An Automated System based on Incremental Learning with Applicability Toward Multilateral Negotiations

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Abstract: In this paper we propose a negotiation agent system based on the incremental learning in order to increase the efficiency of bilateral negotiations and to improve the applicability toward multilateral negotiations. For the proposed system, we also introduce a framework for multilateral negotiations in an e-marketplace in which the components can dynamically join and disjoin. In order to evaluate the performance of the proposed system, the bilateral negotiation systems based on the trade-off mechanisms have been implemented, and we have extended the systems so that they can perform multilateral negotiations. The experimental results show that the proposed system achieves better agreements than others except for the system under the ideal assumptions that one party knows the personal negotiation information of the other party. Furthermore, the system proposed in our paper carries out negotiations at least twice faster than other negotiation systems implemented in this paper.

Keywords: Artificial neural network, incremental learning, multi-attributes, multilateral negotiation, pervasive computing environment.

1. INTRODUCTION

Agent mediated negotiations have received considerable attention in the field of automated trading [1]. They, however, have not been developed sufficiently at the level of robust systems applicable to commercial web sites for e-commerce. Such underdevelopment is due to the facts that the attributes cannot be defined precisely and that the success of a negotiation is dependent not only on the price but on other factors such as diverse personal inclination of the participants. Moreover, multilateral negotiations are more complicated and time consuming than bilateral negotiations due to the consideration of multilateral matching among the participants.

In the earlier studies of automated negotiations, Faratin et al. [2,3] proposed several negotiation systems, which are capable of dealing with multiple attributes in bilateral negotiations and of reaching agreements through interactions among the agents. The bilateral negotiation systems in [2], however, did not seem to consider the execution time in reaching agreements for negotiations and their applicability toward multilateral negotiations. For adaptive agent-based negotiations, Oliver [4] showed that agents could learn strategies using a genetic algorithm-based learning technique and Oprea [5] suggested a negotiation system that uses a feed forward artificial neural network as the learning ability of a negotiation model in the context of agent-based e-commerce. These studies have shown satisfying results on bilateral negotiations under long-term deadlines. But their systems do require longer time intervals to obtain better profits. As the technologies advance, the e-commerce environments have been diversified from the traditional networks to short range ad hoc networks, and they are shifting towards the pervasive computing environments [6]. In e-commerce for pervasive computing environment, dynamic networking such as numerous and unpredictable join and/or disjoin of participants should be allowed, and the limitation of the physical area in an ad hoc network should be overcome. In a pervasive computing environment, an automated negotiation system requires efficient negotiation processes and the facilities of discovering services [7].

In this paper, we propose a bilateral negotiation scheme with learning ability, which can carry out negotiations efficiently and have the applicability toward multilateral negotiation. We also propose a multilateral negotiation system based on the bilateral negotiation scheme proposed in this paper. For the multilateral negotiation system, we introduce a framework for a pervasive computing environment in which the components can dynamically join and disjoin a community network. In order to evaluate the performance of the proposed system, the bilateral negotiation system presented by Faratin et al. [3] has been implemented. The experimental results show that our system produces about 2% higher joint profits and carries out about two times faster on the average than the comparable negotiation systems with the same conditions of negotiation.

In Section 2, we present a bilateral negotiation process. Section 3 presents a multilateral negotiation system for a virtual market. Section 4 describes the experimental environments, and Section 5 provides the experimental results. Finally, the conclusions and future work are given in Section 6.

2. BILATERAL NEGOTIATION

2.1 Evaluating profits

The profits of the participants, buyers or sellers, are quantified with numerical values in order to measure the degree of satisfaction for the participants. In this study, the multi-attribute utility theory (MAUT) [8] is applied to evaluate the profits of the participants. Each attribute of the merchandise has a weight indicating a relative preference to each of other attributes. The offer value of
an attribute is defined as a value of the attribute in a contract. The offer values of all the attributes can be regarded as a “proposal” in the real-world negotiations. The value of the utility function can be regarded as the profit of either a buyer or a seller. The utility function can be expressed as follows.

\[
\text{profit}(x) = \sum_{i=1}^{n} w_i E(x)_i , \quad \sum_{i=1}^{n} w_i = 1 ,
\]

where \( n \) is the number of attributes, \( x_i \) is a variable representing the offer value of the \( i \)th attribute, \( w_i \) is the weight of the \( i \)th attribute, and the evaluation function \( E(x)_i \) of the \( i \)th attribute is expressed in terms of the request values (request_value) and the allowable values (allowable_value) as follows;

\[
E(x)_i = \frac{x_i - \text{allowable_value}}{\text{request_value} - \text{allowable_value}} ,
\]

where allowable_value is the maximum value of the \( i \)th attribute to which the participant wants in the negotiation, request_value is the maximum value of the \( i \)th attribute that the participant wants in the negotiation. If \( x_i = \text{request_value} \), the degree of satisfaction of the \( i \)th attribute is assumed to be the highest, and \( E(x)_i \) becomes 1. On the contrary if \( x_i = \text{allowable_value} \), \( E(x)_i \) is set to 0. If \( E(x)_i < 0 \), it is set to zero, and if \( E(x)_i > 1 \), it is set to one. The following equation obtained from Eq. (2) computes the variable \( x_i \)

\[
x_i = (1 - E(x)_i) \cdot (\text{allowable_value}) + E(x)_i \cdot (\text{request_value})
\]

Therefore, from Eq. (3) we can obtain an offer from its corresponding normalized value set.

2.2 A negotiation scenario

In this study, although various commodities can be traded in the negotiation agent system, we have chosen used cars for trading, because used cars could reflect various propensities to consume.

The typical attributes of a used car are its price, the year when it was manufactured, the mileage on its odometer, and the warranty of the car. Table 1 shows a sample of negotiation information of a buyer.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Request Values</th>
<th>Allowable Values</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price (Dollars)</td>
<td>8,000</td>
<td>12,500</td>
<td>0.5</td>
</tr>
<tr>
<td>Year (year)</td>
<td>2003</td>
<td>1999</td>
<td>0.2</td>
</tr>
<tr>
<td>Mileage (miles)</td>
<td>30,000</td>
<td>50,000</td>
<td>0.1</td>
</tr>
<tr>
<td>Warranty (months)</td>
<td>24</td>
<td>12</td>
<td>0.2</td>
</tr>
</tbody>
</table>

In Table 1 a buyer wishes to purchase a car with $8,000, and may make a concession to a seller up to $12,500 if the seller proposes a contract that is more profitable to the buyer in the other attributes. Furthermore, the buyer wants a car manufactured in 2003, and may also make a concession to the seller up to the year 1999 if better offers in other attributes are proposed. The negotiation information of the mileage and the warranty can similarly be explained. The weights of the attributes indicate that the buyer conceives the price as the most important factor in purchasing a car, and the mileage as the least significant factor. Negotiation information for a seller can be given similarly.

2.3. The learning process

In this paper, the effects of the learning method are investigated with focusing on the reciprocity and on the execution time in a negotiation system. An online learning such as the incremental learning, therefore, is more appropriate for a negotiation agent system in the e-commerce than batch learning, considering the environment of the online and real-time negotiations with unspecified persons [9]. The negotiation system proposed in this paper is designed to conduct a negotiation by using the incremental learning in generating a contract. Fig. 1 illustrates the structure of an artificial neural network for our negotiation model.

The input and the output layers of the experimental system have four nodes each, since we consider four attributes for a used car. Each node corresponds to an attribute of a product. The sigmoidal function is established as the activation functions of both the hidden and the output layers [10]. Fig. 2 shows the negotiation procedures including two learning process.

![Fig. 1 The structure of an artificial neural network for the proposed negotiation system](image-url)

**The initial learning process** establishes the initial weights of the artificial neural network through repetitive learning, which will be used for the run-time learning process. In the initial learning process, the input layer node \( m \) has the value of \( E(x)_m \) (\( m = 1, 2, \ldots, n \)) which is the evaluation value of the initial offer from the other party. The target of the output layer node \( k \) is \( E(x)_k \) (\( k = 1, 2, \ldots, n \)) which is an offer that has the same value of utility (profits) as its own contract, and simultaneously, is very close to the first contract proposed from the other party. The criterion of the similarity (closeness) is based on the distance between a pair of contracts. Therefore, each node in the input and output layers has a value between zero and one. The run-time learning process, however, is not dependent on the similarity. For updating the weights of the artificial neural network, the backpropagation algorithm [11] is exploited in our study. The backpropagation algorithm learns weights for a multilayer network, given a network with a fixed set of nodes and interconnections. It employs gradient descent to attempt to minimize the squared error between the network output values and the target values for these outputs. In Fig. 1 the error terms \( \delta_h \) and \( \delta_o \) in the output and the hidden layers can be expressed as follows, respectively.
The tolerance value is set to 0.01, which is the difference between the profits of the buyer and the seller, since the difference of profit under the assumption that the profit is not partial to any single participant in a bilateral negotiation and that the learning rate is set to 0.1 during the negotiation process.

### 3. MULTILATERAL NEGOTIATION

#### 3.1 An e-commerce framework

An e-commerce structure in a pervasive computing environment is shown in Fig. 3. We named our framework ‘P2P-based lookup server’, a PLUS for short. In order to find other lookup services (PLUSs), a P2P network is adopted as a communication backbone because of its scalability of networking. In the system structure of Fig. 3 each PLUS can federate with other PLUSs, and then provides its own services for other PLUSs within the same federation, and requests services to them as well. A PLUS may become a member of other federations simultaneously. The scope of the structure as shown in Fig. 3 may be composed of a sub-network of a LAN, a LAN itself, or a WAN.

![Fig. 3 An e-commerce structure with federations of lookup services](Image)

![Fig. 4 A schematic diagram of the proposed multilateral negotiation system based on PLUS](Image)

### 3.2. The multilateral negotiation system

A multilateral negotiation system for a pervasive computing environment consists of a virtual market and client agents -- buyer and seller agents -- on the devices of the participants.
utilize a simple and robust method of forming the bilateral connection between two lookup services by registering the proxy of each lookup service with the other party. The infrastructure layer is based on the platforms such as network infrastructures, or the hardware resources of the PLUS framework.

3.3. Participation in the multilateral negotiation

A mediator agent registers its proxy through the service connection agent on nearest PLUS, e.g., $PS_A$. The proxy of the mediator agent has the name of the item (product $K$) as an proxy’s attribute and includes the connection information such as the location (URL) and the contact point (a port number) of the mediator agent. The service connection agent on $PS_A$ appends the service properties (such as the name of the item) of the mediator agent to the service list, which is a list of services available in the PLUS, and registers the proxy of the mediator agent in the lookup service on $PS_A$. When the buyer agent wants to purchase $K$, the buyer agent requests the service connection agent on nearest PLUS, e.g., $PS_B$, to find a mediator agent of trading $K$. The service connection agent requests the lookup service to provide the proxy of the mediator agent with the client agent if the service is on $PS_B$. If there is no service in $PS_B$, the service connection agent requests the federation agent to find it. In the listed order in the location list, which has the location information such as the URLs of other PLUSs, the federation agent requests the service connection agents on other PLUSs to find the service. If a requested service is not available in any PLUS listed in the location list, the federation agent can request a service to neighboring PLUSs through a P2P protocol. The location information of the newly found PLUS is added into the location list by the federation agent. If the service is now available on $PS_A$, the service connection agent on $PS_A$ informs the federation agent on $PS_B$ of the existence of the service, and then the federation agent on $PS_B$ federates with $PS_A$. The buyer agent, thereafter, can download the proxy of the mediator agent from $PS_A$ and connect with the mediator agent using the connection information included in the downloaded proxy. Note that all the services on a PLUS in a federation are available to all the client agents in the same federation. Seller agents also follow the same procedures.

3.4. Matching in the multilateral negotiation system

A client group consists of client agents who have connected with a mediator agent. In each round of negotiations, a client group is reorganized with the clients who entered newly for the current round and the clients who have failed to reach agreements in the previous rounds. In multilateral trading a mediator agent must determine the final couple in the client group according to a given matching criterion. The process of determining the final couples in a round is described below:

**Step 1: Constructing the negotiation partners**

A negotiation partner is a pair of a buyer agent and a seller agent who have the common negotiation ranges of all the attributes. The common negotiation range denotes the range overlapped between the negotiation ranges of both parties for the attribute, and the negotiation range of $i^{th}$ attribute means the range between $request_value_i$ and $allowable_value_i$ for a participant. Since a mediator agent finds all possible negotiation partners in a client group, a buyer agent can be related with more than one seller agent and vice versa.

**Step 2: Determining the final couples**

A mediator agent is designed to determine the final couples among the negotiation partners according to the matching criterions. In case of the maximum profit criterion, the mediator agent collects the negotiation results of each bilateral negotiation in the client group and the final couples are determined by the decreasing order of joint profit. The time complexity of determining the final couples is $O(N\log N)$, where $N$ is the number of negotiation partners, since sorting takes longer time than any other operations. In case of the maximum cardinality criterion, a mediator agent gets as many final couples as possible without concerning the profits. In this criterion Ford-Fulkerson algorithm is adopted and can finds the final couples in $O(NM)$ time, where $M$ is the number of client agents participated in the negotiation [14]. The mediator agents prepare the next round with the client agents who have failed to get matched along with newly entered client agents. In Fig. 5 illustrates an example of a round in a multilateral negotiation.

**4. EXPERIMENTAL ENVIRONMENTS**

**4.1. The comparable negotiation systems**

In the previous negotiation system based on trade-off mechanism in [3], a trade-off for agent $q$ with respect to $Y$ can be defined as follows

$$\text{tradeoff}_q(X, Y) = Z,$$  \hspace{1cm} \hspace{1cm}  \hspace{1cm} \hspace{1cm} \hspace{1cm} \hspace{1cm} (7)

where $X$ is an offer of one party to the other party, $Y$ is a subsequent offer from the other party, $q$ is either a buyer agent or a seller agent and $Z$ is the offer that satisfies $\text{Profits}_q(Z) = \text{Profits}_q(X)$ and is assumed to be the offer that is the most similar to $Y$.
When the similarity between two offers is evaluated with the information of the other party such as the weights, an agreement can be found with high profits of the participants in a negotiation [3]. Further information regarding the negotiation systems based on trade-off mechanism can be found in [2,3].

In order to compare the incremental learning system (ILS) proposed in this paper, three negotiation agent systems in [3] have been implemented; the system using the similarity based on the information of the other party (Similarity-Information System, SIS), the system using the similarity based on the distance between contracts (Similarity-Distance System, SDS) and the system generating offers randomly without considering the other party (Random System, RS). Note that, among these negotiation agent systems, SIS is more advantageous in utility than other systems, because SIS operates under the ideal assumption that one party knows the personal information of the other party such as the weights of attributes. We have also extended these systems to the multilateral negotiation systems.

4.2. Experimental datasets and equipments

The negotiation information of sellers and buyers are randomly generated from Tables 2 and 3, respectively, in order to simulate the real-world trading model. In Table 2, \( P_{req} \) and \( M_{req} \) are the request values of price and mileage, respectively, and they are predetermined prior to the allowable values of price and mileage. In Table 3 \( P_{aw} \) and \( M_{aw} \) are the allowable values of price and mileage, respectively, and they are chosen prior to the request values of price and mileage.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Request values</th>
<th>Allowable values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price (Dollars)</td>
<td>([22000, 32000])</td>
<td>([P_{req} - 6000, P_{req} - 3000])</td>
</tr>
<tr>
<td>Year (year)</td>
<td>([1997, 2000])</td>
<td>([2001, 2004])</td>
</tr>
<tr>
<td>Mileage (1000mile)</td>
<td>([100, 150])</td>
<td>([M_{req} - 70, M_{req} - 10])</td>
</tr>
<tr>
<td>Warranty (months)</td>
<td>([2, 6])</td>
<td>([12, 36])</td>
</tr>
</tbody>
</table>

In our experiments we simplified the structure of networks and devices as shown in Fig. 6 since we focus only on the efficiency of the multilateral negotiations. Note that buyer agents and seller agents may or may not belong to the same PLUS with a mediator agent because the services on PLUSs in a federation are available to the all clients in the federation.

For the convenience of experiments buyer and seller agents are created in the thread unit from the desktop servers, respectively. They work independently without having the negotiation information of other client agents. Each mediator can treat a single product and carries out a multilateral negotiation for rounds independently.

5. EXPERIMENTAL RESULTS

In this paper, we compare ILS with the Faratin’s systems in [3] for bilateral negotiations. In addition, we have extended ILS and Faratin’s systems to the multilateral negotiation systems. In experiments, we focus on the efficiency of a system with respect to joint profit, execution time, and the capability of extending toward multilateral negotiations in a virtual market.

![Fig. 6 The structure of simplified equipments for evaluating the efficiency of a negotiation system](image)

![Fig. 7 The average joint profits for the bilateral negotiation systems; (a) The average joint profits, (b) The relative differences with respect to SIS](image)

![Fig. 8 The average execution time for the bilateral negotiation systems](image)

100 bilateral negotiations are carried out and the average joint profits of them are shown in Fig. 7(a). As shown in this figure, SIS obviously achieves the better agreements for reciprocity than the other systems, because SIS operates under the ideal assumption that the personal information of one party such as the weights of...
the attributes is available to the other party. In Fig. 7(a) ILS produces better agreements than SDS and RS which have the same conditions of not using the information of the other party as that of ILS. Fig. 7(b) shows the average relative differences of ILS, SDS and RS with respect to SIS. The average relative difference of ILS is 4.6%, which is 2.4% smaller than the average profits of SDS and RS. Fig. 8 shows the average execution time for the bilateral negotiation systems. The average execution time of ILS is about 500 ms; ILS is at least twice faster than others.

Fig. 9 shows that the traces of the average execution time of a mediator every 10 round in the systems extended to the multilateral negotiation with maximum profits matching criterion. In each round, 10 agents (5 buyers and 5 sellers) who are newly entered and the agents who have failed to be matched in the previous round are participated in multilateral negotiations. As the rounds are going on, the execution times of SIS, SDS and RS differs greatly from that of ILS.

![Fig. 9 The average execution time for each system in multilateral negotiation](image)

6. CONCLUSIONS

In this paper, we have proposed an automated negotiation system that can efficiently carry out multilateral negotiations with multi-attributes in pervasive computing environments. In order to achieve the applicability toward multilateral negotiations, the bilateral negotiation scheme based on incremental learning has been proposed. The effects of learning ability are investigated with focusing on the reciprocity of participants and on the execution time of negotiation. We have also introduced a framework of a virtual market which is suitable for a multilateral negotiation in pervasive computing environments. The virtual market can make a federation with other virtual markets.

For experiments the trade-off negotiation system has been implemented and compared with our system for the efficiencies of negotiations. The experimental results show that under the realistic and practical environment of negotiations the proposed system is more efficient in negotiations than others in terms of both the profits for reciprocity and the execution time.

The issues in relation to the improvement in the incremental learning and the development of delicate protocols for agent interoperability will be included in the future work.

REFERENCES


