Solver Agent: Towards Emotional and Opponent-Aware Agent for Human-Robot Negotiation

Extended Abstract

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ABSTRACT

Negotiation is one of the crucial processes for resolving conflicts between parties. In automated negotiation, agent designers mostly take opponent's offers and the remaining time into account while designing their strategies. While designing a negotiating agent interacting with a human directly, other information such as opponent's emotional changes during the negotiation can establish a better interaction and reach an admissible settlement for joint interests. Accordingly, this paper proposes a bidding strategy for humanoid robots, which incorporates their opponents' emotional states and awareness of the agent's changing behavior.

KEYWORDS

Human-Agent Negotiation; Emotional Awareness; Opponent Behavior; Human-Robot Interaction

ACM Reference Format:
Mehmet Onur Keskin, Umut Çakan, and Reyhan Aydoğan. 2021. Solver Agent: Towards Emotional and Opponent-Aware Agent for Human-Robot Negotiation: Extended Abstract. In *Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), Online, May 3–7, 2021*, IFAAMAS, 3 pages.

1 INTRODUCTION

Negotiation is usually a complex process where various parties with different preferences aim to reach a consensus [7]. To fully automate this process, a variety of approaches [1, 3, 4, 10, 21, 26] have been proposed so far. Those agents mostly make their offers based on their opponent's offer history and remaining time in case of having a predefined deadline [6, 24]. The main challenge is generating acceptable offers for the opponent under the uncertainty of the opponent's preferences and strategies while concerning the agent's preferences. This challenge becomes harder when they are supposed to negotiate with a human negotiator. The nature of human-agent negotiation requires considering different dynamics such as bounded rationality, reciprocity, fairness, and emotional awareness [13]. On average, the number of offers typically does not exceed 20 offers in human-agent negotiation [8, 16, 17]; therefore, there is a limited amount of information exchanged among negotiating parties. Furthermore, human negotiators also care about reciprocal behavior – if they make a pleasant move, they also expect their opponent to act similarly; otherwise, their attitude may change drastically [18]. As a result, awareness of the other side's attitude plays a crucial role in human negotiations.

Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), U. Endriss, A. Nowé, F. Dignum, A. Lomuscio (eds.), May 3–7, 2021, Online.

Moreover, emotions can play a key role in how we think and act. Therefore, it is important to consider the emotional factor while designing agents negotiating with their human counterparts. There are a number of studies investigating the effect of emotions in negotiation [19, 23, 25]. However, those studies focus on only the agent's emotional expression. For better interaction, negotiating agents should be able to express their emotions in line with the underlying situation as well as be capable of **perceiving their human partner's emotional state and adapting their strategy and interaction accordingly**. Exchanging emotional state through emoji is supported by the IAGO framework [14]; however, the opponents' emotional state has not been elaborately addressed in this framework as a part of Human-Agent Negotiation Competition so far [15, 16]. Furthermore, the **physical embodiment** may also influence human interaction. Human participants may express their emotions more intensively while interacting with a humanoid robot rather than interacting with a virtual agent [11]. Therefore, this study focuses on human-robot negotiations where a humanoid robot interacts with human negotiators by following a speech-based negotiation protocol [2]. Accordingly, this work proposes a novel negotiation strategy, which considers the opponent's emotional state and awareness of the behavioral changes while taking the opponent's moves and remaining time into account.

In the rest of the paper, Section 2 describes the *Hybrid agent*, which evaluates only the remaining time and the opponent's latest bids' difference. Section 3 describes the *Solver agent*, which considers the opponent's emotions and the opponent's awareness of the Solver agent's behavior differences as the Hybrid agent's extension. Finally, Section 4 concludes the paper with future work directions.

2 HYBRID AGENT: TIME AND BEHAVIOR

Since agents need to deal in a limited time, the remaining time should be considered during the negotiation. However, only considering the time and adopting a time-based concession strategy would not be sufficient. Therefore, it is crucial to consider the opponent's attitude during the negotiation and act accordingly. Faratin *et al.* propose behavior-dependent bidding tactics, mimicking to some extent opponent's behavior [6]. Similar to [20], we suggest adopting a hybrid-strategy that uses both time and behavior-based strategy as a baseline strategy. Accordingly, we introduce a bidding strategy that calculates the target utility, as shown in Equation 1. The principal intuition is that when time is not crucial (e.g., at the beginning of the negotiation), our agent pays more attention to its opponent's behavior while deciding its next bid's target utility. As the deadline approaches, it tends to find an agreement urgently; therefore, it cares more about the remaining time.

$$TU_{Hybrid} = (t^2) \times TU_{Times} + (1 - t^2) \times TU_{Behavior} \quad (1)$$

To estimate target utility (TU_{Times}), the tactic uses a time dependent concession function proposed by Vahidov [24]. Equation 2 represents the adopted concession function where t denotes the scaled time $t \in [0, 1]$ and P_0, P_1, P_2 are the maximum value, the curvature, and minimum value of the curve respectively.

$$TU_{Times} = (1 - t)^2 \times P_0 + [2 \times (1 - t) \times t \times P_1] + t^2 \times P_2 \quad (2)$$

For the behavior-based target utility, we present an extension of Tit-For-Tat Strategy [6], which mimics the opponent's moves to some extent. One of the main differences is that our tactic changes mimicking ratio dynamically rather than using a fixed ratio. Moreover, [6] considers only the opponent's last two offers and ignores the opponent's other offers. Therefore, it is inclined to miss the opponent's general bidding pattern. Our tactic considers a window of opponents' bids and estimates the utility changes of the opponent's bids within this window by prioritizing the most recent ones.

$$TU_{Behavior} = U(O_j^{t-1}) - \mu \times \Delta U \quad (3)$$

$$\Delta U = \sum_{i=1}^{n} [W_i \times (U(O_h^{t-i}) - U(O_h^{t-i-1}))] \quad (4)$$

$$\mu = P_3 + t \times P_3 \quad (5)$$

To mimic our opponent's behavior, we scale the overall utility change by a time-dependent parameter, μ to estimate a target utility as seen in Equation 3 where $U(O_j^{t-1})$ denotes the utility of the agent's previous offer. The positive changes mean that the opponent concedes; hence, the agent should concede as well. Equation 4 shows how we calculate the overall utility changes by considering the opponent's last n consecutive bids where W_i denotes the weights of each utility difference. As seen in Equation 5, the value of coefficient μ is determined by the current time and P_3, controlling the percentage of mimic. The agent tends to decrease/increase the target utility less than its opponent does initially, and afterward, the degree of mimic increases over time.

3 SOLVER AGENT

Solver Agent extends the hybrid negotiation strategy by incorporating the opponent's emotional state and awareness for our bidding behavior. To achieve this, we introduce two new parameters in our behavior-based target utility calculation, as shown in Equation 6 where P_A and P_E denote the awareness and the emotion.

$$TU_{Behavior} = U(O_j^{t-1}) + ({P_A}^2 \times P_E) - [(1 - {P_A}^2) \times (\mu \times \Delta U)] \quad (6)$$

One of the challenges here is how to estimate the emotion coefficient capturing the opponent's emotional state during the negotiation. Instead of classifying the opponent's primary emotional state and adopting a rule-based behavior in line with the perceived emotion, we aim to use the perceived emotions as a complementary or diminishing effect for the decision vector. We thought this approach is a more dynamic approach for interactions, instantly changing expressions such as negotiation. Therefore, the proposed agent creates and updates a vector of the opponent's emotions.

To generate this vector, we use the pre-trained emotion recognition model presented by Li [12]. This model provides 75% accuracy with the RAF-DB, one of the most robust facial recognition databases. It presents a wide range of training instances in terms of gender and race. Note that Scherer and Ekman suggest that this dataset fits the best while capturing the images under daylight in an experimental environment [5, 22]. This pre-trained emotion recognition model recognizes seven emotions; surprised, fearful, disgust, happy, sad, angry, and neutral from the given human facial expressions. Since disgust and fearful categories do not play a role in negotiation, those categories are discarded in our work.

During the negotiation, the agent collects instant images of human negotiators. Those images feed the mentioned emotion recognition model earlier. The model outputs each emotion's prediction. P_E is calculated as a weighted average of certain values of each emotion. That is, a low value of P_E denotes a negative emotion, whereas the higher values represent more positive emotions. Therefore, the Solver agent will demand more if its opponent is in a positive emotional state. Otherwise, it will tend to concede more to reduce the level of the human opponent's negative emotions (i.e., avoiding frustrating its opponent more) and building a rapport.

To estimate opponent awareness coefficient P_A – degree of the opponent's response to the agent's behavior changes, both agents' subsequent moves [9] (e.g., silent, nice, concession, unfortunate, fortunate, selfish) are analyzed. First, the agent calculates the number of times the opponent changes its behavior from one type to another when the agent changes its behavior type. This number is divided by the number of total behavior changes of the agent, which corresponds to P_A as a control mechanism for understanding the correlation between emotion changes received with the camera and the opponent's offer.

The value of P_A is higher when the opponent adapts his/her move in line with the agent's changing moves more. In such a case, our agent cares about its opponent's emotional state more. If the opponent is not sensitive, then the low value of P_A reduces the effect of the opponent's emotional state. Against the opponents who may try to manipulate the agent with their facial expressions to make it concede more, a higher P_A value reduces this effect slightly.

4 CONCLUSION

This work introduces a novel bidding strategy, Solver Agent, which incorporates the opponent's awareness of the agent's changing behavior and opponent's emotional state and considers its bidding behavior and remaining time. Our preliminary experimental results showed that Solver Agent gained higher individual scores while not diminishing the human participants' score. As future work, we are planning to conduct a more detailed analysis of human-robot negotiation experiments and explore other ways of considering the opponent's emotional states.

ACKNOWLEDGMENTS

This work has been supported by a grant of The Scientific and Research Council of Turkey (TÜBİTAK) with grant number 118E197. This article's contents reflect the authors' ideas and positions and do not necessarily reflect the opinions or positions of TÜBİTAK.

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