotiations, the main source that agents can obtain useful information about properties of other negotiation parties is the negotiation history [9, 15]. Other assumption about the agents -like knowing preferences or willingness to cooperate

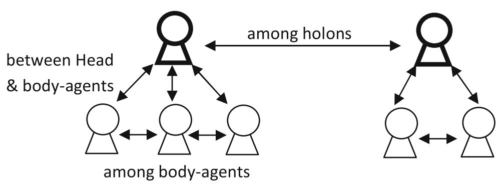

Fig. 2 Three different negotiation types in HOMAS

of each other- may be in conflict with the fact that each agent tries not to reveal its privately owned information. So, if an agent wants to learn to improve its negotiation result, it should use the negotiation history. The learning method which is used in holonic environments must be simple and fast. This issue becomes more important when we consider the environments where HOMAS are usually used in. HOMAS usually are used in complex and very large systems which have too many agents. In these systems, holonic structure helps to design the system in more simple and efficient way. In these cases, the system's goal is divided into smaller goals, and each goal is assigned to a holon. Several agents join together and make a holon, and Head decides what each agent should do. In this manner a holonic negotiation scheme should be simple and efficient. It should be fully operable in real time usages.

Other specifications, which make Holonic negotiations distinct, are:

- In HOMAS, an agent can be body-agent of a holon and Head of another holon in the same time. According to this, the agent should always consider its role in the negotiation process in order to choose proper strategy or utility function. As a Head, an agent has totally different responsibilities from when it negotiates as a body-agent.
- When Head negotiates with the holon's body-agents, it may encounter similar agents which have similar properties and negotiation style or they may be dissimilar agents. In HOAMS terms, Head may be in a homogeneous holon or in a heterogeneous holon. In the case where the agents have distinct properties, Head should learn different negotiation styles/strategies.
- Another issue about Head is that Head has such a utility function which has direct relation to the holon's utility. In other words, Head's utility increases when the utility of holon increases. Head tries to increase holon's payoff as a whole. According to this introduction we introduce our method for negotiations in HOMAS.

Among different negotiation protocols available within the multi-agent systems community, some of them could be considered similar to the characteristics of HOMAS negotiations. Specially, negotiation methods that are designed for hierarchical domains are very similar to the idea of holonic negotiations [6, 14].

4 A Specific Mechanism for Negotiations in HOMAS

Here, a special negotiation framework for HOMAS is proposed. In this framework, whenever a negotiation process starts, body-agents propose their offers in every round and Head checks the proposed offers and if the agreement criterion was met, it will inform others about the agreement.

Head and body-agents both try to learn. Linear regression is the learning method which is used in our method. Linear regression is a simple and powerful method which can efficiently be used in real time and dynamic usages. Determining proper independent variables (terms whose values are known) which affects dependent variables (terms which should be predicted) is too important in the regression learning ability. Head wants to know how many rounds the negotiation will last, or when the negotiation will reach to agreement. This is because Head cannot allow body-agents to negotiate for unlimited period. In the other hand, a body-agent is willing to know what other agents propose in each round. It can use this information in order to decide what offer to propose.

A common point among negotiations in humans or artificial agents is that in order to choose the most appropriate offer to propose, they usually try to predict others' offers. Here, for prediction of other agents' next offers, an agent uses linear regression. The independent variables of regression algorithm are previous offers which other agents proposed in the previous round plus the current round number. Holonic agents have special behavior which makes them simultaneously self-interested and cooperative. This behavior is somehow like the semi-cooperative behavior which was described earlier. Semi-cooperative behavior is implemented in different ways. One of these implementations assumes that the agent tries to maximize its utility until some round, and after that point the agent tries to cooperate. In our method, we assumed that this point is a round called *warning round*'. Warning round is the round which Head decides to terminate the negotiation in several rounds later. In this round, Head tells other agents how many rounds they have before negotiation overrule.

In every round, each body-agent runs a thread of regression algorithm in order to predict other agents' next offer. Then, the agent uses this information to decide what offer to propose in the next round. The details of this decision making will be illustrated later. Head uses the same learning approach to predict when the current negotiation will reach to an agreement. Head records the offers that each agent proposes in every round, and like other body-agents it predicts body-agents' next offer using regression. When the negotiation starts, using this data, it predicts body-agent's offers in two round later and then three and so on. Also, based on this information it predicts the agreement round. After this, Head decides when to inform body-agents about the number of remained rounds which they can reach agreement (announcing warning round). Head makes this decision based on the problem configuration. It mainly depends on the time pressure of the holon's domain. As the time pressure increases, Head decreases the number of remained rounds. Head uses warning round as a tool to force body-agents to compromise more.

During the first runs of negotiation, an agent mainly tries to gather useful information which helps it in learning phase. In order to implement this behavior an exploration probability', P_a, is assigned to each agent. An agent explores the environment with probability of P_a and during this period, it uses a simple greedy approach that only selects the option with maximum utility. As the negotiations proceed, this probability decreases. In addition, every agent has a discount ratio, "Ω". This parameter demonstrates the utility of an offer in the next rounds. Ω is like the Ω parameter in bargaining domains. This parameter has the same effect as *time* in other similar negotiation mechanisms. The value of Ω is between 0 and 1. A greater value of Ω means less importance of time.

The process which a body-agent selects what offer to propose in the next round is different before and after the warning round. Before the warning round, a body-agent firstly sorts all of the offers which it can propose based on its utility function. The offer which maximizes its utility is called as *maximal option* or o_m. The agent will propose this option, if the option guarantees agreement in this round. Otherwise, it checks utility of options which guarantee agreement. The option with maximal utility among these options is called $o_{m'}$. If the utility value of o_m in next round was less than $o_{m'}$ utility in current round, the agent will propose $o_{m'}$. In other words, the agent proposes the option which certainly maximizes its utility.

After the warning round, a body-agent knows that if the agreement is not met within the remained rounds, Head may overrule its decision to all of negotiation's participants. At that time the agent must do something that might have no utility for it. So, to avoid this, body-agents should compromise more. It is logical for this compromise to be proportional to the number of remained rounds, or n. In the warning round, Head tells body-agents how many rounds they still have to reach agreement. The general idea is that the agent firstly selects the maximal option, then the agent checks within the options which guarantees agreement. If there was an option with the utility of equal or greater than $(n'/n * maximal\,option's\,utility + option's\,utility)$ the agent will propose that option (here, n' is number of rounds which are passed after the warning round). In other words, the agent compromise $1/(number\ of\ passed\ rounds)$ of maximal option in each round. Ω has the same effect as previous. Figures 3 and 4 show two examples of the negotiation process for a body-agent before and after warning-round.

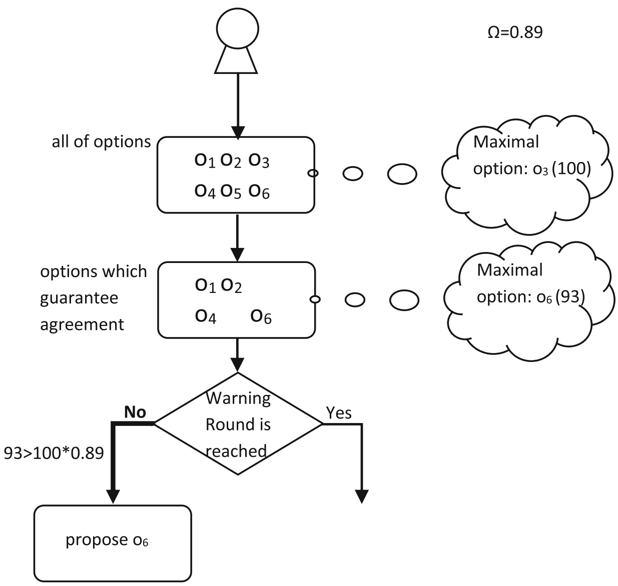

Fig. 3 Warning round is not reached

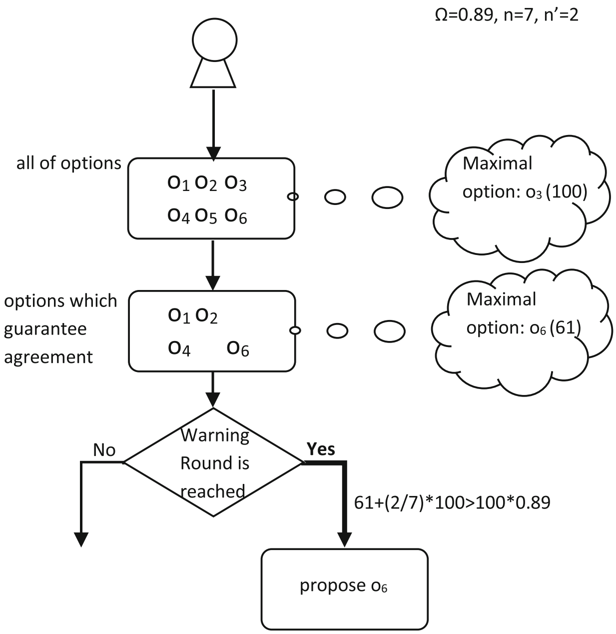

Fig. 4 Two rounds is passed after the warning round, and five rounds is remained until final round

5 Experimental Results

In this section, the results of bench-marking the proposed method in several experiments are illustrated. We compare the proposed method with several existing negotiation methods. The first method is a simple method which an agent just selects the option with maximal utility in each round and proposes it without caring about any other criteria. The second is a Bayesian learner based approach [7]. This method uses a Bayesian learning mechanism to learn other agents' preferences, and use them to make better coordinated decisions. The last method is a similar negotiation mechanism which is proposed for semi-cooperative environments (SC-Ordered-Learner) [8]. In this method, agents use regression based learning in order to learn others' preferences. In the experiments, a population of 1000 and 10000 agents were studied. The initial exploration probability was equal to 0.89, and the number of available tasks was equal to the number of agents. Also, the value of Ω was between 0.7 and 1.

Table 1 shows parameter settings for the experiments which were used.

Table 1 Parameter settings for the proposed method's experiments

Holon's agents	Initial expl. prob.	Num. of tasks	Dis. rate (Ω)
1000–100000	0.89	Equal to agents	Random btw. 0.7 and 1

The designed scenario for the experiments is a task assigning problem. There are a number of tasks which each body-agent should sponsor exactly once. In each round, body-agents propose their offers and Head checks all of these offers. Based on the previous proposed offers, if a permutation was found that all of the tasks could be assigned to the agents, Head announces the agreement. The utility value that agents receive after negotiation and negotiation time are two main factors that agents try to optimize in the negotiation. These two measures have been used in other similar studies in order to show the performance of negotiation mechanisms [2, 3]. Accordingly, in order to compare a negotiation mechanism with other mechanisms, utility and time factors are the basic measures which should be considered.

Figures 5 and 6 show the comparison between negotiation time using the proposed approach and other described methods. Since the negotiations are happening within a consecutive set of rounds, time of negotiation relates to the number of rounds that

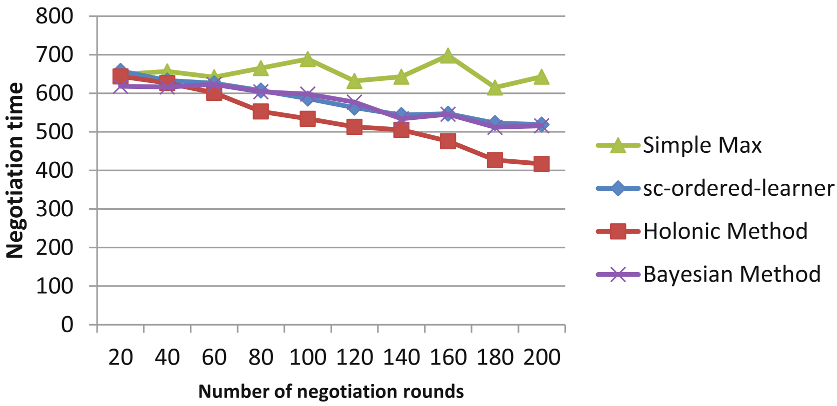

Fig. 5 Average negotiation time for 10000 agents

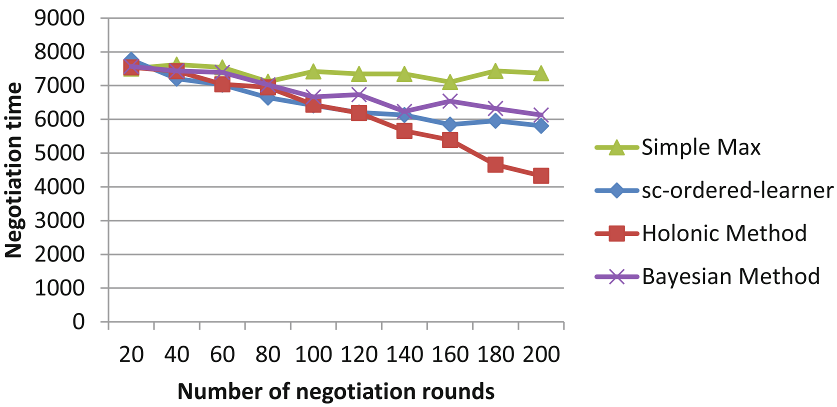

Fig. 6 Average negotiation time for 100000 agents

the negotiation lasts. This is the average number of negotiation rounds. As the figures show, the simple max approach has approximately fixed results, it does not use any learning method and consequently, its performance does not change. The results for other two methods which employ learning algorithms, improve as the number of negotiations increases. The sc-ordered-learner method which seems a better fit to the holonic environments than Bayesian method, has better results than Bayesian method. Another point regarding to this set of results is that as the number of agents increases (from 1000 to 10000) the performance of the proposed holonic method in comparison with other methods increases. We mentioned earlier that HOMAS usually are used in systems which include a very large number of agents, so these results show that the proposed approach can work better in usual Holonic systems environments.

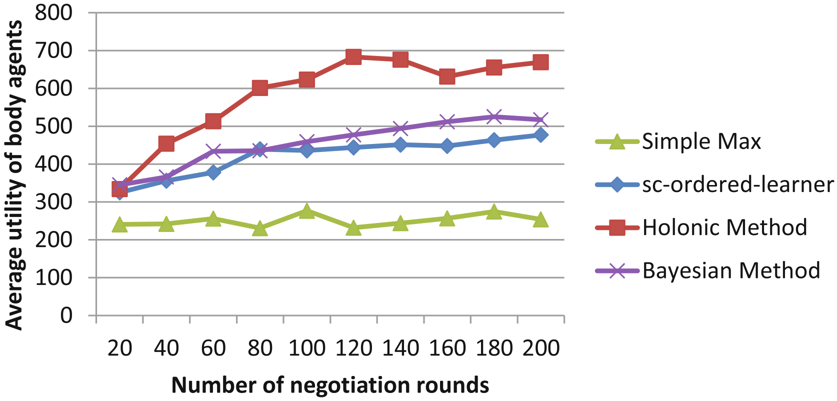

Fig. 7 Average utility obtained by body-agents for 1000 agents

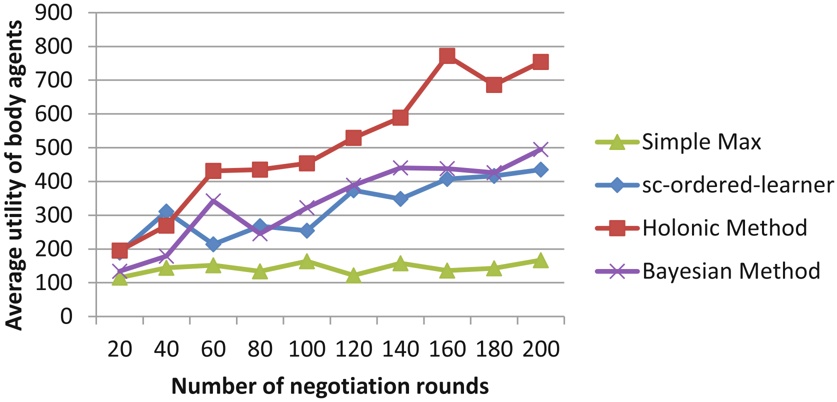

Fig. 8 Average utility obtained by body-agents for 1000 agents

In Figs. 7 and 8, the average utility of all agents involved in the negotiation is shown. This value refers to the average utility value of all of agents after they finished a negotiation with another agent. Like previous results, simple max method did not obtain more than some almost fixed results. Bayesian and sc-ordered-learner methods performance improve when negotiation rounds pass. They approximately have competitive results. Holonic method obtained better results and its results improve as the number of agents increases. Once again, holonic method's performance gets better when the environment becomes larger.

6 Conclusions

In this paper, negotiations in holonic multi-agent systems are studied. The main differences which make this kind of negotiation distinct from general negotiations are illustrated. Most of these differences result from the holonic agents' properties, and others are outcome of the holonic structure. Based on these differences, a specific negotiation mechanism for these domains is proposed. Initial results show that this method can work well in holonic multi-agent systems.

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