Collecting social signals in constructive and destructive events during human-robot collaborative tasks

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ABSTRACT

Adapting behaviors based on others' reactions is a fundamental skill for a social robot that must interact with people. In this work, we to develop a systematic method to collect ecologically plausible data of human reactions to robot behaviors and associated valence. We designed a dyadic interaction were 24 participants played a board game in a human-robot team for a chance to win a chocolate. The "Grumpy robot" is responsible for losing an easy-to-win game, while the "Kind robot" for winning a seemingly impossible-to-win game. Questionnaires show that participants recognize both robots' critical impact on the game's outcome, but show similar social attraction towards both. Videos' reactions are distinct: smiles and neutral faces to the "Kind robot", and laughter, confusion, or shock to the "Grumpy robot". Collected data will be used to teach the robot to understand human reactions.

KEYWORDS

Social robotics, HRI design, social signals, data collection

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1 INTRODUCTION

Mutual knowledge of how one's behaviors impact others leads to the maintenance of social order [15]. Humans usually share this knowledge through facial expressions, body movements, and sounds. More than representing a state of mind, they actively regulate others' behaviors. Studies argue humans perceive and use them to act as young as 12 months old [16]. Following these ideas, we believe a social robot capable of adaptation and evolution should recognize humans' natural feedback to its actions [3, 11].

However, to develop such a system, researchers need rich datasets of ecologically plausible human reactions and self-reported feedback. Current datasets of expressions [8, 12, 13, 17, 18] do not contain human self-reports and reactions to robot actions. Other systems gathered laughter reactions to a comedian robot's jokes [4]. Although several works regarding human-robot expressions exist[7], we did not find any works or available datasets with reactions and self reports to robot constructive/destructive behaviors.

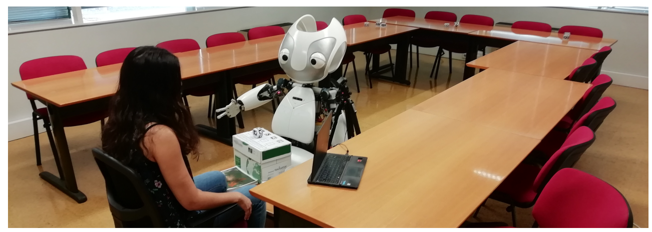

Figure 1: Human-robot team ready for the challenge.

Thus, given the lack of data and ways to extract it, we performed a study to test a novel interaction paradigm to elicit human responses. We use traditional HRI methods (audiovisual recordings and surveys).

2 METHODOLOGY & STUDY

The interaction paradigm consists of a robot that acts in two distinct ways: (i) helps the participant to achieve an otherwise impossible goal; or (ii) destroy the participant's progress toward an easy goal. We expect these actions to elicit feelings of frustration/appreciation of the participants. By assigning a **(i) Kind** (supportive, team player) or **(ii) Grumpy** (selfish, disdainful) personality to the robot and giving a prize, we intend people's feelings to be strong enough for them to react to the robot.

We test the interaction paradigm through a dyadic between-subjects design study where a human-robot team plays a cognitive board game for the chance of winning a bar of chocolate. The Vizzy robot [14] is left alone in a closed room with the participant (Fig. 1). We use a board game with 14 hexagonal prism blocks detected with computer vision methods. A laptop tracks the game state in real-time and provides audiovisual feedback to the team. The interaction consists of three phases:

Preparation phase: the participant has 30 seconds to collect scattered blocks in the room (a total of 14). The robot tracks time and alerts the participant to go back when time is running out.
Game phase: the participant has to stack blocks according to the total number of faces with a written word, per block. The board has four areas (5, 6, 7, and 8), and thus, the number of faces with words varies between 5 and 8 per block. The team loses points with time and wins/loses 100 points per correct/incorrect block. One can fetch forgotten blocks, but time does not stop. It is impossible to win with less than 11 blocks.
Validation phase: the block construction must remain stable for 1 minute, or the team loses.

The "Kind Robot" makes the person win a seemingly lost game while the "Grumpy Robot" makes the person lose an easy-to-win game (with a critical action). For each condition, we manipulate the game by scattering the blocks differently before starting the experiment:

Kind: 10 blocks on the tables (easy to see) and 3 blocks on a whiteboard (on the left of Fig. 1). The 3 blocks are visible, but we use attention tricks to make them stay unnoticed: block height [5], cognitive overloading (timed task) [6], and lack of saliency [9]. Nonetheless, if the participant gets them, the robot becomes "Grumpy".
Grumpy - 13 blocks on the tables (easy to see).

The 14$^{\text{th}}$ block is above the whiteboard for both cases and is hard to see. The critical actions were:

Kind robot critical action: the participant puts their last block and notices that it is not possible to win. The robot looks around and points at the missing blocks. With them, they can win.
Grumpy robot critical action: the participant has enough points to win and proceeds to the validation phase. The robot points at the 14$^{\text{th}}$ block, mocks the participant, and clumsily knocks down all the blocks. The team loses and the robot blames the participant.

Next, participants rated the robot's behavior (1-bad to 4-good) and answered if their score was enough to win the game before and after the validation phase (error check). Then, they answered to the following items (rated from 1 to 6): (i) *"I would be able to win the prize if the robot was not present"*, (ii) items on perceived likeability from [2], (iii) items propose by [10] for Social attraction, and (iv) the "Inclusion of Other in the Self (IOS) Scale" [1]. Everyone received the prize. We recruited 24 naive participants on campus and online ($\mu_{\text{age}} = 21.54$, $\sigma_{\text{age}} = 2.93$, 15 male, 9 female, $n_{\text{kind}} = 14$, $n_{\text{grumpy}} = 10$) .

3 RESULTS

There were 6 participants whose responses to the error check questions were unexpected. 5 participants on the "Kind robot" condition did not follow the rules. In a "Grumpy robot" experiment, the robot failed to knock down the blocks. Hence, we excluded these samples, resulting in 9 participants per condition. A summary of the questionnaire results is shown in Fig. 2.

We tested the data for normality with the Shapiro-Wilk test, using parametric tests for data that does not violate the normality condition. Every "Kind robot" participant rated the robot's behavior with the maximum value (4). For the "Grumpy robot" it had the following descriptive statistics: $\mu_{\text{grumpy}} = 2.67, \sigma_{\text{grumpy}} = 1.23$.

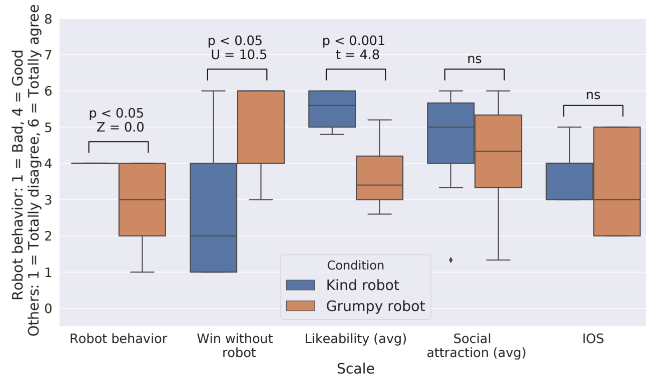

Figure 2: Questionnaire results.

Given the null σ of "Kind robot" data, we used the One-Sample Wilcoxon Signed Rank Test, with significant results. However, the positive rating for the "Grumpy robot" was a surprise. A Mann-Whitney U for "winning without the robot" ($\mu_{\text{kind}} = 2.44$, $\sigma_{\text{kind}} = 1.81$, and $\mu_{\text{grumpy}} = 5.11$, $\sigma_{\text{grumpy}} = 1.17$) showed that the robot's impact on the game was understood. We averaged the items for perceived likeability ($\alpha = 0.91$, $\mu_{\text{kind}} = 5.49$, $\sigma_{\text{kind}} = 0.49$, and $\mu_{\text{grumpy}} = 3.71$, $\sigma_{\text{grumpy}} = 0.99$) and performed an Independent samples t-test that showed significant differences. We also averaged social attraction items ($\alpha = 0.94$, $\mu_{\text{kind}} = 4.59$, $\sigma_{\text{kind}} = 1.51$, and $\mu_{\text{grumpy}} = 4.25$, $\sigma_{\text{grumpy}} = 1.52$), and an Independent samples t-test showed no significant differences. Finally, we did not obtain significant differences in the IOS scale ($\mu_{\text{kind}} = 3.78$, $\sigma_{\text{kind}} = 0.83$, and $\mu_{\text{grumpy}} = 3.44$, $\sigma_{\text{grumpy}} = 1.33$) with a Mann-Whitney U test.

In qualitative video analysis, we could identify less expressive reactions to the "Kind robot" with smiles, neutral expressions, and acknowledgment gestures. Reactions to "Grumpy robot" were more extreme, with laughter, shocked faces, and perplexed hand gestures.

4 CONCLUSIONS AND FUTURE WORK

Results showed us that people recognized the robot's role in winning/losing the game and that "Grumpy robot" was less likable than the "Kind robot", as expected and desired. Videos also showed some expected behaviors in both conditions. However, people rated the "Grumpy robot's" behavior higher than expected, with positive (> 2) median and mean values. Social attraction, IOS, and videos suggest that, somehow, many people enjoyed the interaction with the "Grumpy robot". We guess that "Grumpy robot's" unexpected ill manners are more characteristic of humans than robots, and that might charm people. We intend to verify and devise strategies to mitigate this effect (like having a better prize). Finally, we aim to extract and analyze features from the audiovisual data.

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COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest No conflict of interest declared.
Informed consent All participants agreed to take part in this study and signed the informed consent.

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