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

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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. In order to understand an opponent's attitude, agents can only use offer exchanges during the negotiation. While designing a negotiating agent interacting with a human directly, other information such as emotional changes during the negotiation can be considered to establish a better interaction and consequently reach an admissible settlement for joint interests. Accordingly, this paper proposes a bidding strategy for autonomous humanoid robots, which incorporates their opponent's emotional states and awareness of the agent's changing behavior during the negotiation. To study the impact of emotional awareness in bidding, we conducted human-robot negotiation experiments. The results showed that considering emotional awareness has a significant impact on negotiation.

Hybrid Agent: Time and Behavior

Since agents need to deal in a limited time and consider the opponent's attitude during the negotiation and act accordingly, Hybrid Agent contains:

- **Time Based Concession Strategy:** Conceding over time [1]
- **Behavior-Based Strategy:** Mirroring opponent's behavior

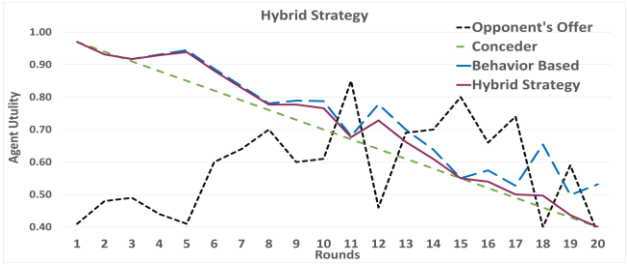
$$TU_{Hybrid} = (t^2) \times TU_{Times} + (1 - t^2) \times TU_{Behavior} \quad (1)$$

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

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

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

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

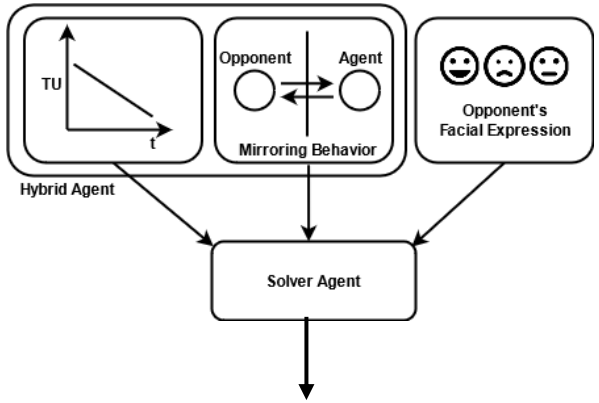


Solver Agent: Emotion and Awareness Based

Solver Agent extends the hybrid negotiation strategy by incorporating

- The opponent's emotional state and
- Awareness for our bidding behavior

Challenge: How to estimate the emotion coefficient capturing the opponent's emotional state during the negotiation?

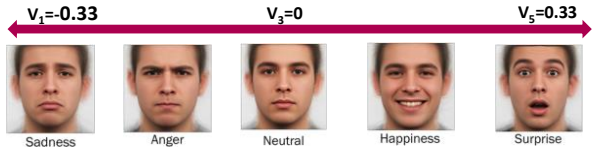


$$TU_{Behavior} = U(O_j^{t-1}) - [(1 - P_A^2) \times (\mu \times \Delta U)] + (P_A^2 \times P_E) \quad (6)$$

We use the emotion recognition model which provides 75% accuracy with the RAF-DB, which is the most robust facial recognition databases [2].

Emotion recognition model recognizes 5 emotions such as surprised, happy, sad, angry and neutral from the given human facial expressions.

Emotions are ordered from negative to positive mood like valence score (i.e., sad, anger, neutral, happy, surprise). That is, P_E is the weighted average of certainty values of each emotion.

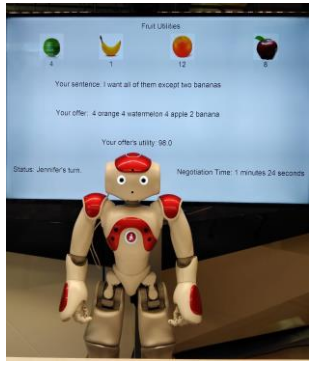


$$P_E = \sum_{i=1}^{5} V_i \times (\sum_{k=1}^{m} F_i^k)/m \quad (7)$$

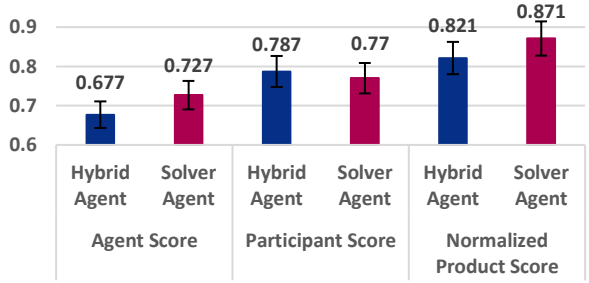
Experimental Evaluation

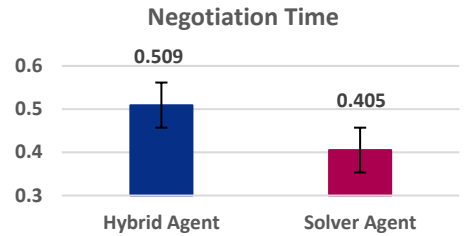
To evaluate the performance of proposed negotiation agents, we design a user experiment:

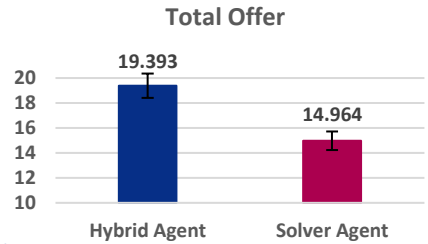
- Alice negotiates with participants on resource allocation.
- Each participant is asked to negotiate with Alice in both settings.
- 28 participants (i.e., university students; 23 males, 5 females; median age: 23.7)



Results







Conclusion

This work introduces a novel bidding strategy, Solver Agent, which incorporates

- Opponent's awareness of the agent's changing behavior
- Opponent's emotional state
- Opponent's bidding behavior
- Remaining time

Solver Agent

- Gained higher Individual & Social Welfare (Nash Product)
- Reached agreements sooner than the Hybrid agent

References

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2. Shan Li and Weihong Deng. 2019. Reliable Crowdsourcing and Deep Locality-Preserving Learning for Unconstrained Facial Expression Recognition. IEEE Transactions on Image Processing 28, 1 (2019), 356–370.

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