Scalable Negotiation Protocol based on Issue-Grouping for Highly Nonlinear Situation

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Abstract

Most real-world negotiation involves multiple interdependent issues, which makes an agent's utility functions nonlinear. Traditional negotiation mechanisms, which were designed for linear utilities, do not fare well in nonlinear contexts. One of the main challenges in developing effective nonlinear negotiation protocols is scalability; they can't find a high-quality solution when there are many issues, due to computational intractability. One reasonable approach to reducing computational cost, while maintaining good quality outcomes, is to decompose the utility space into several largely independent sub-spaces. In this paper, we propose a method for decomposing a utility space based on every agent's utility space. By employing the simulated annealing technique based on agents' votes, it is not necessary for the proposed method to reveal private utility information. This method allows good outcomes with greater scalability than the method without issue-grouping.

1 Introduction

Negotiation is an important aspect of daily life and represents an important topic in the field of multi-agent system research. There has been extensive work in the area of automated negotiation; that is, where automated agents negotiate with other agents in such contexts as e-commerce[5], large-scale argumentation [7], collaborative design, and so on. Even though many contributions have been made in this area [1], most have dealt exclusively with simple negotiations involving one or more independent issues. Many real-world negotiations, however, are complex and involve interdependent issues. When designers work together to design a car, for example, the utility of a given carburetor is highly dependent on which engine is chosen. The key impact of such issue dependencies is that they result in agent utility functions that are nonlinear, i.e. that have multiple optima. Most existing negotiation protocols, though well-suited for linear utility functions, work poorly when applied to nonlinear problems [4]. Recently, some studies have focused on negotiation with nonlinear utility functions[2, 9, 8]. For example, a bidding-based protocol was proposed by Ito et al.[3]. Agents generate bids by finding high regions in their own utility functions, and the mediator finds the optimum combination of submitted bids from the agents. However, an unsolved problem is the scalability of the protocols against the number of issues. Most of the existing works focus on small size negotiations (less than ten issues), therefore, the scalability of negotiation protocols isn't

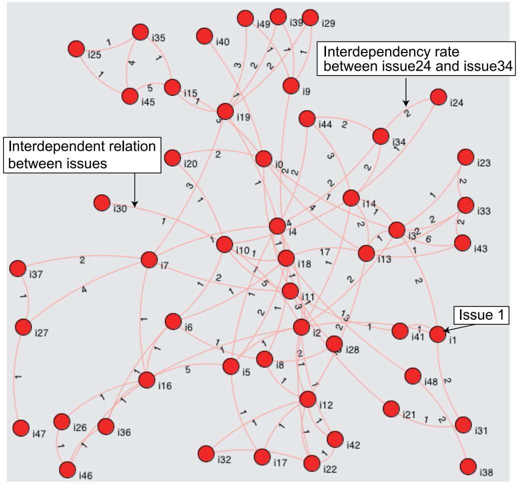

Figure 1: Interdependency Graph (50 issues)

enough to employ to the real-life negotiations. Our protocol focuses on the large-scale (nearly 50 issues) and interdependent multi-issue negotiations as Figure 1 shows.

We propose a new protocol in which a mediator tries to reorganize a highly complex utility space into several tractable utility subspaces, in order to reduce the computational cost. First, we have to define a measure for the degree of interdependency between issues, and generate a weighted non-directed interdependency graph. Second, we propose an efficient and scalable protocol based on the issue-groups. Agents generate the idea of issue-groups based on their utility information, and the mediator combines the idea of issue-grouping from all agents. After that, the mediator finds the contracts in each group based on the votes from all agents, and combines the contract in each group. This protocol also doesn't reveal private information (utility information). In addition, we can improve the truthful-voting protocol by employing the limitation of strong votes. Finally, we demonstrate that our protocol, based on issue-groups, has a higher optimality rate than previous efforts, and discuss the impact on the optimality of the negotiation outcomes. In addition, this protocol is influenced by the idea of issue-grouping from each agent. We also analyze it from the experimental results.

The remainder of this paper is organized as follows. First, we describe a measure for assessing the degree of issue interdependency, and the testbed based on real-life negotiation. Second, we present a technique for finding issue sub-groups, and propose a protocol that uses this information to enable more scalable negotiations. Third, we present the experimental results. Finally, we describe related works and draw conclusions.

2 Interdependency among Issues

The basic negotiation settings are almost same as Ito et al.[3]. We employ the highly nonlinear utility space based on constraints to our new method. By using this negotiation setting, the interdependency between issues, nonlinear utility function, and multilateral negotiation are achieved.

An issue interdependency for multi-issue negotiations is defined as follows. If there is a constraint between issue X (i_X) and issue Y (i_Y), then we assume i_X and i_Y are interdependent. If, for example, an agent has a binary constraint between issue 1 and issue 3, those issues are interdependent for that agent.The strength of issue interdependency is measured by the *interdependency rate*. We assume that there are l constraints, $c_k \in C$. Function $\delta_a(c_k, i_j)$ is a region of i_j in c_k, and $\delta_a(c_k, i_j)$ is $\emptyset$ if c_k has no region regarded as i_j. We define a measure for the interdependency between $issue\ i_j$ and $issue\ i_{jj}$ for agent a: $D_a(i_j, i_{jj}) = \sharp\{c_k | \delta_a(c_k, i_j) \neq \emptyset \ \wedge \ \delta_a(c_k, i_{jj}) \neq \emptyset\}$. This measures the number of constraints that inter-relate the two issues. The agents capture issue interdependency information as an interdependency graph. An interdependency graph is represented as a weighted non-directed graph, in which a node represents an issue, an edge represents the interdependency

Votes	Numeric value
Accept	2
Weakly Accept	1
Weakly Reject	-1
Reject	-2

Table 1: Votes and numeric values

(Utility of next situation) - (Utility of present situation)	Vote
$X_1 \sim$	Accept
$0 \sim X_1$-1	Weakly Accept
$X_2 \sim -1$	Weakly Reject
$\sim X_2$-1	Reject
(X_1, X_2 are arbitrary integer numbers.)	

Table 2: Votes and utility in agents

between issues, and the weight of an edge represents the interdependency rate between the issues. Figure 1 shows an example of an interdependency graph. An interdependency graph is thus formally defined as: $G(P, E, w) : P = \{1, 2, \ldots, |I|\}(finite\ set),\ E \subset \{\{x, y\}|x, y \in P\}, w : E \rightarrow R.$

The method of determining the interdependency between issues is as follows. **(Step 1)** Small issue-groups are generated by connecting the issues randomly. **(Step 2)** The interface issues are decided randomly among issues in each issue-group. The interface issues are for connecting other small issue-groups. In small issue-groups, only the interface issues can connect to other issue-groups. **(Step 3)** Each issue-group connects to other small issue-groups. Specifically, all combinations of each issue-group are searched for, and it is decided whether connection or disconnection according to the possibility of generating connections.

3 Negotiation Protocol based on issue interdependency

[Step 1: Analyzing issue interdependency] Each agent analyzes issue interdependency in its own utility space by analyzing all constraints, and generates an interdependency graph. After that, each agent generates his/her own idea of issue-grouping using the Girvan-Newman algorithm[6], which is for computing clusters in weighted non-direct graphs based on edge betweenness. The edge betweenness shows the weighted shortest path in our protocol. Running time of this algorithm is $O(kmn)$, where k is the number of edges to remove, m is the total number of edges, and n is the total number of vertices.

[Step 2: Grouping issues] In this step, the mediator combines the ideas of issue-grouping submitted by each agent. For example, agent 1 submits the idea $A_1 = \{i_1, i_2\}, \{i_3, i_4, i_5\}$ and agent 2 submits the idea $A_2 = \{i_1, i_2, i_6\}, \{i_3, i_4, i_7\}$ when the number of issues is seven. The mediator combines A_1 with A_2, and decides the issue-groups: $\{i_1, i_2, i_6\}\{i_3, i_4, i_5, i_7\}$.

[Step 3: Finding the Solutions] We find the solutions based on simulated annealing techniques[4] in order to find the optimal contract in each issue-group. The details of algorithm 1 are as follows. The mediator proposes a contract that is initially generated randomly (line 1 in Algorithm 1). Each agent then votes to accept, weakly accept, weakly reject or reject the next contract. When the mediator receives these votes, it maps them into numeric values and adds them together according to Table 1. If the sum of the numeric values from all agents is a positive value or zero, the mediator mutates the contract (by randomly flipping one of the issue values) and the process is repeated. If the sum of the numeric values from all agents is a negative value, a mutation of the most recent mutually acceptable contract is proposed instead (line 7∼16 in Algorithm 1). Each agent votes based on the utility space in each issue-group. In our protocol, the agents decide based on the difference between the utility of the present situation and the utility of the next situation in each issue-group. When the agents vote, it maps the differences into accept, weakly accept, weakly reject and reject according to Table 2. This step is based on the simulated annealing technique[10]. Each simulated annealing is fixed at a virtual *temperature* T, such that it will accept contracts worse than the last one accepted with the probability $P(accept) = max(1, e - \Delta U/T)$, where ΔU is the utility change between the contracts (line 8∼15 in Algorithm 1). In other words, the higher the virtual temperature, and the smaller the utility decrement, the greater the probability that the inferior contract will be accepted.

4 Experimental Results

We conducted several experiments to evaluate our approach. In each experiment, we ran 100 negotiations. The following parameters were used. The domain for the issue values was $[0, 9]$. The number of constraints was 10 unary constraints, 5 binary constraints, 5 trinary constraints, and so on.

Algorithm 1 Simulated_Annealing()

$Value(N)$: the sum of the numeric values mapped from votes to N from all agents

S := initial solution (set randomly)
for $t = 1$ **to** ∞ **do**
  $T := schedule(t)$
  if $T = 0$ **then**
    return $current$
  end if
  $next$ **:= a randomly selected successor of** $current$
  if $next.Value \geq 0$ **then**
    $\Delta E := next.Value - current.Value$
    if $\Delta E > 0$ **then**
      $current := next$
    else
      $current$ **:=**$next$ **only with probability** $e^{\Delta E/T}$
    end if
  end if
end for

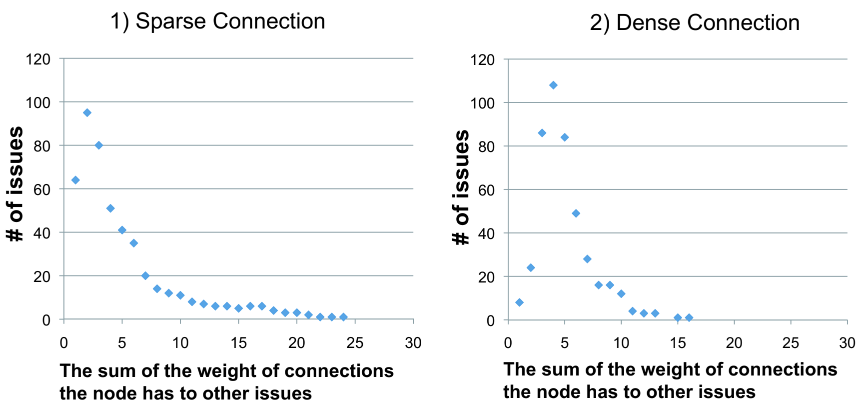

Figure 2: The Sparse and Dense Connection

(a unary constraint relates to one issue, a binary constraint relates to two issues, etc). The maximum value for a constraint was *100* $\times$ *(Number of Issues)*. The maximum width for a constraint was 7. In the experiments, we use the testbed in Section 2. The number of small issue-groups is ten in these experiments. Interdependency graphs are generated by the following two types based on the testbed: “1) Sparse Connection” and “2) Dense Connection.” Actually, the difference between the two types is only the possibility of connecting to other ones: the possibility of “1) Sparse Connection” is 0.4, and the possibility of “2) Dense Connection” is 0.8. Figure 2 shows the examples of the distribution between the number of issues and the sum of the weight of connections the node has to other issues in two cases. As plotted graphs in Figure 2 show, the property of “1) Sparse Connection” is closer to the scale-free distribution, in which the number of links originating from a given node exhibits a power law distribution, than that of “2) Dense connection.” We compare the following methods. “(A) Issue-grouping” is the issue-group protocol proposed in this paper, using a simulated annealing based on the agents’ votes we described above. “(B) Simulated Annealing” is a method proposed in [4], using a simulated annealing based on the agents’ votes without generating issue-groups. The parameters for simulated annealing in each group in (A) are as follows. The SA initial temperature is 50.0 and decreases linearly to 0 over the course of 500 iterations in each group. The initial contract for each SA run is randomly selected. The number of edges to be progressively removed from the graph for all agents is 6. The parameters for simulated annealing in (B) are as follows. The SA initial temperature is 50.0 and decreases linearly to 0 over the course of 500 iterations. The initial contract for each SA run is randomly selected. We used simulated annealing (SA) [10] gathering all the individual agents’ utility functions into one central place in order to approximate the optimum social

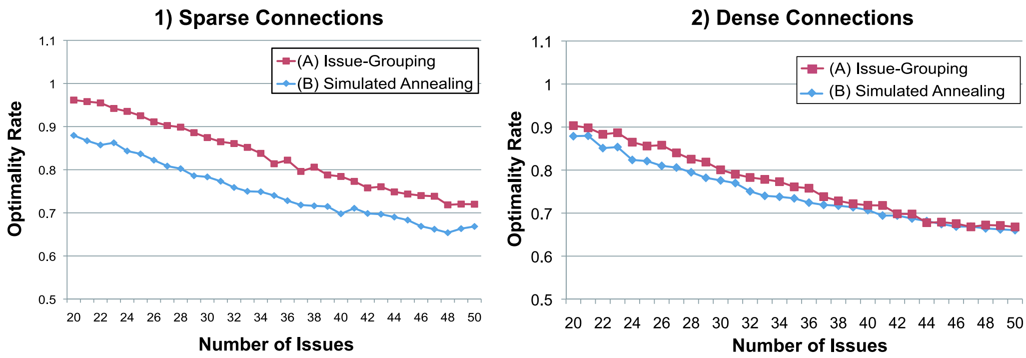

Figure 3: Comparison of optimality

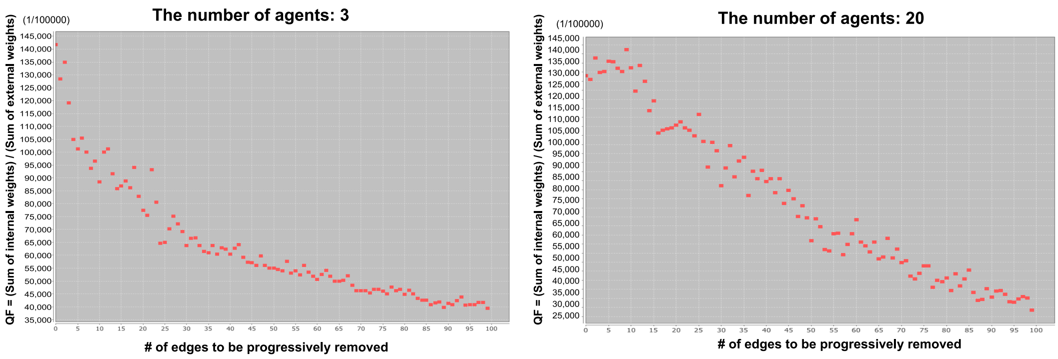

Figure 4: Number of edges to be progressively removed v.s. QF

welfare for each negotiation test run. The optimality value for a negotiation run is defined as *(social welfare achieved by each protocol) / (social welfare calculated by SA)*. Our code is implemented in Java 2 (1.6) and run on a core i5 CPU with 2.0 GB memory on Mac OS 10.6.

Figure 3 compares the optimality rate in the sparse connection and dense connection cases. "(A) Issue-grouping" proposed in this paper achieves higher optimality than "(B) Simulated Annealing," which means that the issue-grouping method achieves efficient and scalable negotiation. "(A) Issue-grouping" decreases the optimality rate as the number of issues increases. The main reason is that the complexity of negotiation is higher as the number of issues becomes larger. Another reason is that the temperature in Simulated Annealing is constant. In the bumpy utility space, it is necessary for temperature in simulated annealing to adjust based on the number of issues and ruggedness. The optimality rates of "(A) Issue-grouping" in "1) Sparse Connections" are lower compared with those in the "2) Dense Connections." This is because the issue-grouping method proposed in this paper can achieve high optimality if the number of ignored interdependencies is low; In fact, there can be more independent issues or small interdependent issues in "1) Sparse Connections." In real-world negotiation, a situation like sparse connection is more.

Figure 4 shows a scatter diagram (vertical: QF, axis: number of edges to be progressively removed) when the number of agents is 3 and 20. *QF = (Sum of internal weights of edges in each issue-group) / (Sum of external weights of edges in each issue-group)*. The ignored weights of edges in generating issue-groups are fewer as QF increases. The axis line means the parameter of generating issue-groups in all agents. The number of issues is 500 in the "1) sparse connection" case. As Figure 4 shows, QF becomes smaller when the number of edges to be progressively removed is larger. This is because the number of issue-groups generated by each agent is higher as the number of edges to be progressively removed becomes larger. Comparing the results with 3 agents and 20 agents in Figure 4, QF is higher when the number of agents is 20. This is because the mediator tends to generate a small number of issue-groups when the number of agents is large. The agents submit many kinds of ideas of issue-groups if many agents exist. Therefore, the mediator generates largesized issue-groups by combining the ideas of issue-groups from agents. This result means that our protocol guards against ignoring the interdependency between issues. In other words, our protocol tries to keep the quality of contracts if some agents submit bad ideas of issue-groups.

5 Related Work

Klein et al.[4] presented a protocol applied with near optimal results to medium-sized bilateral negotiations with binary dependencies, but was not applied to multilateral negotiations and higher order dependencies. A bidding-based protocol was proposed by Ito et al.[3]. Agents generate bids by finding high regions in their own utility functions, and the mediator finds the optimum combination of submitted bids from the agents. However, the scalability of this protocol is limited, and the failure rate of making agreements is too high. Hindriks et al.[2] proposed an approach based on a weighted approximation technique to simplify the utility space. The resulting approximated utility function without dependencies can be handled by negotiation algorithms that can efficiently deal with independent multiple issues, and has a polynomial time complexity. Our protocol can find an optimal agreement point if agents don't have in common the expected negotiation outcome. Maestre et al.[8, 9] proposed an auction-based protocol for nonlinear utility spaces generated using weighted constraints, and proposed a set of decision mechanisms for the bidding and deal identification steps of the protocol. They proposed the use of a quality factor to balance utility and deal probability in the negotiation process. This quality factor is used to bias bid generation and deal identification, taking into account the agents' attitudes toward risk. The scalability of the number of issues is still a problem in these works.

6 Conclusion

We proposed a new negotiation protocol, based on grouping issues, which can find high-quality agreements in interdependent issue negotiation. In this protocol, agents generate their private issue interdependency graphs, the mediator identifies the issue-groups based on ideas of issue-groups from agents, and multiple independent negotiations proceed for each issue sub-group. We demonstrated that our proposed protocol has a higher optimality rate than the method without issue-grouping. In future work, we will conduct additional negotiation, after the concurrent sub-contract negotiations, to try to increase the satisfaction of constraints that crossed sub-contract boundaries.

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