Experimental Analysis of Negotiation Meta Strategies

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ABSTRACT

In this paper we present a meta strategy that combines two negotiation tactics. The first one based on concessions, and the second one, a trade-off tactic. The goal of this work is to demonstrate by experimental analysis that the combination of different negotiation tactics allows agents to improve the negotiation process and as a result, to obtain more satisfactory agreements. The scenario proposed is based on two agents, a buyer and a seller, which negotiate over four issues. The paper presents the results and analysis of the meta strategy's behaviour.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent Systems*

General Terms

Algorithms

Keywords

Multi Agent systems, Automated Negotiation, Negotiation Strategies

1. INTRODUCTION

During the last years automated negotiation has become an important challenge in the MAS field. It is the main key for autonomous agent interaction. In a multi agent system we find autonomous agents who decide which actions to execute, when and how. In consequence it is often the case that their own interests conflict with others agents' interests. To solve these conflicts, we must provide them a mechanism to solve this situation.

In this paper we use two negotiation tactics. The first one, that we will call *negoEngine*, based on concessions [1], and the second one, the *trade-off* strategy [2] where multiple decision variables are traded off against one another Then we propose a meta strategy which combines both tactics in order to improve the negotiation process and as a result, the agent's utility obtained by the agreement achieved. We also propose a modification to the trade-off algorithm in order to improve its performance. Somehow we try to guess the opponent's preference to propose more acceptable offers.

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2. NEGOTIATION STRATEGIES

Given an agent a and the set of n decision variables (attributes of our negotiation object), we define for each decision variable i:

- domain: real domain (i.e. $x_i^a \in D_i^a = [min_i^a, max_i^a]$) or a partially ordered set (i.e. $x_i^a \in D_i^a = \{q_1, q_2, \ldots, q_p\}$).
- scoring function: $V_i^a : D_i^a \to [0,1]$ that gives the score it assigns to a value of decision variable i in the range of its acceptable values.
- weight: w_i^a represents the relative importance of the decision variable i (assuming normalized weights).

An agent's scoring function for a given *contract*, represented as $\mathbf{x} = (x_1, \ldots . x_n)$ in the multi-dimensional space defined by the decision variables' value ranges, is computed as

$$V^a(\mathbf{x}) = \sum_{1 \le i \le n} w_i^a \cdot V_i^a(x_i)$$

We assume both parties have a deadline by when they must complete the negotiation. This deadline can be different for each agent and if it is reached the agent withdraws from the negotiation. An agent accepts a proposal when the value of the offered contract is higher than the offer it is ready to send at that moment in time.

2.1 NegoEngine

The first negotiation model (for details refer to [1]) is based on defining a set of tactics to be used, either one at a time or as a combination of them. Tactics are the set of functions that determine how to compute the value of a decision variable. For instance: *Time dependent* (as time passes, the agent will concede more rapidly trying to achieve an agreement before arriving to the deadline), or *Behaviour dependent* (tries to imitate the opponent's behaviour).

Once we define the tactics to be used during the negotiation process, we also define a combination strategy. We compute the values for the decision variables under negotiation according to each tactic. The final value of each decision variable is a linear combination of these values.

2.2 Trade-off

The main idea of this tactic is to find a proposal with the same utility as the previous one offered, but expecting to be more acceptable for its opponent (see [2]). Given an agent a, who receives a proposal $\mathbf{y}$ from agent b, the mechanism should allow agent a to choose a new proposal $\mathbf{x}'$ to offer to its opponent which fulfills two conditions:

- the new proposal $\mathbf{x}'$ must have the same utility as the offer previously proposed, $\mathbf{x}$ (a's aspiration level);
- the new proposal $\mathbf{x}'$ must be the most similar to the offer $\mathbf{y}$ proposed by b.

An iso-curve is defined as the curve formed by all the proposals with the same utility value for an agent. The algorithm performs an iterated hill-climbing search in a landscape of possible contracts. The search begins with the last offer received from our opponent and generates a set of proposals that lie closer to the iso-curve. At the end of each iteration, the most similar contract is selected using similarity functions. The algorithm terminates when the iso-curve of the previous proposal is reached.

Some modifications are introduced in the algorithm expecting to offer more satisfactory proposals to our opponent. The algorithm chooses the next decision variable to modify its value in a given order. If a satisfactory contract is not found yet, it continues with the next variable and so on. We study our opponent's history in order to detect those decision variables with minimum variation of the offered values of the variable. A low variation means high preference, and a high variation, low preference. Then we order the decision variables from high variation to low variation. Ordering the decision variables leaving the most preferred ones at the end, increases the probability of finding a contract without modifying the values proposed by our opponent. We bias the exploration in the similarity landscape.

3. META STRATEGY

The main idea is to exploit as much as possible the current aspiration level. If no agreement is reached in a given negotiation step, we must reduce the aspiration level expecting to find a new proposal that satisfies both participants. To manage this behaviour the agent first applies a trade-off strategy to maintain the aspiration level until a deadlock is achieved. This is detected when the last offer proposed by the opponent does not improve the utility of the offer proposed two steps before. Then, the negoEngine tactic is used in order to decrease the current aspiration level.

Algorithm

1. *While* deadline is not reached, t_{max}, *or* no agreement is found, $V^a(x) \leq V^a(y)$, *do*
   (a) Given the last offer $\mathbf{x}$ proposed by agent a, compute $\theta = V^a(\mathbf{x})$
   (b) *While* no deadlock is observed, propose a new offer $\mathbf{x}'$ using the trade-off strategy.
   (c) Propose a new offer $\mathbf{x}'$ using the negoEngine strategy.
   (d) Go back to (a).
2. *If* the deadline t_{max} is reached, withdraw and terminate. *Else* accept the proposal $\mathbf{y}$ and terminate.

$agent_i$	$V^a(\mathbf{x})$	$V^i(\mathbf{x})$	$*$	$\|-\|$
NegoTO	0.611	0.572	0.350	0.039
Random	0.649	0.514	0.333	0.135
Sequential	0.634	0.514	0.326	0.120
TO	0.734	0.490	0.360	0.244
Nego	0.742	0.303	0.224	0.439

Table 1: Where $*$ refers to the utility product, and $|-|$, to the utility difference.

4. EXPERIMENTS

The experiments involve two players, a and b bargaining over cloth. The decision variables under negotiation are color, material, price and time delivery. Different combinations of strategies are designed to compare the performance of our meta strategy. Thus, we define the next types of agents: *NegoTO agent* (employs the meta strategy), *Random agent* (chooses the next strategy randomly), *Sequential agent* (altering both strategies), *TO agent* and *Nego agent* (each applying only one strategy).

Two measures were obtained during the experimentation: *utility product* and *utility difference*. The first measure indicates us the joint outcome, while the second one, indicates the distance between both utilities. Compromise between both measures should be taken in account. Even though a high joint outcome is expected, it is also important that the difference between both utilities is low.

We realized 100 bilateral negotiations for every pair of agents. The negotiation deadline was fixed to 40 steps for both agents. After running the experiments we could see that in general the *NegoTO agents* improve the negotiations achieving satisfactory agreements for both participants fulfilling the desired properties. Table 1 shows the outcomes of a *NegoTO agent* vs. the rest of agents.

5. CONCLUSIONS AND FUTURE WORK

This paper presents the design of meta strategies to combine negotiation tactics: a model based on decision functions and a trade-off strategy. After the experiments we could see that the meta strategy developed obtains better results compared to other meta strategies. We also presented a mechanism to detect our opponent's preference in order to propose more satisfactory offers. As future work we propose to extend the bilateral negotiation to a multilateral negotiation, and to include other negotiation models (such as argumentative models) and time restrictions ([3, 4]).

6. REFERENCES

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