A Fuzzy Constraint-based Agent Negotiation With Opponent Learning

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Abstract: This work offers a general framework of fuzzy constraint-based agent negotiation with opponent learning. The proposed approach via fuzzy probability constraint clusters the opponent's information in negotiation process as proximate regularities to increase the efficiency on the convergence of behavior patterns, and eliminates the bulk of false hypotheses or beliefs to improves the effectiveness on beliefs learning. By using fuzzy instance method, our approach can not only reuse the prior opponent knowledge to speed up problem-solving, but also reason the proximate regularities to acquire desirable outcomes on predicting opponent behavior. Besides, the proposed interaction method enables the negotiating agent to adapt dynamically based on expected objectives. Moreover, experimental results suggest that the proposed framework allowed an agent to achieve a higher reward, fairer deal, or less cost of negotiation.

Key–Words: Intelligence systems, multi-agent systems, agent negotiation, opponent modeling, beliefs learning, fuzzy constraints.

1 Introduction

Agents need to achieve communication and sociability each other in a multi-agent system. In order to successfully interact, it is necessary to endow agents with the ability to negotiate with others. Agent negotiation has been recognized as an important activity in e-commerce and has become one of principal research subjects. In a multi-agent system, an agent typically has incomplete information about the preferences or decision-making processes of other agents. To that end, many machine learning models [6, 13] have been proposed for predicting opponent's beliefs. In the reinforcement learning model [1, 16], the agent receives an indication of the current state of the environment as an input in each interaction. Then, the agent performs an action to generate an output and to change the state of the environment toward a more desirable resulting state by providing a reward or penalty. However, the problem of slow convergence reveals formidable computational obstacles to develop such a model. On the other hand, the model-based learning [3, 7] presented an architecture to learn the models of rival agents. The learning models are used to infer a best-response strategy and an algorithm is specified to elucidate an opponent's strategy from the earlier beliefs of the opponent. Nevertheless, all such frameworks assume that agents can observe the states and actions of other agents and share common knowledge. Then, the Bayesian learning algorithm [15, 18] manipulates occurrences of interest using probability distributions. The probabilistic evaluation over the set of occurrences of interest can be summarized from the a priori knowledge as the reference of next proposed offer. Even so, it needs a large set of training examples to converge toward a correct prediction.

The theoretical concepts and practical applications [2, 4, 11, 17] of fuzzy constraints are ready, so fuzzy constraint not only can be used to treat imprecise and vague information inherited from fuzzy logic, but also can be used to adapt to a continually changing environment by adding or eliminating constraints. Accordingly, fuzzy constraints are regarded as very suitable for addressing the imprecision and inter-dependencies involved in agent negotiation. Several studies [9, 12] have addressed this issue.

Complying with our previous work [10], this research presents a general framework of agent negotiation with opponent learning via fuzzy constraint-based approach. The fuzzy constraint-based approach involves the fuzzy probability constraint where each fuzzy constraint has a certain probability, and the fuzzy instance reasoning where each instance is represented as a primitive fuzzy constraint network. The proposed approach via fuzzy probability constraint clusters the opponent's information in negotiation process as proximate regularities to increase the efficiency on the convergence of behavior patterns, and eliminates the bulk of false hypotheses or beliefs to improves the effectiveness on beliefs learning. By using fuzzy instance method, our approach can not only reuse the prior opponent knowledge to speed up problem-solving, but also reason the proximate regularities to acquire desirable results on predicting opponent behavior. Besides, the proposed interaction method enables the agent to adapt dynamically based on expected objectives. Moreover, experimental results suggest that the proposed framework allowed an agent to achieve a higher reward, fairer deal, or less cost of negotiation.

The rest of this article is organized as follows. Section 2 introduces the theoretical basis of fuzzy constraint-based negotiation. Section 3 discusses the opponent's beliefs learning from an agent negotiation process. Section 4 presents the effectiveness of the method by experiments. Finally, Section 5 draws some conclusions.

2 Fuzzy Constraint-Based Agent Negotiation

Agent negotiation is closely related to a distributed fuzzy constraint satisfaction processing in that coming up to a mutually acceptable agreement between two or more agents [14] is the same as uncovering a consistent solution satisfying all the constraints in a fuzzy constraint network specifying the fuzzy relationships inside each agent and among agents. Thus, many approaches [**?**, 12] have formulated agent negotiation via distributed fuzzy constraints or prioritized fuzzy constraints to discover agents' potential agreements in order to reach a common satisfactory outcome.

2.1 Agent Negotiation as the Problem Solving of Distributed Fuzzy Constraints

Fuzzy constraint satisfaction problems (FCSPs) [8] are defined by a collection of objects with the associated domains and a set of crisp or fuzzy constraints that relate the objects to the objective of determining whether a tuple exists that satisfies all the constraints to an extent that is greater than or equal to the threshold of acceptability. However, real-world environments are inherently distributed. Thus, the FCSP is extended to a distributed FCSP (DFCSP), which can be represented as a set of fuzzy constraint networks (FCNs) that are connected by constraints. Following [9], a distributed fuzzy constraint network (DFCN) is defined as below.

Definition 1 ***Distributed fuzzy constraint network :*** *A distributed fuzzy constraint network $(\mathcal{U}, \mathbf{X}, \mathbf{C})$ can be defined as a set of fuzzy constraint networks $\{\mathfrak{N}^1, ..., \mathfrak{N}^L\}$, $\mathfrak{N}^{\mathrm{k}} = (\mathcal{U}^k, \mathbf{X}^k, \mathbf{C}^k)$ representing an agent k, where*

- *$\mathcal{U}^k$ is a universe of discourse for agent k;*
- *$\mathbf{X}^k$ is a tuple of n^k non-recurring objects $X^k_{1^k}, \ldots, X^k_{n^k}$;*
- *$\mathbf{C}^k$ is a set of $m^k \geq n^k$ fuzzy constraints, which is the union of a set of internal fuzzy constraints $\mathbf{C}^{k_i}$ existing among objects in $\mathbf{X}^k$ and a set of external fuzzy constraints $\mathbf{C}^{k_e}$ referring to at least one object in $\mathbf{X}^k$ and another not in $\mathbf{X}^k$;*
- *$\mathfrak{N}^{\mathrm{k}}$ is connected to other agents by $\mathbf{C}^{k_e}$;*
- *$\mathcal{U}$ is a universe of discourse;*
- *$\mathbf{X} = \left(\cup_{k=1}^{L} \mathbf{X}^k\right)$ is a tuple of all non-recurring objects;*
- *$\mathbf{C} = \left(\cup_{k=1}^{L} \mathbf{C}^k\right)$ is a set of all fuzzy constraints.*

The *intent* of a distributed fuzzy constraint network $(\mathcal{U}, \mathbf{X}, \mathbf{C})$, written $\Pi_{\mathcal{U},\mathbf{X},\mathbf{C}}$, meaning the set of solutions of DFCN can be regarded as an agreement among agents that satisfy all of demands. No agent knows about its opponents' feasible proposals and possible agreements *a priori*. Agents take turns to propose offers to explore potential agreements, thereby moving the negotiation toward a consensus.

The overall course of agent negotiation is a consecutive process of offer generation and evaluation. The offer generation of agent not only directly decides the aggregated satisfaction value (ASV) at next round but also is a representation of agent's desires and beliefs. The offer evaluation is to decide whether to accept the counteroffer along with the aggregated satisfaction value of counteroffer by an agent. If the aggregated satisfaction value of counteroffer is superior to the one of offer at current or next round for agent k and the counteroffer is one of feasible proposals or a potential agreement in $\Pi_{\mathcal{U},\mathbf{X},\mathbf{C}}$, then agent k will accept the counteroffer as an agreement. Otherwise, agents will perform the negotiation until one of agents withdraws. The following aggregated satisfaction value of the solutions is defined to evaluate offers or counteroffers.

Definition 2 ***Aggregated satisfaction value:*** *Given the value of an offer (or counteroffer)* $\mathbf{u}$ *involving a number of issues* $(x_1, \ldots, x_n)$*, the aggregated satisfaction value of the offer* $\mathbf{u}$ *to agent* k*, denoted by* $\Psi^k(\mathbf{u})$ *, can be defined as a function of the values of satisfaction with the issues as follows:*

$$\Psi^k(\mathbf{u}) = \frac{1}{n}\sum\nolimits_{j=1}^{n} \mu_{C_j^k}(x_j), \tag{1}$$

where $\mu_{C_j^k}(\cdot)$ *is the satisfaction degree of the constraint* C_j^k *of agent k over issue j.*

2.2 Negotiation Strategy

In agent negotiation, a strategy explicitly represents agent's expectation and intent. A strategy usually consists of the concession strategy and the tradeoff strategy. In the concession strategy, an agent makes a concession by decreasing its previously aggregated satisfaction value to generate an offer from a certain solution space. In that space, the satisfaction degrees of the constraints associated on the solutions equal or exceed a certain threshold of acceptability. Even if no solution enables the preference within the proposal space to be met, an agent can use self-relaxation to lower gradually the threshold of acceptability and thus generate new, feasible proposals without giving up on any of the agent's demand. In the tradeoff strategy, an agent generates and develops alternative in a specific solution space without reducing its aggregated satisfaction value. In that space, the degrees of satisfaction in the constraints associated with the solutions equal or exceed a particular threshold.

3 Opponent's Behavior Learning with Fuzzy Constraints

To learn opponent's beliefs, a fuzzy constraint-based approach, including strategy identification, instance matching and adaptive interaction, is presented as follows.

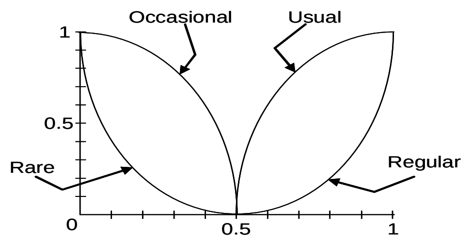

Figure 1: The membership function of fuzzy probability constraints.

3.1 Strategy Identification

In our pervious work [9], the definition of meta strategy is based on the different concession scales of aggregated satisfaction values at adjacent negotiation cycles. That is, a strategy can be described with some critical concession scales. *Instead of using exact concession value like traditional Bayesian method, we adopt a fuzzy concession value to group proximate paradigms for avoiding the problem of slow convergence.* Hence, a strategy can be conveyed by a set of related fuzzy concession values. To recognize an opponent's strategy, an agent can reduce or enlarge concession value during afterward negotiation round, and observe the variance of following fuzzy probability constraints.

$$Usual(\mathbf{p}^{k'} \ is \ \widetilde{\Omega}_j^{k'}), \tag{2}$$

which means that $P(p^{k'} \ is \ \widetilde{\Omega}_j^{k'}) \ is \ usual$, in which $P(\cdot)$ denotes a probability; $p^{k'}$ means the set of fuzzy concession values for opponent agent k'; $\widetilde{\Omega}_j^{k'}$ is the satisfaction degree of identifying the j^{th} kind of strategy for opponent agent k', "$p^{k'} \ is \ \widetilde{\Omega}_j^{k'}$" is a fuzzy event and "*usual*" indicates a fuzzy probability. The membership functions of fuzzy probability constraints can be denoted as Figure 1.

If an agent's strategy always reveals regularities, it would need many evidences to support its behavior. *Using the fuzzy probability constraint, the noisy hypotheses or beliefs of opponent beyond the behavior regularities can be eliminated.* When the set of fuzzy concession values matches one of the regularities of meta strategies within the threshold of fuzzy probability constraint, an agent may conclude the belief of opponent's strategy.

3.2 Fuzzy Instance Matching

An agent may filter out approximate instances with the same belief of opponent's strategy from historical instances. To further match the proximate instances, the proposed model employs least-squared error approach to measure the degree of proximity among historical instances.

Definition 3 ***Instance match:*** *let $\mu_{C_j^k}(x_t^i)$ $(\mu_{C_j^k}(y_t^i))$ be the agent k's (the opponent's) satisfaction degrees of offer value x_t^i (y_t^i against agent k) for issue j at the t^{th} round during the i^{th} historical instance. $\mu_{C_j^k}(u_t)$ $(\mu_{C_j^k}(v_t))$ denotes the agent k's (the opponent's) satisfaction degrees of offer value u_t (v_t against agent k) for issue j at the t^{th} round over the current negotiation instance. It can be claimed that the i^{th} historical instance is proximate with the current negotiation instance, if the following constraints are satisfied.*

$$\arg_{i=1..n,j=1..m} \sum_{t=1}^{l} \left(\mu_{C_j^k}(x_t^i) - \mu_{C_j^k}(u_t)\right)^2 \leq \lambda, \text{ and} \tag{3}$$

$$\arg_{i=1..n,j=1..m} \sum_{t=1}^{l} \left(\mu_{C_j^k}(y_t^i) - \mu_{C_j^k}(v_t)\right)^2 \leq \lambda, \tag{4}$$

where n is the total number of historical instances; m denotes the number of negotiating issue; l means the maximum negotiation round for each historical instance; λ indicates a proximate threshold among behavior clusters.

3.3 Adaptive Interaction

After familiarizing an opponent's behavior, an agent may also adapt itself for achieving its objectives.

Definition 4 ***Adaptive interaction:*** *let $\mathbf{u}_t$ and $\mathbf{v}_t$ be the offer and the counteroffer proposed by agent k and opponent agent k' at the t^{th} negotiation round. The designate situations may apply the following constraints.*
If an agent's negotiation goal is to maximize its aggregated satisfaction value for selfish purpose, the selfish-based interaction must satisfy the constraint

$$Usual(\cap_{i=1}^{l} \Psi^k(\mathbf{u}_i) > \Psi^{k'}(\mathbf{v}_i)); \tag{5}$$

if an agent's negotiation goal is to minimize the difference of aggregated satisfaction value for both agents, the fair-based interaction must satisfy the constraint

$$Usual(\cap_{i=1}^{l} \Psi^k(\mathbf{u}_i) = \Psi^{k'}(\mathbf{v}_i)); \tag{6}$$

if an agent's negotiation goal is to obtain an agreement unscrupulously, the economic-based interaction must satisfy the constraint

$$Usual(\cap_{i=1}^{l} \gamma_i^k > \gamma_i^{k'}), \tag{7}$$

```
   Opponent_Learning(M̄_t)
1  Begin
2  Time_bounded ← ρ; vSTimeStep ← 0; vFTimeStep ← 0; S ← “”
3  H ← {}; C ← {}; Ā ← 0.0; d*_t ← 0.0; v*, u ← (0.0, 0.0, ..., 0.0);
4  S ← Strategy_Identification(M̄_t);
5  if S ≠ “Unknown” then
6    H ← Instance_Retrieve(S);
7  end if
8  for i = 1 to Count(H) do
9    if Negotiation_Result(C ←) = “Success” then
10     Ā ← Ā + Ā · P(Ā_i);
11     vSTimeStep ← vSTimeStep + Final_Round(H_i) · P(Final_Round(H_i))
12   else
13     vFTimeStep ← vFTimeStep + Final_Round(H_i) · P(Final_Round(H_i))
14   end if
15 end for
16 if Usual(M̄_t is fail) and (vFTimeStep ≤ Time_bounded) then
17   Report(“Failure”);
18   Exit; end if;
19 if Usual(M̄_t is success) and (Time_bounded ≤ vSTimeStep) then
20   Report(“Failure”);
21   Exit; end if;
22 if Acceptable(Ā) = True then
23   C ← Instance_Match(M̄_t, H);
24   d*_t ← Next_Concession_Degree(t + 1);
25   v*_{t+1} ← Next_Offer(d*_t);
26   u_{t+1} ← Adaptive_Interaction(v*_{t+1});
27 else
28   Report(“Failure”);
29 end if;
30 End
```

Figure 2: An algorithm of opponent learning.

where γ_i^k and $\gamma_i^{k'}$ mean the concession values for agent k and opponent agent k'; $\cap_{i=1}^{l}$indicates to implement the "and" operator from the first round to the final round l.

3.4 Learning Algorithm

To demonstrate the complete concept of the proposed model, the algorithm of opponent learning is illustrated as Figure 2. In Figure 2, the parameter of opponent learning algorithm, $\overline{M}_t$, denotes the set of offers from the 1^{st} to the t^{th} round for current negotiation instance. Lines 2 to 3 present some variables definitions for opponent learning mechanism. An agent applies the approach of strategy identification to recognize an opponent's possible strategy as $\mathcal{S}$ from line 4. In lines 5 to 7, if an opponent's strategy can be identified, an agent retrieves the instances with the same belief of opponent's strategy into the set of candidate instances $\mathcal{H}$. In lines 8 to 15, the successful historical instances can be employed to calculate the possible agreement for the reference of current negotiation instance. However, the failure instances can also show the limitation of negotiation rounds to reduce the negotiation resource or cost. Lines 16 to 21 proceed the process of conflict detection. If the negotiation result matches the fuzzy probability constraint, $Usual(\overline{M}_t \ is \ fail)$, and the predictive failure round, $vFTimeStep$, is less than or equal to the bounded negotiation round, $Time\_bounded$, it means that the proximate historical instances would result in the failure outcome during the bounded round. If the negotiation result fits the fuzzy probability constraint, $Usual(\overline{M}_t$ $is\ successful)$, and the predictive success round, $vSTimeStep$, is larger than or equal to the bounded negotiation round, it denotes that the proximate historical instances would result in the successful outcome until the bounded round is exceeded. In lines 22 to 27, if the predictive agreement $\overline{A}$ is acceptable, the learning mechanism $Instance\_match(\cdot)$ would be used to match the proximate instances into the set of match instances $\mathcal{C}$ from historical instances with the current instance $\overline{M}_t$. Then, the functions $Next\_concession\_degree(\cdot)$ and $Next\_offer(\cdot)$ are applied to predict the beliefs of next concession degree and next offer for the opponent agent according to the proximate instances. Otherwise, mechanism would report a failure message. Based on the belief of next offer for the opponent agent, the learning mechanism $Adaptive\_interaction(\cdot)$ would further adopts flexible adaptation method to construct the set of feasible offers for agent itself at $(t+1)^{th}$ round. Finally, an agent proposes an appropriate offer to the opponent agent until one of agents withdraws.

4 Experiments

A negotiation may often be approved by maximizing the aggregated satisfaction value, minimizing the number of proposals exchanged and ensuring fairness. Fairness in negotiation is the minimization of the difference between the aggregated satisfaction values of agents, which is achieved by maximizing the *product of the aggregated satisfaction values* (PASV) of the negotiating agents. The *joint aggregated satisfaction value* (JASV), defined as the sum of the aggregated satisfaction values of negotiating parties, is used to measure the quality of the negotiation results. The *average number of proposals exchanged* is calculated to evaluate the cost of the negotiation process. Therefore, the following experiments are probed for above different kinds of views.

A multi-issue bargaining scenario, which consists of one buyer and one seller, is described as follows.

- The negotiation issues are price and time.
- The intervals associated with the issues are [1000-3000] for price and [0-10] for time. Each party's membership function is monotonic decreasing and is constructed by generating a pair of random real numbers from the interval associated with the issues.

Table 1: The negotiation outcomes of the different approaches over various views

Method		Superificial learning		Opponent learning		
		Bayesian	FCAN	Fair-based interaction	Selfish-based interaction	Economic-based interaction
Run		100				
Seller's ASV	Price	0.2393	0.2808	0.204	0.1908	0.2957
	Time	0.4307	0.4035	0.3703	0.3607	0.4637
Buyer's ASV	Price	0.1342	0.2359	0.3161	0.3317	0.2117
	Time	0.2597	0.2101	0.2441	0.2532	0.1481
Avg. Seller's ASV		0.335	0.3421	0.2871	0.2757	0.3797
Avg. Buyer's ASV		0.197	0.223	0.2801	0.2925	0.1799
Avg. JASV		0.532	0.5651	0.5673	0.5682	0.5596
Avg. PASV		0.066	0.0772	0.0797	0.0795	0.0665
Avg. Round		21	20.59	22.11	22.49	19.45
Failure Case		33	0	0	0	4

- The buyer agent's and the seller agent's urgency values are 0.1 and 0.07 respectively.
- The buyer agent employs the opponent learning mechanism and the seller agent applies a negotiation method with superficial learning heuristics.
- The party that first proposes an offer is randomly determined.

The following experiments introduce the Zeuthen's negotiation strategy in [15] to make its decision of concession based on how much it has to lose by running into conflict at that time, and integrate the tradeoff strategy presented by Faratin in [5] as the Bayesian approach with superficial learning heuristics. Our pervious work in [10], fuzzy constraint-based agent negotiation (FCAN), applying an undeveloped learning heuristic is also viewed as a superficial learning. To compare the performance of negotiation, the Bayesian learning, FCAN, and the proposed approach run 100 experiments for each arrangement.

The negotiation outcome in Table 1 shows that the average ASV for the buyer agent of Bayesian learning, FCAN, and the selfish-based interaction are 0.197, 0.223, and 0.2925 respectively. These data illustrates that our approach can require a higher reward than FCAN and Bayesian learning. Also the outcome indicates that the tuple of average JASV and PASV of Bayesian learning, FCAN, and fair-based interaction are (0.532, 0.066), (0.5651, 0.0772), and (0.5673, 0.0797). This fact demonstrates that our approach can obtain a fairer deal than FCAN and Bayesian learning. Furthermore, the data exhibits that the average number of proposals exchanged of Bayesian learning, FCAN, and economic-based interaction are 21, 20.59, and 19.45 respectively. Such information reveals that our approach can earn a less cost of negotiation than FCAN and Bayesian learning. To sum up, the proposed approach did allow an agent to achieve a better reward, impartial deal, or less round of negotiation.

As Table 1 shown, the Bayesian learning method enables an agent to estimate opponents' beliefs with the probability distributions in occurrences of interest. Though 500 instances are constructed as a priori knowledge before running, it still shows the necessity that needs a large amount of data to converge the correctness of prediction. Furthermore, the FCAN approach just applies the variance of satisfaction degrees for counteroffers to get the opponent's coarse beliefs, and utilizes the similarity function to support negotiating agent's desire. It did not further refine the opponent's beliefs to adjust its concession value toward expected outcome. However, the proposed model with opponent learning may react dynamically to speed up toward the correctness of prediction with the fuzzy probability constraints, to predict an opponent's next behavior from the proximate instances resulting from fuzzy instance based method, and to revise a negotiating agent's concession value with adaptive interaction for achieving the desire objectives. Therefore, it is understandable for the opponent learning approach to outperform the superficial learning heuristics.

5 Conclusions

By using fuzzy constraints, this work presented a general framework of multilateral agent negotiation with opponent learning mechanisms. Despite the lack of adequate information of other agents, the results of the proposed experiments indicate that our approach can obtain an effective negotiation in respect of achieving different kinds of objectives.

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