“I know how you performed!” Fostering Engagement in a Gaming Situation Using Memory of Past Interactions

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ABSTRACT

Studying long-term human-robot interactions in the context of playing games can help answer many questions about how humans perceive robots. This paper presents the results of a study where the robot Flobi [11] plays a game of pairs against a human player and employs a memory with information about past interactions. The study focuses on long-term effects, namely the novelty effect, and how a memory with statistics about past game-plays can be used to cope with that effect. We also investigate how an autonomous interaction compares to a remotely controlled system that plays flawlessly. Results showed that providing information about how players performed throughout the interaction can help to keep them more interested and engaged. Nevertheless, results also showed that this information in combination with perfect playing skills tended to promote a more negative perception of the interaction and of the robot.

ACM Classification Keywords

I.2.1 Applications and Expert Systems: Games.

Author Keywords

Human-Robot Interaction; Interaction Aware Robot; Socially Interactive Robot; Entertaining Robotic Game-Play; Memory of Past Interactions

INTRODUCTION

Whenever humans interact with agents, like robots, these agents should be designed to act as social partners, for example as assistive companions or entertainers. The agent should be able to become an interaction partner that supports us in our daily lives. Its behaviors ought to offer alternation and engagement in case of boredom or loneliness.

To investigate effects of long-term interactions a promising context is playing games. Humans know how to play games and therefore can more easily understand how to interact with an agent in such a situation. One advantage of games is their mostly structured procedure. This allows the systems designers a more controlled flow for the whole interaction. Another benefit of such an interaction is that games allow interaction in either a cooperative or a competitive manner, resulting in greater engagement between agent and human. Additionally, for each game there is the effect of chance, resulting in different interactions throughout repeated situations.

For most people, interacting with a robot is exciting and interesting. This can be observed from the first interactions. A robot’s ability to act and to react in a human-like manner can make a person curious about what the agent may be capable of. But when the interaction is repeated, and the human becomes used to the robot’s behaviors, s/he will tend to establish static behavior patterns. If the interaction remains static and nothing new occurs, then s/he may become bored, with the novelty effect wearing off [6, 7, 3, 14]. Consequently, most people tend to minimize or even avoid further interactions.

To avoid static behaviors, the interaction itself should offer more dynamic parts that allow alternation at each interaction. We investigated how an interaction in the context of a gaming situation could be enhanced by using information from the preceding interaction in subsequent situations. We describe a system that collects information about past interaction. This information is stored inside a memory and used in further interaction through the systems dialog capabilities. The system is evaluated over four consecutive weeks in which each participant played once per week.

RELATED WORK

A great deal of work has been done on single interaction in the field of human-robot interaction. Long-term interaction, on the other hand has only recently begun to be heavily investigated, motivated by the difficulties that arise in its implementation and performance. In contrast to a single interaction study, a study with reoccurring interactions is time consuming and needs more structured planning from the point of design through to each single interaction. This often leads to much more overhead [5]. Measuring data over longer periods requires careful consideration of the methods used, as well as how data should be stored and analyzed. In addition, interpretation of results becomes more difficult. The nature of changing perceptions in the interaction can give rise to multiple extraneous effects.

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One such effect is the novelty effect. It describes situations in which humans tend to rate new experiences more positively early on, and less positively once the novelty has worn off. In this case, human participants react very positively when first interacting with the robot, but lose their curiosity, or even become bored if its behavior becomes predictable. Another effect is familiarization or habituation [9]. Once humans know how the interaction needs to be handled, they tend to create static behaviors. Humans tend to utilize these behaviors for all upcoming interactions when the system proceeds in a static manner.

Another common approach is to design interactions in a simple manner to limit the number of variables to be analyzed. Whenever an autonomous robot interacts in a complex scenario, the possibility of errors and misbehaviors increases. Often scenarios are chosen that do not represent interactions in the real world or are not familiar to a naive user. Interactions based on playing games can help humans to interact with robots more naturally. In research scenarios, the gaming context can help to detract participants from the artificiality of their surroundings and situations.

In [12] the game "Rock-Paper-Scissors" was implemented for the humanoid robot Nico. The authors investigated the effect of a cheating robot in the context of this game. They were interested in research on how people characterized cheating, and how the mental state and engagement of the robot was rated. To this end, they used a robotic hand that was capable of displaying the three figures of the game. A dialog system announced the outcome of a round. Three conditions were tested. In condition one, the robot cheated by announcing an incorrect result. In condition two, the robot changed the outcome after the result of the participant was known. Condition three was a control-condition where no cheating was used. The authors found that a cheating robot was more engaging compared to a fair robot. The participants rated an incorrect announcement in the dialog as a malfunction. These behaviors are not rated as bad, although the action-cheating was rated as cheating, and not rated very positively.

Becker-Asano and Meneses [2] implemented a gaming interaction with the hybrid agent MARCO. The authors combined the virtual agent with a robotic arm and implemented the game of chess. While playing, the system displayed emotions in response to game events. The system was designed to evaluate how artificial agents could influence human emotions. The authors speculated that *"a human player's enjoyment will increase together with higher levels of emotional contagion"*.

In 2014 Leite et al [10] published results of a long-term interaction between a robot and children. The robot iCat was used in a school as a companion playing games over several weeks. The game of choice was chess and the robot played the counterpart to one child at a time. Several factors were analyzed: social presence, engagement, help and self-validation, and perceived social support. Social presence was equivalent between weeks one and five, indicating no effect of decrease over the long term. The same effect was found for engagement, help and self-validation. The authors concluded that in the given setting, the children saw the robot as a supportive companion. The authors noted that a limitation of the study was that the children did not understand the questionnaires as well as the adults. Also for the interviews, children sought to please the interviewer in following with the effect of suggestibility [4].

Another approach on human-robot interaction using a gaming context was done by [13]. The authors tested how a robot is perceived and compared to a human counterpart throughout playing a game. The study conducted also covers how the parties were perceived in case of dishonest manipulation while interacting. From the findings the authors stated, that a robot that acts not as expected, like cheating in a game was perceived to be more intelligent. The authors also stated that dishonest manipulation made by a human being results in the counter perception, stating that such a person is perceived as not intelligent.

The system described in this paper evaluates effects by playing a game of pairs with a robot in a one-to-one situation. In contrast to the mentioned studies, our system investigated how gaming situations could be enriched with the usage of memory of past interaction and how applying the knowledge from that memory is perceived throughout later interactions.

SCENARIO

Playing games with a robot offers several advantages. Game interactions are familiar to humans given that most have played games before. A gaming context normally comes with a predefined structure and therefore allows designing the interaction more precisely by using a manageable number of elements. In a game, it is common for two or more parties to play together, allowing to focus on either cooperation or on competitive tasks. Also, a benefit is the effect of chance, which allows each interaction to run differently, thus offering a new experience for every new game played.

Figure 1: The robot head Flobi.

To evaluate how information about past interactions could be used to enhance gaming interactions, a scenario using the child's game of pairs was selected. The game involves searching for pairs among a set of cards uncovered throughout a round. By remembering the position of the turned cards, each player tries to collect pairs and to outsmart their opponent. Every round of the game follows a strict procedure.

The robotic system used for the interaction is the anthropomorphic robot head Flobi [11]. The robot has a human-like face to show basic emotions (see fig. 1). It is capable of focusing on objects in its vicinity using cameras placed in the eyeballs. Due to the lack of manipulators, the robot head itself can not physically interact with objects, therefore the robot communicates its needs and wishes to its human counterpart by using dialog. This helps to promote communication with, and engagement from the human.

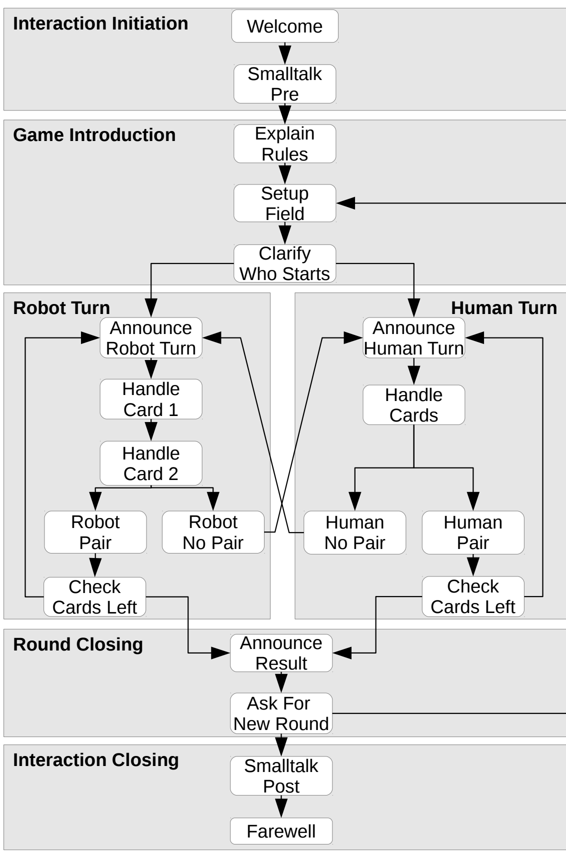

Figure 2: The structure of the predefined interaction. Shown is the entire flow, beginning with the introduction, turns made by both parties, and the dismissal at the end.

The structure of the game of pairs was based on the original rules and a two player version (see fig. 2). Throughout each game played, the robot announced cards to be turned, evaluated results and reacted upon humans actions. A vision pipeline detected and classified cards placed in front of the robot and transformed positions into a coordinate system presented to the human player [8].

The designed system ran completely autonomously using different components to handle card detection, as well as speech recognition and speech synthesis (see fig. 3). Due to misclassification based on susceptible sensor information the system could produce incorrect announcements abouts pairs or could misunderstand instructions from the human player. The used dialog system is capable to handle these flaws and allowed the human player to repair incorrect announcements. Nonetheless, these situations could slow down the interaction.

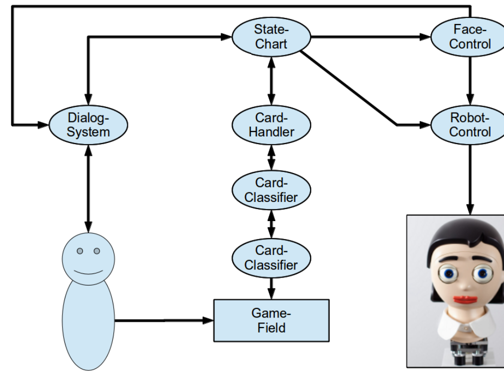

Figure 3: The components implemented for the gaming interaction. The system runs autonomously and is capable of detecting cards using a vision pipeline. A dialog handles speech recognition and interpretation. Text-to-Speech synthesis is used to communicate with the human player.

Memory of Past Interactions

Each game offers different statistics about how the player and the robot played throughout each interaction. For every round played, the number of cards turned or the time played are recorded. Also statistics about the number of turns or how many pairs were found by the players can be tallied. By storing all these information over consecutive game-plays, a memory can be filled containing contextual knowledge for both parties and how they performed.

The system collects this information in a local and a global manner. The local memory contains data about the round currently being played. A global memory stores all data that was accumulated over all rounds played with the robot. The data collected by the system contains the number of rounds and games played, the number of wins and losses for each player, pairs found by each player, turns taken and also how long each session lasted. This information was stored across all sessions and can be applied to the dialog system.

The dialog component controls the selection of sentences for each action to be communicated using speech synthesis. The data collected throughout the game-play is stored by a memory component and can be queried by other components. The dialog component uses this functionality to select outputs and to enrich the created speech synthesis. Based on how the player and the robot perform, a corresponding sentence is selected, and the data itself is applied to the sentences (for an example dialog see listing 1). By adding the collected statistic to the output itself, the sentences used to communicate with the human player become more dynamic. Additionally, the system can be configured to produce a more static interaction. Within this configuration the data from the memory component is ignored within the dialog and therefore the speech production. This allows to use default sentences without enriched sentences and results in a static dialog for consecutive game-plays.

Listing 1: Example of a dialog pattern using memory data. This example is used whenever a round closes. The first sentence matching the given condition is selected for speech synthesis.

```
[...]
  //Announce stats if robot (Ro) and
  //human (Hu) played 10 rounds
  if gl_GamesPlayed == 10
    "We played 10 rounds together with a rate
    of %gl_GamesWonRo% to %gl_GamesWonHu%."
  //The robot is in the lead. Start motivating
  else if gl_GamesDiffRoToHu >= 2
    "Again I am the winner. Keep up!"
  //Announce that the robot leads by one game.
  else if gl_GamesDiffRoToHu >= 1
    "I am leading by one game!"
  else if gl_GamesDiffRoToHu == 0
    "Thats a draw for all games."
  //Output if data should not be used.
  else if use_data == 0
    "This round is over."
[...]
```

Remote Control using Wizard of Oz

To investigate the effects of a perfectly playing robot, we additionally realized a remote controlled version of the interaction. Like the autonomous system, the remote version of the system uses the same dialog elements and memory capabilities. In contrast to the autonomous system, it uses input from a human controller to identify and select cards, as well as to forward human speech input correctly to the dialog component. The human controller can only select from predefined actions, but is not capable to directly select the used dialog sentences. Each actions results in the selection of speech outputs equally to the autonomous system. This allows the system to use the same structures, as compared to the autonomous version, however it avoids flaws and errors and plays more precisely.

STUDY DESIGN

To evaluate the effects of using memory of past interactions, we conducted a long-term study at an university campus. Each participant played with the robot over four sessions distributed over four weeks. In each session the participants played in a one-to-one setting with the robot (see figure 4). After each session, the subject completed a questionnaire to evaluate how the interaction was perceived. Additionally, two HD cameras recorded each session. The subjects were advised to play a minimum of one round per session. They were briefed that they were allowed to play as many rounds as they liked.

Throughout the study, three conditions were tested:

- **Basic:** A basic system playing autonomously. The system does not use the memory component and the dialog provides no statistics.
- **Context:** The basic system enhanced with the usage of the memory data for the dialog. The statistics are acquired over consecutive games.
- **Remote:** The game-play was controlled by a human in the background. The human in control uses the same memory component and the same dialog elements to structure the interaction. The player is not aware that a human is in control.

The first two conditions *Basic* and *Context* were compared to evaluate the effects of applying contextual knowledge.

The second comparison is made between conditions *Context* and *Remote*. This evaluated how a perfectly playing system offering knowledge is perceived compared to a system with possible flaws and errors.

Because the remote system was not used without the data provided by the gathered memory the condition *Basic* and *Remote* were not compared.

Hypotheses

We developed three hypotheses about the effects of collecting data for a memory of past interactions and applying these in a gaming situation for long-term HRI.

- **Hypotheses 1** - Applying collected knowledge throughout the interaction would result in a more positive perception of both, the interaction and the robot over the long-term. Therefore, we predict that ratings about likability would be increased when using memory of past interactions.
- **Hypotheses 2** - Subjects would invest more time in interactions taking place whenever feedback on past interactions is provided. If this feedback is omitted, we predict that subjects would mainly play the advised number of rounds and that less engagement can be found.
- **Hypotheses 3** - A robot system playing too perfectly and using memory of past interactions would result in a more negative perception of the interaction. Subjects would not like a more difficult opponent, especially when exposed to statistics about their game progression.

Measurement

To test the hypotheses, a questionnaire was designed to evaluate different items. For each item, a 7-point Likert scale was used.

The first items measured how the interaction and the robot were perceived. Items compared how machine-like or human-like the robot performed, and how the robot's likability was perceived over time. The items were based on the Godspeed questionnaire series [1]. Additionally, the complexity of the interaction was rated.

The second group of questions focused on how much the participants liked to play the game throughout each session. Ratings included how strongly the participants wanted to win against their robotic opponent.

In addition to the analysis of the questionnaires, the video data was annotated by marking the number of rounds played.

Figure 4: Views from the camera used during the study. The participant is placed opposite the robot. The gaming elements are placed in a marked area.

Study Procedure

In the first session, the subjects got introduced to the robot and how the robot communicates actions performed throughout a game. The participants were advised to play a minimum of one round, and to play as many rounds as they liked. After the introduction, the examiner left the room. The interaction began when the participant greeted the robot. After the subjects played their last round for the session they were asked to complete a post-experiment questionnaire. For sessions two, three and four, the subjects were lead into the experimental room, and began the interaction directly by greeting the robot.

The procedure comprising playing one session and completing the questionnaire took about 25 minutes on average. After the last session, the subjects were paid 20€ for their expanses. Figure 4 shows the setting with a participant playing the game with the robot. The participant is placed opposite the robot. Gaming cards must be placed inside an area marked in-front of the player. Pairs are removed and placed outside the area.

Throughout the study, a total of 16 Cards (8 pairs) was used. This allowed a moderate level of difficulty to keep the players interested, as well as for several rounds to be played throughout one session.

For the condition *Remote* the human controlling the interaction is applied with the same cards used for the player. These cards were placed in front of the controller. Every time the player turns a card, the controller turns the same card on the remote side. In difference to the player the controller turns no cards back. With this ability no cards can be forgotten and the controller is directly aware whenever a pair is visible. As a strategy the controller directly selects all known pairs whenever the robots turn is executed.

RESULTS

For the study, a total of 39 university students were recruited (25 females, 14 males, age M = 26.54, SD = 5.684). The study was conducted from June to October. Participants were randomly assigned to the three conditions, such that for condition *Basic* we had 13 participants, for condition *Context* 14 participants and for condition *Remote* 12 participants.

To measure effects between conditions, we conducted an independent samples t-test. The differences between the mean values for the first (session 1) and the mean values for the last session (session 4) were computed for each condition. At this point the collected results of session two and three are not analyzed due to time limitations.

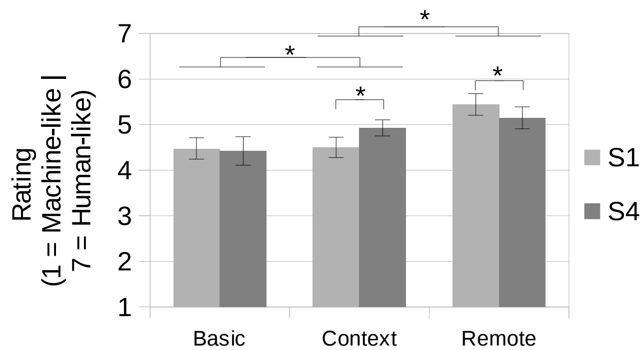

Figure 5: Ratings for the item *Human-like vs. Machine-like*. S1 shows mean values for the first session. S4 show the mean values for session 4. Bars marked with * indicate a significant difference below .05.

We conducted a paired t-test to control the order effects between sessions one and four for each condition. We compared means for each item for each condition.

The first item evaluated whether the interaction and the robot were perceived as *more machine-like or more human-like* (see fig. 5). The within effects for the condition *Context* showed a significant increase (t(13) = -2.328, p = .019). The analysis of between conditions effects showed a significant increase for condition *Context* compared to *Basic* (t(25) = 1.851, p = .038). Condition *Remote* showed a significant decrease compared to condition *Context* (t(25) = 3.062, p = .003). This suggests that applying memory of past interactions may promote a more dynamic and vivid perception. An accurate interaction with a strong opponent appears to result in the reduction of a lively perception. Ratings for the condition *Remote* were found to be higher compared to the other conditions.

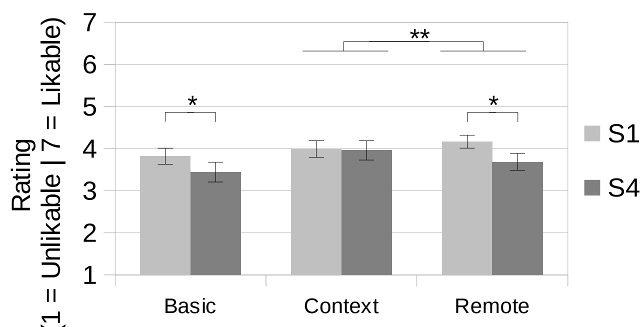

Figure 6: Ratings for the item *Unlikable vs. Likable*. Bars marked with * indicate a significant difference below .05, ** indicates a marginally significant difference below .1.

For the ratings on how *likable* the interaction was perceived (see fig. 6) we found that the ratings for a system without memory of past interactions decreased over time. The results within each condition showed a significant reduction for the condition *Basic* (t(12) = 2.627, p = .011). The ratings were nearly constant for the condition *Context*. This suggests that using memory may keep the interaction more interesting, even over repeated interactions. For the condition *Remote*, a decrease in the ratings was found as well, showing a significant effect (t(11) = 2.605, p = .012). This suggests that a system may become unlikable when playing too perfect, and when reminding the player about this circumstance using memory of past interactions. Comparing *Context* with *Remote*, a marginally significant preference for a not perfectly playing system was found (t(24) = 1.557, p = .092). This suggests that playing too perfect may reduce sympathy over time.

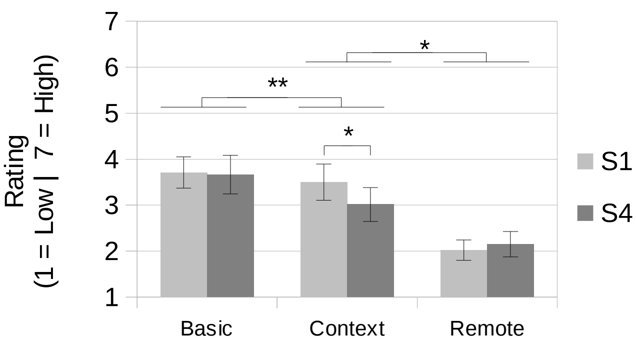

Figure 7: Ratings on the complexity of the interaction. Bars marked with * indicate a significant difference below .05, ** indicates a marginally significant difference below .1.

For the last item of the first group, the participants rated how they *perceived the complexity of the interaction* (see fig. 7). Results show that the condition *Context* decreased significantly over all sessions (t(13) = -2.474, p = .014). It seems that providing statistics using a memory favors a learning effect, resulting in a better understanding and therefore more positive ratings. This suggests that additional information keeps the participants interested even during later interactions. For between conditions effects, the condition *Context* showed a marginally significant difference compared to condition *Basic* (t(13) = -1.373, p = .091). This suggests a trend that using a memory may help to promote understanding of the interaction. We found that for *Context* and *Remote*, the later condition increased marginal significantly (t(24) = 1.557, p = .067). Nevertheless, the results showed that the remotely controlled system was perceived to be less complex over all sessions.

For the second group of questionnaire items, the subjects rated how strongly they wished to defeat the robot throughout each session (see fig. 8). The effects within conditions showed a marginally significant increase for *Context* (t(13) -1.422, p = .090). This suggests a trend for promoting ambitions to defeat the robot. For the condition *Remote*, we found a marginal decrease (t(11) = 1.773, p = .052). This suggests that the interaction partner may have been too strong. By playing

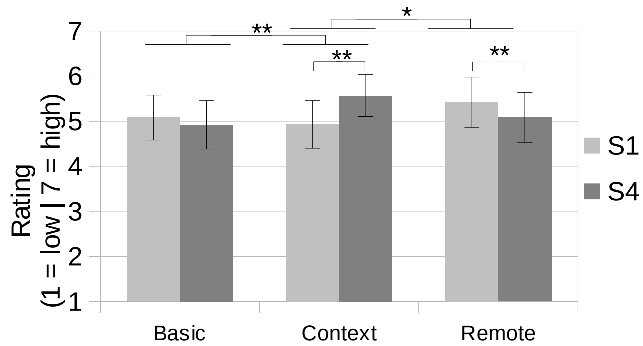

Figure 8: Ratings for the participants wish to defeat the robot. Bars marked with * indicate a significant difference below .05, ** indicates a marginally significant difference below .1.

strongly and announcing this advantage at each session, subjects seemed to begin to lose interest in defeating the robot. The between conditions analysis found a marginal significant effect that using memory of past interactions appears to promote ambition if the system was not too strong (t(25) = -1.325, p = .099). On the other hand compared with condition *Remote*, it appeared to diminish ambition if the opponent was too strong (t(24) = -1.993, p = .031).

From the videos recorded throughout each session, the number of rounds played was annotated (see fig. 9). Results showed that for both conditions that used the memory information, participants tended to play more rounds in later interactions. For the condition *Context*, the number of rounds increased significantly (t(13) = -2.294, p = .020). For the condition *Remote*, the increase was marginal but showed a trend (t(11) = -1.595, p = .071). This suggests that providing additional information may promote more engagement and interest in interacting with the robot. The between conditions analysis found that the increase between *Basic* and *Context* was marginally significant (t(25) = 1.346, p = .096). This underscores the effects within conditions by showing a trend towards a more interesting interaction when memory of past interactions is provided.

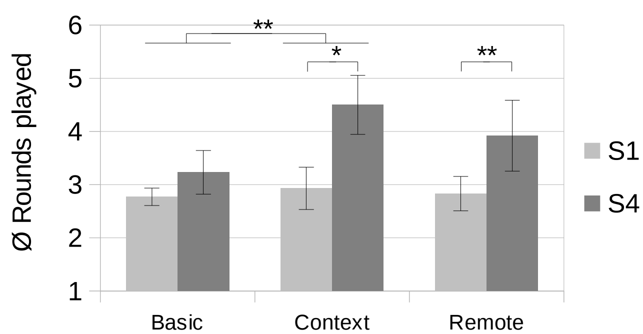

Figure 9: Mean number of rounds played per session. Bars marked with * indicate a significant difference below .05, ** indicates a marginally significant difference below .1.

One interesting outcome of the study was the subjects tendency towards cheating. Different types of cheating were found. Some players peeked under cards to find matching pairs. Other players exchanged cards whenever the robot was about to uncover a pair known to the player. Based on annotations of video data, occurrences of cheating behaviors were marked. The annotations showed no normal distribution, therefore a non-parametric tests was used (Mann-Whitney for between conditions, Wilcoxon Signed Rank Test for within conditions). We found that in the condition *Remote*, participants tended to cheat against the robot during all sessions (see fig. 10). No cheating occurred in the condition *Basic*. For the condition *Context*, cheating occurred in the first session, and then decreased marginally significantly over time ($p = .059$). The between conditions analysis for *Context* and *Remote* found a significant difference ($p = .046$). It seems that the perfectly playing robot played somehow too strongly. To compensate their disadvantage, subjects started to exchange cards whenever the robot announced a card leading to a pair, or to peek under cards to gain an advantage. The video data showed that these behaviors occurred even when the robot was looking directly at the playing field. Nevertheless, for all conditions the system was not designed to react to cheating behaviors and therefore did not recognize cheating or react to in any way.

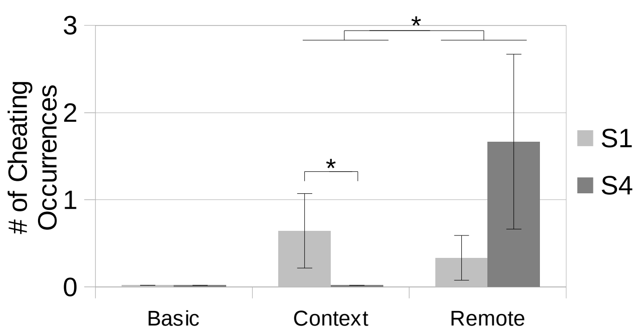

Figure 10: Mean number of cheating occurrences per session. Bars marked with * indicate a significant difference below .05, ** indicates a marginally significant difference below .1.

DISCUSSION

The results of the study were analyzed with regard to the hypotheses. For *hypothesis 1* we found supporting evidence that applying memory of past interactions to a gaming interaction promoted a more positive perception of both, the interaction and the robot itself (see fig. 5 and fig. 6). Participants showed more interest even after later interactions when it comes to handle the sometimes complex interaction (see fig. 7). The additional information about how both parties performed seemed to encourage playing more rounds and to strengthen the wish to defeat the robot (see fig. 8).

Hypothesis 2 was also supported. Subjects played more rounds throughout conditions *Control* and *Remote* whenever the dialog provides information from the memory (see fig. 9). Applying additional information, such as how many rounds were played or who led throughout all played games, seemed to boost the participants ambitions to even the odds and to defeat the robot.

The results also supported *hypothesis 3*. We found that after several games in which the data from the memory of past interactions was applied, participants lost interest and ambition to win when playing against a strong opponent who played flawlessly (see fig. 5, 6 and 8). Providing information on how poorly each participant performed throughout all sessions seemed to foster a more unlikable perception of the interaction and the robot. In the remote condition, the provided statistics also led to cheating behaviors, presumably to compensate for any disadvantages and to defeat the robot (see fig. 10).

CONCLUSION AND OUTLOOK

Static behaviors can lead to a decrease in engagement and interest in humans during gaming interactions used to study long-term human-robot interaction. To address this novelty effect, we introduced the integration of a memory that statistics of past interactions. A more dynamic dialog and interaction was created by providing information about how players performed over time. Results of a user study show that the incorporation of information from past interactions can help to retain and even increase the users interest and engagement through later interactions. For the system implemented, the gathered memory consisted of simple statistics recorded throughout each session. By forwarding the information to the dialog, and using the data in later interactions, effects were found that favored the usage of memory on past interactions.

Additionally to an autonomous system, we tested a perfectly playing system. This system performed flawlessly, and was used to evaluate how such a system was perceived in combination with memory capabilities. The results showed that a strong opponent providing game statistics promoted a decrease in likability. Some subjects also started cheating to compensate for their disadvantages.

The findings suggests that a memory on past interactions can help to keep interactions interesting. Nevertheless, providing feedback about how players perform throughout a gaming interaction should be used wisely, especially when the robotic system has a greater advantage. In this situation, a more adaptive usage of the data should be employed.

In further studies, we will use the idea of creating statistics and to memorize these to steer the strength of the autonomous system in an adaptive way. Whenever in a drawback the system could have the ability to adapt and play more strongly. The same procedure can take place whenever the human player shows some disadvantage. In such situations, the system can begin to hold back its gaming skills, and try to motivate the human to keep the player engaged and interested.

Additionally, we plan to enhance our current setup to include other games such as connect four or chess. Also, we will integrate collection of memory for multiple users. Using statistics for different game types, the system may be capable to motivate users to play their preferred games, as well as foster competition between different users interacting with the same agent.

Acknowledgment

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