Approximately Fair and Secure Protocols for Multiple Interdependent Issues Negotiation

(Extended Abstract)

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ABSTRACT

Multi-issue negotiation has been studied widely. Our work focuses on the important special case of negotiation with multiple *interdependent* issues, in which agent utility functions are nonlinear. In this paper, we propose a Distributed Mediator Protocol (DMP) for securely finding Pareto optimal agreements . We also propose a measure for selecting final agreements from the set of Pareto-optimal contracts, based on "approximated fairness" and the "rate of Nash bargaining solution". We demonstrate that the DMP finds the Nash bargaining solution better than previous work in this area.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence - Multi-agent System

General Terms

Algorithm, Design, Experimentation

Keywords

Multi-Issue Negotiation, Non-linear Utility Function

1. INTRODUCTION

Multi-issue negotiation protocols represent an important field of study. While there has been a lot of previous work in this area, most of it deals exclusively with simple negotiations involving independent multiple issues. Previous efforts have also not yet been concerned with minimizing the revelation of agents' private information. Our aim is to create a protocol that will find high-quality agreements while concealing agent's utility information.

We propose the Distributed Mediator Protocol (DMP). DMP makes agreements while concealing agent utility values using a multi-party protocol[3]. Existing work[2] on multi interdependent issue negotiation has focused mainly on maximizing aggregate utilities. However, the Nash bargaining solution, which is the most popular agreement point in game theory, also should be considered. The objective for our protocol, accordingly, is to find the agreement point that satisfies the Nash bargaining solution, defined as follows: $\arg\max_{\vec{s}} \prod_{i\in N} u_i(\vec{s})$.

We also propose an approximated fairness metric that measures how fair a contract is for each agent, as well as a rate of Nash bargaining solution that represents how close the agreement is to the Nash bargaining solution. These measure are used to select one agreement point from the Pareto-optimal contract set. We present experimental results comparing how well our protocol finds the Pareto-optimal contract set and Nash product, compared with existing protocols[2].

The remainder of the paper is organized as follows. First, we describe a model of nonlinear multi-issue negotiation. Second, we define Pareto optimality and approximated fairness in multi interdependent issue negotiation. Third, we present the Distributed Mediator Protocol (DMP) with approximated fairness. Finally, we present the experimental results and conclusions.

2. APPROXIMATED FAIRNESS

The agreement point that satisfies the following function fulfills Pareto optimality.$\arg\max_{\vec{s}} \sum_{i\in N} u_i(\vec{s})$. To fulfill Pareto optimality, in other words, the protocol needs to find contracts that maximize social welfare.

We focus on approximated fairness as the measure of how fairly an agreement divides total utility across agents. This approximated fairness is used in selecting one agreement from the Pareto-optimal contract set. We define "approximated fairness" as follows: $V(u_1,\ldots,u_n) = \sum_{i=1}^{n} \frac{(u_i-\overline{u})^2}{n}$ ($u_1,\ldots,u_n$: $agent's\ utility\ value, \overline{u}$: the average of all agent's utility value). As we see, approximated fairness is defined as the deviation of each agent's utility. The agent utilities at an agreement point have a low deviation if each agent's utility value is nearly equal.

We propose a rate of Nash bargaining solution that represents how close an agreement is to the Nash bargaining solution, and approximate that solution using our approximated fairness measure. We do this because there is a correlation between approximated fairness and the Nash bargaining solution.

Figure 1 shows the utility space for a pair of negotiat-

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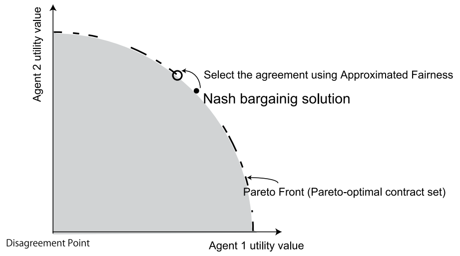

Figure 1: Pareto-Optimal and Approximated Fairness

ing agents. The Pareto Front in multi interdependent issue negotiation is usually drawn as the kind of dotted curve, because it is difficult at best for negotiation protocols to find all the contracts in the Pareto Front, due to the sheer size of the agent's utility spaces. In this case, the protocol needs to find an agreement point that is as close as possible to the Nash bargaining solution. By minimizing the approximated fairness value, the protocol can find an agreement point close to the Nash bargaining solution.

3. DISTRIBUTED MEDIATOR PROTOCOL

We assume n mediators $(M_0, \ldots, M_n)$ who can calculate the sum of all the agent utility values if k mediators get together, and there are m agents $(Ag_0, \ldots, Ag_m)$. All mediators share q, which is preliminarily a prime number. **(Finding the Pareto-optimal contract set)** The mediators divide the utility space and choose a mediator who manages each portion. Each mediator searches his/her search space with a local search algorithm. The local search implements an objective function that aims to maximize social welfare. During the search, the mediator declares a Multi-Party Protocol if he/she is searching for the first time. After that, the mediator selects k mediators from all mediators and asks them to generate v(shares) from all agents. A_i randomly selects a k dimension formula, which fulfills $f_i(0) = x_i$, and calculates $v_{i,j} = f_i(j)$. (x_i: agent's i's utility value). After that, A_i sends $v_{i,j}$ to M_j. M_j receives $v_{1,j}, \ldots, v_{m,j}$ from all agents. M_j calculates $v_j = v_{1,j} + \cdots + v_{m,j} \ mod \ q$ and reveals v_j to the other mediators. The mediators calculate $f(j)$, which fulfills $f(j) = v_j$ by Lagrange's interpolating polynomial. At the end, s, which fulfills $f(0) = s$, is the sum of all agent utility values. This step is repeated until they fulfill the at-end condition in the local search algorithm. **(Selecting the Nash bargaining solution)** Each mediator communicates the maximum value (alternative) to all mediators. After that, the mediators select the maximum value from all alternatives. The mediators find the contract point which has the optimal approximated fairness, and thus the maximum Nash product. When they calculate the variance, they use the Multi-party protocol to protect agent privacy.

4. EXPERIMENTS

We conducted several experiments to evaluate the effectiveness of our approach. The settings for the experiments are similar to those in [1]. (A), (B) and (C) are the distributed mediator protocol, using simulated annealing, hill-climbing, and genetic algorithms, respectively, as the local search procedure. (D) is the hybrid secure protocol[1], and the search algorithm in the distributed mediator step is the hill-climbing algorithm. (E) is the protocol proposed in [2].

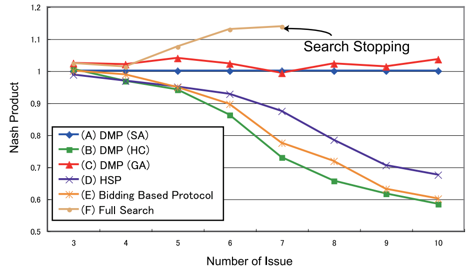

Figure 2: Comparison of the Nash product

Figure 2 compares the Nash product for the 4 methods. Our key metric was *(The maximum Nash product calculated by each method) / (The Nash bargaining solution)*. (A) $\sim$ (C) show higher values than (E). This is because they are better at finding Pareto optimal contracts and selecting the agreement that maximizes approximated fairness. Moreover, DMP produces higher performance than previous protocols.

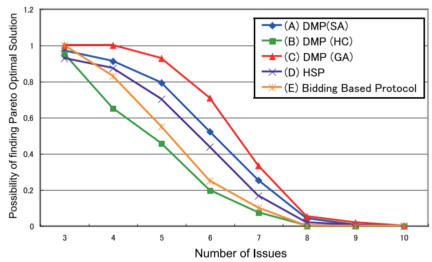

Figure 3: Finding Pareto-optimal contracts

Figure 3 shows the difference in the number of Pareto-optimal contracts found by the proposed methods. (C) finds a higher percentage of Pareto-optimal contracts for all number of issues. There are two reasons. One is that GA is inherently suitable for finding sparse solutions, like the Pareto-optimal contract set, in nonlinear spaces. Also, in this experiment, if (C) found one Pareto-optimal contract, then nearby Pareto-optimal contracts are also found as its children. For all methods, however, when the number of issues increases, the ability to find Pareto-optimal contracts decreased drastically.

5. CONCLUSION

In this paper, we have presented a Distributed Mediator Protocol (DMP) that uses an approximated fairness metric to select the agreement point closest to the Nash bargaining solution from the Pareto-optimal contract set, while concealing agent's utility information, in negotiation with multi interdependent issues and thus nonlinear utility functions.

6. REFERENCES

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