A Mediation Mechanism for Automated Negotiating Agents whose Utility Changes over Time

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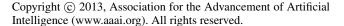hara.keisuke@itolab.nitech.ac.jp, ito.takayuki@nitech.ac.jp

Introduction

Multi-issue negotiation protocols are an important field of study because real-world negotiation problems are often complex and involve multiple issues. Although much previous work has only addressed linear utility function, that is, simple negotiations involving independent issues, recently, non-linear utility functions for complex negotiations involving interdependent issues have gained attention(Ito and Klein 2006). Most studies, however, do not focus on the changes in utility space over time. In economic theory, it is often assumed that the utility function changes dynamically over time(Strotz 1955). It is important to seek the Pareto front, which refers to the set of Pareto optimal points, in negotiation problems. Therefore, in this paper we propose a complex utility space that changes over time and a negotiation mechanism in which the mediator takes the lead in negotiation based on the genetic algorithm (GA). The experimental results show that our approach is suitable for utility that dynamically changes over time, and finds and follows the Pareto front effectively.

Negotiation with Nonlinear Utilities That Change Over Time

We consider the situation where n agents want to reach an agreement. There are m issues, $s_j \in S$, to be negotiated. The number of dimensions of the utility space is the number of issues $+1$. For example, if there are two issues, the utility space has three dimensions. An issue s_j has a value drawn from the domain of integers $[0, X]$, i.e., $s_j \in [0, X]$. A contract is represented by a vector of issue values $\vec{s} = (s_1, \cdots, s_m)$.

An agent's utility function is described in terms of constraints. There are l constraints, $c_k \in C$. Each constraint represents a region with one or more dimensions and has an associated utility value. A constraint c_k has value $w_i(c_k, \vec{s})$ if and only if it is satisfied by contract $\vec{s}$.

Figure 1 shows a model of a utility space that changes with time in which issues are interdependent. A node indicates an issue and an edge indicates a constraint. This model can represent unary constraints, binomial constraints, and ternary constraints. Consider now the utility that changes
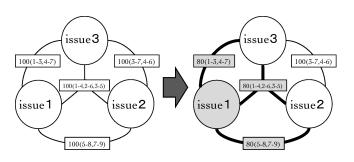
Figure 1: Utility graph (decreasing on issue 1)

over time by introducing a changing rate (increasing rate or decreasing rate). In this example, we discuss only decreasing. Figure 1 shows the influence of decreasing of issue 1. By decreasing issue 1, the utility obtained from constraints that relate to issue 1 (bold edges) is reduced. In this example, the decreasing rate is 0.8 and decreasing happens once. By comparing Figure 1 (left) and Figure 1 (right), the utility obtained from constraints that relate to issue 1 is reduced. On the other hand, the utility obtained from the constraints that do not relate to issue 1 is unchanged and stays at 80.

An agent's utility for a contract $\vec{s}$ is defined as $u_i(\vec{s}) = \sum_{c_k \in C, \vec{s} \in x(c_k)} w_i(c_k, \vec{s})$, where $x(c_k)$ is a set of possible contracts (solutions) of c_k. Every agent that participates in the negotiations has its own, typically unique, set of constraints.

The object function for our protocol can be described as equation (1):

$$\arg \max_{\vec{s}} \sum_{i \in N} u_i(\vec{s}) \qquad (1)$$

Mediator Takes the Lead in Negotiation Based on GA

As shown in Table 1, we can map the consensus point on the negotiation as the chromosome, the issue as the genetic locus, and the value of the issue as the gene when we apply GA for the negotiation among the agents. In the proposed algorithm, a mediator facilitates negotiations while accepting the preference of each agent and attempts to obtain as high a consensus point as possible. Figure 2 shows the outline of

negotiation	consensus point	issue	value of issue
GA	chromosome	genetic locus	gene

Table 1: Mapping a negotiation problem into a GA

Figure 2: Flow of proposed method

Figure 3: Search for Pareto front (left) and influence of iterations (Utility space changes with bias) (right)
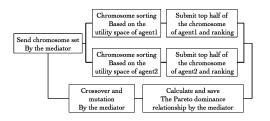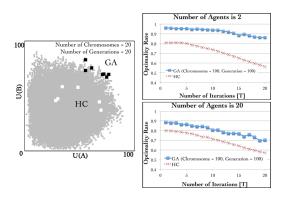

Figure 4: The shape of the utility space

the proposed algorithm. Figure 2 describes the case of two agents, but can be easily extended to n agents. First, the mediator sends a set of chromosomes to each agent. Each agent sorts the chromosomes based on its own utility space. That is, consensus points are sorted by each agent's values. Then, each agent submits the ranking information of the top half of the chromosomes to the mediator. The mediator then calculates the Pareto dominance relations and creates a copy of chromosomes that are not Pareto dominated (better chromosomes), and saves and leaves them to the next generation. Then, the mediator does a crossover and a mutation. The above procedure is repeated until a defined number of times.

The significant point of this algorithm is that it is possible to pass on Pareto dominant points to later generations (called "dominant inheritance"). Also, because each agent sends the additional ranking information, the mediator can decide Pareto dominance relations among chromosomes without knowing the specific utility value of each chromosome.

Experimental Result

We conducted several experiments to evaluate the effectiveness of our approach. In each experiment, we ran 100 negotiations between agents with randomly generated utility functions. 1 negotiation has 20 iterations that means change over time. For each run, we applied an optimizer to the sum of all the agents utility functions to find the contract with the highest possible social welfare. In this paper, the hill-climbing algorithm (HC) is a method in which the mediator takes the lead in a negotiation without GA. The important parameters for our experiments are defined as follows:

The number of agents is 2 and 20. The number of issues is 5. The domain for issue values is [0,9]. The constraints for nonlinear utility spaces are 30 unary constraints, 30 binary constraints, and 30 trinary constraints.

In Figure 3 (left), the vertical axis represents the agent utility value U(B) and the horizontal axis represents the agent utility value U(A). The gray-colored area refers to the negotiable region. Figure 3 also shows the top of some consensus points of GA (white) and HC (black). The number of generations is 20 and the number of chromosomes is 20. GA is able to search for the Pareto front, but HC cannot. That is,
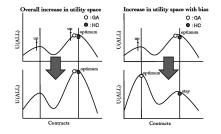
it is difficult to search for the Pareto front.

Figure 3 (right) shows increasing related to only some of the issues. The increasing rate is 1.1. The shape of the utility space changes with time. GA can maintain high optimality by renewing the solutions. HC fails to search a broad area, as in Figure 4. The greater the number of agents, the more complex the shape of the utility space becomes. Thus, it is difficult to optimize with GA, as in Figure 3 (right).

Conclusions and Future work

In this paper, we proposed a mediator that takes the lead in negotiations based on GA and, thus, a nonlinear utility space that changes over time. Our experimental results show that our method is able to follow the change in utility space shape over time and achieve consensus building even with 20 agents. Possible future work includes improving scalability by developing mediator strategies.

Acknowledgement

References

Ito, T., and Klein, M. 2006. A multi-issue negotiation protocol among competitive agents and its extension to a nonlinear utility negotiation protocol. *AAMAS 2006*.

Strotz, R. H. 1955. Myopia and inconsistency in dynamic utility maximization. *Journal of Logic and Computation*.