Genetic-Aided Multi-Issue Bilateral Bargaining for Complex Utility Functions

(Extended Abstract)

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ABSTRACT

In this paper, a non-mediated multi-issue bilateral bargaining model for complex utility functions is presented. Before the negotiation process, a genetic algorithm (GA) is used to sample one's own utility function. During the negotiation process, genetic operators are applied over the opponent's and one's own proposals in order to sample new proposals that are interesting for both parties.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent systems, Intelligent agents*

General Terms

Negotiation algorithms, Negotiation experimentation

Keywords

Negotiation, Bilateral bargaining, Agreement technologies

1. INTRODUCTION

In the last few years, there has been a growing interest in studying negotiation models where agents have their preferences represented as complex non-linear utility functions. However, most of the works focus on mediated protocols whereas only a small body of the literature studies the problem when no mediator is available[2, 4].

In this work, a non-mediated bilateral multi-issue negotiation model where agent preferences are private is presented. The developed strategy is based on the inspiring work of Lai et al. [2]. The main difference between the two approaches resides in the fact that in our work it is assumed that agents are not capable of sampling completely their utility functions. A genetic algorithm (GA) is employed by each agent before the negotiation process in order to sample one's own utility function. During the negotiation process, each agent applies genetic operators over received proposals and their own proposals. The results show that the use of genetic operators during the negotiation process leads to better results in distance to the Nash bargaining point, distance to closest Pareto optimal point, and number of negotiation rounds. More importantly, it is also shown that the use of genetic operators greatly reduces the impact of working with a large number of issues.

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2. NEGOTIATION MODEL

The employed protocol is a bilateral barganing protocol where each agent is allowed to propose up to k different offers each round [2]. We propose a time-dependent negotiation strategy that can be summarized as follows:

1. **Pre-negotiation: Sample utility functions.** Each agent samples its own utility function by means of a niching genetic algorithm (GA) that uses crowding mechanisms [3]. This GA assures that the final population of offers converges to multiple, highly fit, and significantly different offers. This initial population is called P.

2. **Sample new offers** At the start of each round, an agent calculates its current iso-utility curve from P. For each offer x_i received from the opponent in the previous round, the agent selects the M offers from the iso-utility curve that are more similar. A two-parents crossover operator is applied n_{cross} times taking as parents x_i and each one of the M offers selected previously. A mutation operator is also applied n_{mut} times over x_i and new offers generated from crossover operations. The result are new offers that have good

Euclidean distance to Nash Bargaining Point

N.issues	$p_{pnew} = 70$	$p_{pnew} = 0$
4	[0.12-0.13]	[0.18-0.19]
5	[0.13-0.14]	[0.23-0.24]
6	[0.16-0.17]	[0.30-0.31]

Table 1: Nash Distance: The table shows the confidence intervals (95%) of the average Nash distance

Euclidean distance to closer Pareto Optimal point

N.issues	$p_{pnew} = 70$	$p_{pnew} = 0$
4	[0.034-0.039]	[0.090-0.097]
5	[0.040-0.045]	[0.129-0.137]
6	[0.049-0.053]	[0.180-0.189]

Table 2: Pareto Distance: The table shows the confidence intervals (95%) of the average Pareto distance

genetic material (utility) for one's own agent and the opponent. New offers are added to a special population P_{new}.

3. **Select offers to send.** Two iso-utility curves are calculated from P and P_{new}. A percentage p_{pnew} of the k proposals is selected from the iso-utility curve calculated from P_{new}, whereas the rest is selected from the iso-utility curve calculated from P. In both cases, the offers selected are the ones that are closer (more similar) to the previous offers sent by the opponent. When p_{pnew}=0, the strategy ignores new offers sampled during the negotiation process, whereas when p_{pnew}=1, the strategy ignores the offers sampled during the pre-negotiation.

3. EXPERIMENTS

The negotiation model was tested using the weighted constraint utility functions proposed by Ito et al. [1]. For each number of issues, a total of 100 negotiation cases were generated with the following settings: (i) number of integer issues n_i = {4,5,6}. The domain for each issue was set to $[0, 9]$; (ii) n_i∗5 uniformly distributed constraints per agent. For instance if n_i=4, there are 5 unary constraints, 5 binary constraints, 5 trinary constraints and 5 quaternary constraints; (iii) utility for each n-ary constraint drawn randonmly from $[0, 100 * n]$. The utility is normalized to [0,1] for theoretical results; (iv) constraint width for each issue uniformly drawn from $[2, 4]$; (v) agent deadline $d = 10$. Both agents concede linearly with respect to their private deadline; (vi) number of proposals per round $k = 5$; (vii) agent reservation utility $RU = 0$.

The euclidean distance to the closest Pareto frontier point, the euclidean distance to the Nash bargaining point, and the number of negotiation rounds were taken as quality measures for the experiments. The proposed strategy was configured with $|P|$=8192, $p_{pnew} = 70\%$, $M = 15$, $n_{cross} = 5$, and $n_{mut} = 3$. The proposed strategy is compared with a negotiation strategy that only samples before the negotiation process ($p_{pnew} = 0\%$). The results can be observed in Tables 1, 2, and 3.

The three tables present similar results in their respective measures. The proposed strategy ($p_{pnew=70\%}$) statistically outperforms the negotiation strategy that only samples before the negotiation process ($p_{pnew=0\%}$) in every proposed quality measure. The use of genetic operators to sample new offers during the negotiation process allows to achieve better results since it is able to implicitley learn the preferences of the opponent and sample new offers that are interesting for both parties. It can be observed that there is a tendency for the performance of the strategy that only samples before the negotiation process ($p_{pnew} = 0$) to be greatly degraded as the number of issues gets larger. Nevertheless, this decrease is greatly reduced when genetic operators are applied during the negotiation process ($p_{pnew} = 70\%$).

Number of negotiation rounds

N.issues	$p_{pnew} = 70$	$p_{pnew} = 0$
4	[3.79-3.88]	[4.44-4.55]
5	[4.12-4.21]	[5.21-5.32]
6	[4.27-4.34]	[5.72-5.83]

Table 3: Negotiation rounds: The table shows the confidence intervals (95%) of the average number of negotiation rounds

4. CONCLUSIONS

In this paper we have proposed a negotiation model for non-mediated bilateral bargaining with complex utility functions, which has not been widely covered in the literature. It assumes that utility functions cannot be sampled in a complete way. Before the negotiation process, each agent uses a niching genetic algorithm in order to sample highly fit and significantly different offers. During the negotiation process, genetic operators are applied over one's own offers and opponent offers in order to sample new offers that are interesting for both parties. Results show that sampling during the negotiation process by means of genetic operators provides better solutions than strategies that only sample before the negotiation process. Moreover, the designed strategy results more feasible for scenarios with a large number of issues.

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5. REFERENCES

[1] H. Hattori, M. Klein, and T. Ito. Using iterative narrowing to enable multi-party negotiations with multiple interdependent issues. In *AAMAS '07*, pages 1–3, 2007.

[2] G. Lai, K. Sycara, and C. Li. A decentralized model for automated multi-attribute negotiations with incomplete information and general utility functions. *Multiagent Grid Syst.*, 4(1):45–65, 2008.

[3] O. J. Mengshoel and D. E. Goldberg. The crowding approach to niching in genetic algorithms. *Evol. Comput.*, 16(3):315–354, 2008.

[4] V. Robu, D. J. A. Somefun, and J. A. La Poutré. Modeling complex multi-issue negotiations using utility graphs. In *AAMAS '05*, pages 280–287. ACM, 2005.