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Bilateral single-issue negotiation model considering nonlinear utility and time constraint

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ABSTRACT

Bilateral agent negotiation is considered as a fundamental research issue in autonomous agent negotiation, and was studied well by researchers. Generally, a predefined negotiation decision function and utility function are used to generate an offer in each negotiation round according to a negotiator's negotiation strategy, preference, and restrictions. However, such a negotiation procedure may not work well when the negotiator's utility function is nonlinear, and the unique offer is difficult to be generated. That is because if the negotiator's utility function is non-monotonic, the negotiator may find several offers that come with the same utility at the same time; and if the negotiator's utility function is discrete, the negotiator may not find an offer to satisfy its expected utility exactly. In order to solve such a problem, we propose a novel negotiation model in this paper. Firstly, a 3D model is introduced to illustrate the relationships between an agent's utility function, negotiation decision function and offer generation function. Then two negotiation mechanisms are proposed to handle two types of nonlinear utility functions respectively, i.e. a multiple offer mechanism is introduced to handle non-monotonic utility functions, and an approximating offer mechanism is introduced to handle discrete utility functions. Lastly, a combined negotiation mechanism is proposed to handle nonlinear utility functions in general situations by considering both the non-monotonic and discrete. The experimental results demonstrate the effectiveness and efficiency of the proposed negotiation model.

1. Introduction

Agent negotiation is one of the most significant research issues in multi-agent systems (MASs). Many works have been done to solve challenges in agent negotiation. To list a few of them, Narayanan and Jennings [13,14] adopted a Markov chain framework to model bilateral negotiation and employed Bayesian learning to enable agents to learn an optimal strategy in incomplete information settings. Fatima et al. [4] investigated the negotiation outcomes in incomplete information settings through the comparison of the difference between two agent's negotiation deadlines, and proposed an agenda-based framework to help self-interested agents to maximize their utilities. Brzostowski and Kowalczyk [1] proposed an approach to predict the opponent's behaviors based only on the historical offers of the current negotiation. They claimed that time and imitation are two main factors which influence an agent's behaviors during negotiation. Ren et al. [16] proposed a market-based model to handle the uncertainty and concurrency in open and dynamic negotiation environments. However, most existing approaches are based on the assumption that all negotiators employ monotonic continuous linear utility functions, and not much work has been done on negotiations in which agents employ non-monotonic and/or discrete nonlinear utility functions. According to our studies, agents may employ such nonlinear utility functions in many real-world negotiations [11,12]. For example, as shown in Fig. 1, in a scheduling problem for task allocation, an employee feels happy to be assigned work between 9 *AM*–12 *AM* and 1 *PM*–3 *PM*, but feels unhappy to work hard during the first one or last 2 h of a day. The employee's temper in a working day is a non-monotonic function. In Fig. 2, a potential car purchaser may have different preferences on a car's color. Because each model of a car only has limited colors, the car purchaser's preference on a car's color is a discrete function.

In a negotiation with time constraint, an agent usually defines a negotiation strategy to make concessions throughout a negotiation. Firstly, according to the negotiation decision function, agents can calculate the possible maximal utility they can gain at a certain moment. Then, according to the offer generation function, agents can find a particular offer to reach their expected utility. Because most negotiation models assume that agents employ monotonic and continuous utility functions, a particular offer can always be found to satisfy agents expected utilities at any negotiation round. Also, it can be guaranteed that the concessions from opponent's offers are always consistent, i.e., always monotonically increasing or decreasing the agents' utilities. However, when agents employ non-monotonic and/or discrete utility functions, it cannot be guaranteed that the

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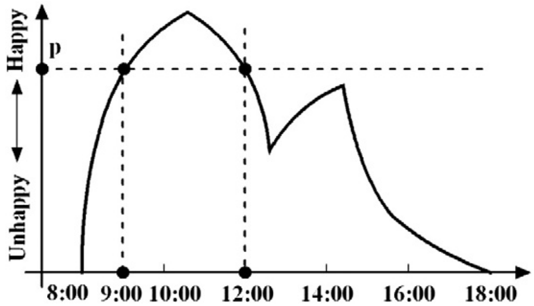

Fig. 1. An employee's temper for a day.

opponent's offers are always in an ascending or descending order. Also, the particular offer which can exactly match the expected utility may not be found. Therefore, when the utility function is non-monotonic, agents may have multiple options on offers in order to reach the expected utility. As shown in Fig. 1, in order to ensure that an employee's happiness is p ($p \in [0, 1]$), a job can be assigned to the employee at either 9 *AM* or 12 *AM*. Also, when the utility function is discrete, an agent perhaps cannot find an offer to satisfy the expected utility exactly. As shown in Fig. 2, none of the available colors can make a car purchaser's happiness equal to q ($q \in [0, 1]$) exactly.

In order to solve the offer generation problem when agents employ nonlinear utility functions, we propose a novel negotiation model in this paper, which can handle both the situations when agents have non-monotonic and/or discrete utility functions. Specifically, for negotiations involving non-monotonic utility functions, the multiple offer mechanism is introduced to allow agents to generate equivalent offers in a negotiation round; for negotiations involving discrete utility functions, the approximating offer mechanism is introduced to allow agents to generate an offer to approximate their expected utilities. Eventually, the two mechanisms are combined to solve general situations in negotiations involving nonlinear utility functions. Furthermore, when utility functions are non-monotonic, the existing alternating offer protocol [15] may become inefficient in enlarging agents' profits. That is because the existing alternating offer protocol assumes an agent has a consistent evaluation on offers' changes, i.e., when an agent gradually makes concessions to decrease own profit, the opponent's profit will be gradually increased, and vice versa. However, such an assumption is not held when agents employ non-monotonic utility functions. In order to help agents to make decisions on trade off in such a situation, a new negotiation protocol is proposed based on the alternating offer protocol.

The rest of this paper is organized as follows. Section 2 briefly introduces a general bilateral single issue negotiation model with linear utility functions. Section 3 introduces our 3D negotiation model, the multiple offer mechanism to handle non-monotonic utility functions, the approximating offer mechanism to handle discrete utility functions, and the combined mechanism to handle general nonlinear utility functions. In Section 4, the Rubinstein's alternating offer protocol is modified to fit the situation caused by non-monotonic and/or discrete utility function. Section 5 demonstrates a negotiation between two agents having nonlinear utility functions. Section 6 compares our work with some related work on handling negotiations with nonlinear utility functions. Section 7 concludes this paper and explores our future work.

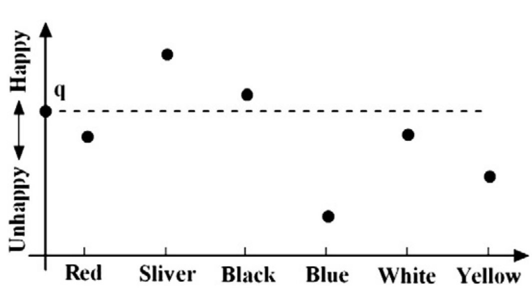

Fig. 2. A customer's flavor on a car's color.

2. A general negotiation model for linear utility function

Before we introduce the negotiation model for nonlinear utility functions, we would like to briefly introduce a general negotiation model for linear utility functions by considering time constraints. A general bilateral single issue negotiation is performed between two agents on a good's price. Let b denote the buyer, s denote the seller, and let $[IP^a, RP^a]$ denote the range of values for prices that are acceptable to Agent a, where $a \in \{b,s\}$. IP^a is Agent a's initial price and RP^a is Agent a's reservation price. Usually, for a buyer agent $IP^b \leq RP^b$, and for a seller agent $IP^b \geq RP^b$. We use $\hat{a}$ to denote Agent a's opponent, $\hat{a} \in \{b, s\}$. Obviously, an agreement can be reached between Agent a and its opponent $\hat{a}$ only when there is an intersection between their price ranges. If the buyer agent's reservation price is smaller than the seller agent's reserved price (i.e., $RP^b < RP^s$), an agreement will not be achieved.

Usually, a negotiation should consider time constraint, and each agent has a negotiation deadline. If an agreement cannot be achieved before an agent's deadline, then the agent has to quit the negotiation, and the negotiation fails. Let T^a denote Agent a's deadline. A negotiation can be started by either the buyer or seller. During the negotiation, the buyer and the seller will send alternating offers to each other until both sides agree on an offer together, or one side quits the negotiation. This negotiation protocol is known as the alternating offer protocol [15]. Let $p^t_{\hat{a}\to a}$ denote the price sent from Agent $\hat{a}$ to Agent a at time t. Once Agent a receives the offer, it will map the price in the offer to a utility value by using its utility function U^a. A general linear utility function used by Agent a is shown in Eq. (1).

$$U^a\left(p^t_{\hat{a}\to a}\right) = \frac{p^t_{\hat{a}\to a} - RP^a}{IP^a - RP^a} \tag{1}$$

It can be seen that a general linear utility function normalizes a price to a utility value in-between [0,1] by using the predefined initial price (IP^a) and reservation price (RP^a). The utility value indicates the profit that the agent can gain by accepting the offer $p^t_{\hat{a}\to a}$. In general, for Agent a, if $U^a(p^t_{\hat{a}\to a})$ is greater than the value of the counter-offer Agent a is ready to send in the next negotiation round t', i.e., $U^a(p^t_{\hat{a}\to a}) \geq U^a\left(p^{t'}_{a\to\hat{a}}\right)$, then Agent a will accept Agent $\hat{a}$'s offer at round t and the negotiation completes successfully with the agreement $p^t_{\hat{a}\to a}$. Otherwise, the counter-offer $p^{t'}_{a\to\hat{a}}$ will be sent from Agent a to Agent $\hat{a}$. Such a procedure will be repeated until an agreement is achieved or one agent reaches its deadline. Thus, the action, A^a, that Agent a takes at each negotiation round t is usually defined as follows:

$$A^a\left(p^t_{\hat{a}\to a}\right) = \begin{cases} \text{Quit} & \text{if } t > T^a, \\ \text{Accept } p^t_{\hat{a}\to a} & \text{if } U^a\left(p^t_{\hat{a}\to a}\right) \geq U^a\left(p^{t'}_{a\to\hat{a}}\right), \\ \text{Offer } p^{t'}_{a\to\hat{a}} & \text{otherwise.} \end{cases} \tag{2}$$

If Agent a does not accept the price $p^t_{\hat{a}\to a}$ and its deadline is not achieved, then it will send a counter-offer $p^{t'}_{a\to\hat{a}}$ to Agent $\hat{a}$ as a response. Usually, agents may employ different negotiation tactics [3] to generate counter-offers based on different criteria, such as time, resources, and previous counter-offers. The time-dependent tactic is the most popular criteria when agents generate their counter-offers by