Evaluation of a Humanoid Robot's Emotional Gestures for Transparent Interaction

Alessandra Rossi[1], Marcus M. Scheunemann[2], Gianluca L'Arco[1], and Silvia Rossi[1](✉)

[1] University of Naples Federico II, Naples, Italy
{alessandra.rossi,silvia.rossi}@unina.it, g.larco@studenti.unina.it
[2] University of Hertfordshire, Hatfield, UK
marcus@mms.ai

Abstract. Effective and successful interactions between robots and people are possible only when they both are able to infer the other's intentions, beliefs, and goals. In particular, robots' mental models need to be transparent to be accepted by people and facilitate the collaborations between the involved parties. In this study, we focus on investigating how to create legible emotional robots' behaviours to be used to make their decision-making process more transparent to people. In particular, we used emotions to express the robot's internal status and feedback during an interactive learning process. We involved 28 participants in an online study where they rated the robot's behaviours, designed in terms of colours, icons, movements and gestures, according to the perceived intention and emotions.

Keywords: Human-robot interaction · Affective robotics · Social robotics · Transparency

1 Introduction

Autonomous social robots are being deployed in human-centred environments where they are exposed to close and unsupervised interactions with people. In such scenarios, robots and humans need to share the working space and work together to complete different tasks. These close interactions are raising the importance for robots of adopting natural communication mechanisms, which usually are bi-directional in human-human (HHI) and human-robot interactions (HRI). Therefore, robots and people need to understand and predict each other's behaviours and intentions, and consequently, robots need to adapt their own

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behaviours for planning the next steps to reach the common goal [15]. Moreover, the use of Artificial Intelligence (AI) techniques, and specifically of Deep and Reinforcement learning approaches, during the human-robot interaction, make this mutual understanding process even harder. Such complex and powerful methodologies are considered "black-boxes" by non-technical users who may consequently develop sentiments of distrust and fear towards robots [12]. In general, people are not inclined to use and interact with systems that they cannot comprehend. To avoid that human users misuse or disuse robots, and ensure a successful model of HRI, it is important to make robots' behaviours more intelligible and transparent for people [7].

Among the mechanisms used to make transparent a robot's internal process and its understanding of a person's mental state, emotions are considered to be a universal and valid mechanism to communicate one's own internal state [3,11]. Indeed, emotions can be defined as "they are parts of the very process of interacting with the environment" [5]. Several studies tried to provide a set of emotional body languages that robots can use to express emotions [9,10]. However, these studies showed that people's perceptions of emotions and feelings may vary according to the situational context [17,20].

In our research, we want to use emotions as a natural mechanism to express the robot's intentions, beliefs and understanding of the situational context. In particular, in this study, we selected two sets of emotions (positive and negative): two for expressing a robot's belief of the goodness of a selected action during an interactive learning process (i.e., fear and hope), and two for expressing a robot's understanding of the situational context (i.e., happiness and sadness). As a first step, before evaluating the effect of using such behaviours during the HRI, here we aim at exploring participants' perception of emotional behaviours in relation to the desired intent in an online study.

2 Design

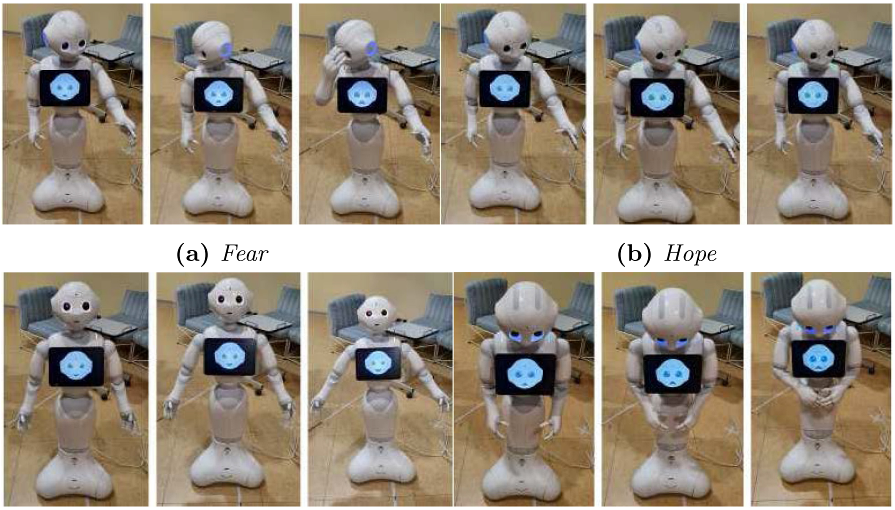
2.1 Robot Platform

The robot used in this study is the humanoid Pepper robot created by SoftBank Robotics. Pepper is 120 cm tall, it has 20 degrees of freedom (DoF), a wheeled base, a tablet at chest high, coloured LEDs around the eyes, on the side of the head (i.e., ears), and on the shoulders. The robot is not able to express facial emotions having a static face. The behaviours of the robot were implemented using ROS Noetic and the robot's libraries NAOqi.

We positioned the robot close to a desk that covered only the lower part of the robot, leaving the robot to be free of movement and the view from the chest to the head. On the desk, there were four objects (a tennis ball, a soccer ball, a kangaroo and a red box).

2.2 The Robot's Emotions and Behaviours

The affective model used in this study is inspired by J. Broekens' emotional theory, called TD-RL [2]. The model is composed of four emotions: fear, hope,



(a) *Fear* **(b)** *Hope*

(c) *Happiness* **(d)** *Sadness*

Fig. 1. Emotions expressed by the robot Pepper according to an increasing level of arousal [from left to right].

sadness and joy. In the model, they are used to express the learning status of the robot during an interactive learning task involving the user to provide the rewards. In particular, they are used to express the internal belief in the goodness of its current action (sadness and joy) and on the foreseen success of the use of such action in achieving the goal (hope and fear). In a previous work [11], this model was used in an HRI task aiming at teaching an I-Cub robot to learn a predefined sequence of objects (coloured balls) placed on a table. The considered learning task required the robot to point at the objects placed in front of it while receiving positive or negative rewards from the user through a joystick interface. Results of this study highlighted that users perceived joy and sadness gestures not as states linked to the current action but, instead, as reactions to the user rewards. Moreover, it was helpful to have behaviours showing internal states, in terms of certainty or uncertainty of the current action, during the learning process, even though the used gestures were not completely recognised.

For this reason, here, we designed new gestures for the Pepper robot to be associated with a pointing gesture for the purpose of showing hope and fear (see Figs. 1.a and 1.b). The emotions of joy and sadness are instead used to elicit the robot's response and awareness to a possible (positive or negative) feedback received by the user (see Figs. 1.c and 1.d).

The emotions expressed by the robot have been inspired by the Color Motion Sound (CMS) model [9] that combines colours, motions and sounds for each emotion. While vocal features play a fundamental role in emotion recognition [16], here we decided to not include the sounds for modelling the emotions because fear and hope do not have any sound associated according to the CMS model. We modelled three different levels (min, mid and max) of intensity for each emotion considering the following characteristics:

- *Joy*: the colour chose to represent Joy is yellow hues with three degrees of intense saturation and high brightness (HSB values: 45/100/100, 45/79/95, 45/40/100). The robot expressed this emotion with fast rotations and circular movements of the arms, and opening the chest and head.
- *Sadness*: Dark blue hues were used to represent Sadness (HSB values: 217/79/53, 230/40/40, 208/69/78). The robot moved arms closing on itself, lowering the head and making slowly rotation away from the user.
- *Fear*: The emotion Fear is expressed through jumpy movements away from the user and with uncertainty while looking at the object it intends to point at and at the user. The colours used for Fear are black and grey (HSB values: 0/0/20,0/0/40,0/0/60).
- *Hope*: The emotion is expressed using the green colour (HSB values: 102/53/66, 101/36/77, 102/75/46), open posture, and very fast and secure movements.

Pepper robot has a static face, hence to enhance the legibility of the emotional behaviours, we designed a set of icons to be displayed on the robot tablet. The icons show a drawing of the pepper face with different facial expressions obtained by modifying the shape of the robot' mouth, eyes and using the same colours as described before.

In total, the set of emotions used in this study consists of 12 animations in which the robot shows three levels of intensity of joy, sadness, fear and hope emotions.

2.3 Procedure and Evaluation Measures

We designed a between-subject study with two conditions. In condition **C1**, the robot used its tablet to show the icon to express the relevant emotions. In condition **C2**, the robot's tablet was left blank. Participants rated 12 video-clips of the robot communicating different emotions and behaviours with or without the use of the tablet and completed the requested questionnaires on Google Forms. The order of the video-clips presented to the participants was randomised to counter possible sequence effects.

The videos were shot from a frontal angle to allow participants to have a full overview of the robot and the objects on the desk. Each video-clips was shot on the same day and with the same background. We tried to recreate the videos in the same way as much as possible, and we did not make any cuts to give a natural continuity to the gestures. The robot expresses the emotions with videos of the same duration (12 s).

We did not give any description of the robot at the beginning of the interaction for capturing participants' perceptions built only on their own experience, personality and considerations [13]. In both conditions, participants were presented with three questionnaires at the beginning, after each video and at the end of the online study.

At the beginning of the study, we collected participants' responses: 1) their demographic data (age, gender, nationality and occupation), 2) their experience with robots, 3) their opinion about robots' roles and robots' ability to express emotions, 4) the affect measuring questionnaire (PANAS) [19] to measure participants' mood (positive or negative) at the time of the study using a 5-point Likert scale [1 = very slightly or not at all, and 5 = extremely], 5) the Ten Item Personality Inventory questionnaire about themselves (TIPI) [6] using a 7-point Likert Scale [1 = disagree strongly, and 7 = agree strongly].

After each video-clip, two 8-point scales, one [1= calm, and 8 = aroused] and the second [−4 = displeasure, and 4 = pleasure] were used to measure the level of arousal and pleasure perceived by the participants [8]. In the questionnaires, we expressed the valence as the pleasure to make the concept easier to understand for the participants [10]. For ranking arousal and valence of the emotions, we decided to use these scales instead of the Affective Slider [1] to not influence participants' choices by showing an emoji that might be associated with the emotion represented on the robot's tablet. We asked participants to select their confidence level for the selection of the arousal and pleasure of the emotion in the video-clip using two 7-point Semantic scales [1 = not at all, and 7 = very much]. We also asked the participants to indicate the perceived discrete emotions expressed by the robot in the video, selecting them between the following set: anger, fear, hope, sadness, uncertainty, joy, pride, surprise, certainty, disgust, embarrassment, and shame. These emotions were selected to include the six universally recognised basic and non-basic emotions from Ekman [4].

Finally, in the last questionnaire, participants were asked to give their opinion: 1) whether they believed that Pepper was able to express emotions, and whether robots, in general, should be able to express emotions, 2) which roles they would assign to Pepper, 3) which emotions they believed a robot should be able to express choosing them from the list of emotions of Ekman previously presented, 4) then, we measure participants' mood using the PANAS questionnaire. We also measured participants' attention through two check questions asking "Which was the object/were the objects in front of the robot Pepper? Please choose all that apply." and "Which gesture/s did Pepper not do in the videos? Please choose all that apply."

2.4 Participants

We recruited 28 participants (18 male, 10 female and none non-binary) aged between 18 and 66 (mean age 26.5, std. dev. 11.20). The majority of the participants consisted of Italian citizens (89%), while one participant was from Switzerland and two participants were from the United Kingdom. The sample of participants was mainly composed of students (79%). The remaining participants were a lawyer, a visual designer, a production manager, a research fellow and a retired teacher. The majority of participants (72%) stated to not have any experience with robots (min = 1, max = 5, mean 1.96, std. dev. 1.5), while the remaining had some or high experience with robots. Participants' previous experiences with robots can be classified into participation in other studies, observing or developing robots. Participants had experience with the following robots: SoftBank Robotics NAO and Pepper, Furhat Robotics, iRobot Corporation Roomba, Qihan Technology Co. Sanbot, and Hanson Robotics Sophia.

We did not exclude any participants due to a failure of the attention check question.

3 Results

3.1 Affect Questionnaire

The affect scores from the PANAS questionnaire [19] before the experiment was within the expected range. Before the experiment, the positive affect score mean was 29.75 (std. dev. 7.25) and the negative affect score mean was 14.57 (std. dev. 6.16). After the experiment, the positive affect score mean was 29.29 (std. dev. 7.26) and the negative affect score mean was 13.25 (std. dev. 6.1). A paired t-test shows that there is not a statistically significant effect between the responses before and after the test.

3.2 Descriptive Statistics

We first analysed the data for interaction effects between gender and video responses. To understand whether the gender of the participant had an effect on the responses, we computed a two-way mixed model ANOVA. The results in Table 1 show that the responses to the dependent variables arousal and valence were not affected by the participants' gender.

A statistically significant effect on the participants' perception of the arousal and valance of the robot can be further observed. This means that participants perceived the robots on these dimensions differently. The next subsections will present an exploratory analysis as to how these differences map our expectations.

Table 1. A two-way mixed model ANOVA analysed whether there is an interaction between the participants' gender and their responses to the videos. The results indicate that there is no evidence for an interaction. However, the results also suggest some statistically significant effects for the participants' responses for arousal and valence.

(a) arousal

	$DF1$	$DF2$	F	p
gender	1	26	0.05	0.82
emotion	11	286	6.44	< 0.01
interaction	11	286	1.48	0.14

(b) valance

	$DF1$	$DF2$	F	p
gender	1	26	0.56	0.46
emotion	11	286	12.01	< 0.01
interaction	11	286	1.51	0.13

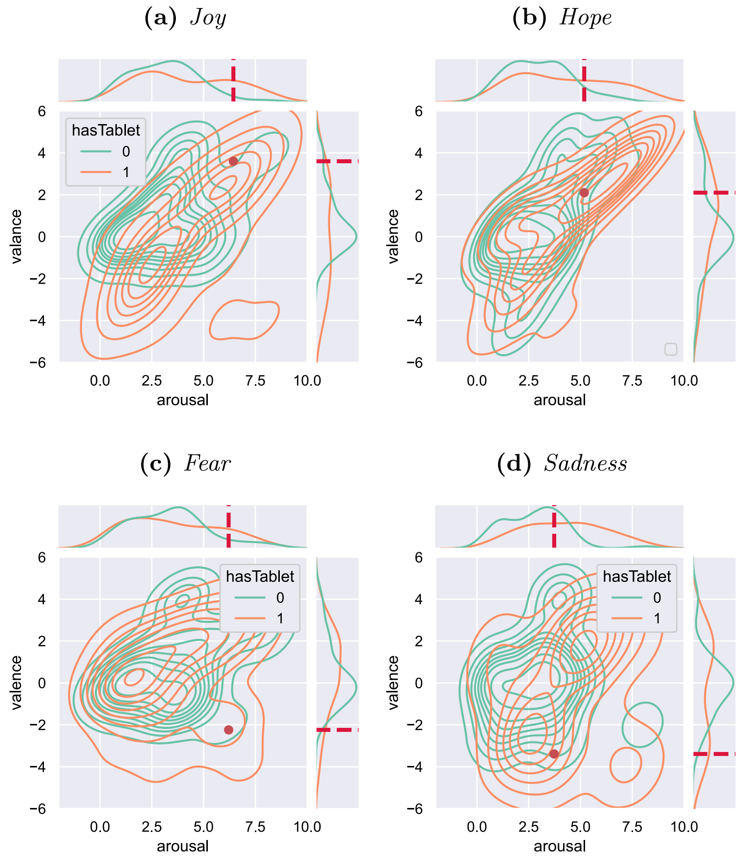


Fig. 2. Kernel density estimates (KDE) for each emotion expressed by the robot. The red point marks the expected perception means. It can be seen that the mean is usually part of the fringe or outside of the distribution. Only if a tablet is used, the expected mean is part of or close to at least one distribution maxima. (Color figure online)

3.3 Exploratory Analysis

In regard to the emotions expressed by the robot, Fig. 2 shows the kernel density estimates for the participants' responses for each of them. The red point depicts the expected mean (see [18]). It can be seen that the participants' perception of the robot without a tablet does not entirely meet our expectations. For the emotion Joy, Hope and Sadness, the robot that also expressed its emotion using a tablet, our expected mean values are part of or close to one of the maxima of the kernel density estimation. This shows that in our experiment, the tablet supports the robot in expressing its emotion to the participants.

Figure 3 shows the participants' perceived arousal in dependence to the chosen arousal level. It can be seen that the overall rating for arousal shows a little variance in the condition where the robot did not have a tablet. Interestingly,

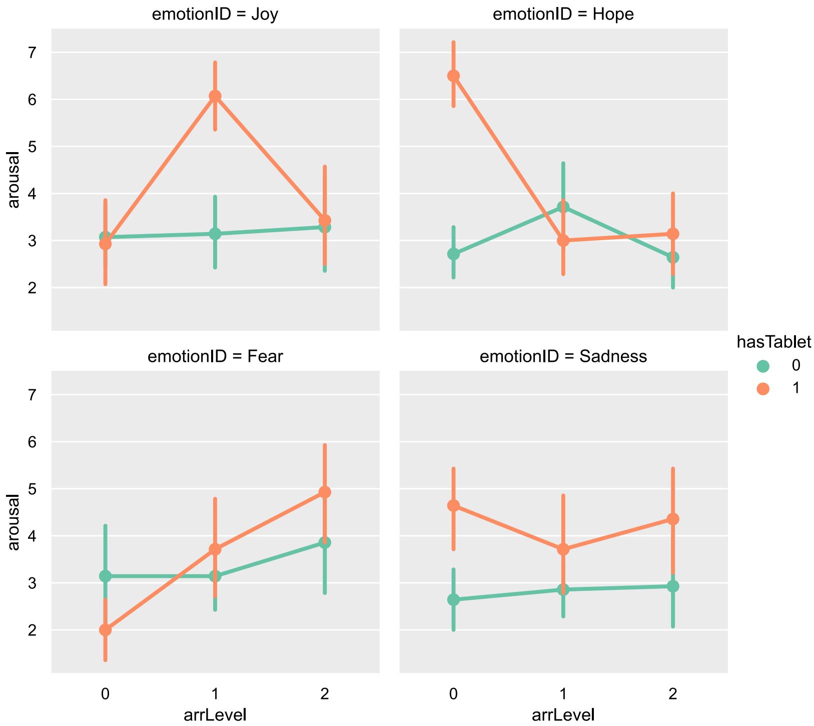


Fig. 3. The effect of the set arousal level on the participants' arousal perception of the robot. It can be seen that for the emotion "Fear" that the perceived arousal increases with the arousal level. For other emotions, this is not the case, but strong effects can be observed.

the "Fear" emotion is the only one that follows our expectation of an increase in arousal for a higher arousal level.

Finally, after each video, the participants were asked to select one or more discrete emotions that they thought represented best the one expressed by the robot in the video-clips. In Fig. 4, it can be seen that there is no clear mapping between a robot's emotion and a participant's perception of said emotion. Participants also associated joy evenly, but they rarely picked hope. This result is not surprising, because it is more difficult to associate a behaviour to a discrete emotion than expressing it according to its level of arousal and valence [1].

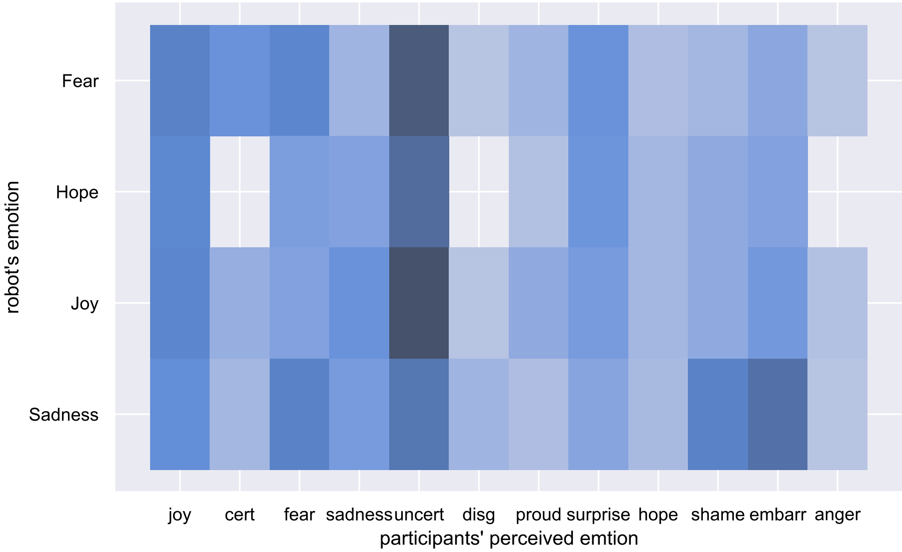


Fig. 4. A hit-map for the emotions participants' associated the robot's behaviour with (x-axis) in relation to the robot's actual expressed emotions (y-axis).

4 Conclusion and Future Works

The main interest of our research is to use personalised emotional expressions for robots to communicate complex internal and external robots' (decisional and behavioural) processes to the users. In particular, we are interested in investigating how to develop emotionally expressive learning robots which actions are legible and helps in achieving transparency of the internal state.

We believed, inspired by the finding of previous studies [2], that emotions can be an effective and transparent solution for communicating the state of the learning process to users. For this reason, in this study, we explore the legibility and predictability of robots' intentions and beliefs (i.e. internal decision-making process, and understanding of people's response) through emotional expressions.

We asked individuals of different ages, gender, background and experience with robots to classify the emotions expressed by the robot in the video-clips according to their level of arousal, valence and discrete emotions. We observed that participants were able to differentiate the emotions according to a dimensional representation (arousal and valence) in the case of having the tablet showing the icon with the emotional "face" of the robot, and that the evaluation was in line with the expected interpretation. This finding is in line with the results observed by Zhang and Sharkey [20]. This further highlights how powerful is facial emotional communication for meeting people's expectations. The only exception is for the Fear behaviour that has to be re-designed.

Moreover, the intended levels of arousal were not correctly perceived. This is also in line with other studies showing that small modifications of non-verbal cues are hardly identified by the subjects [14]. Hence, in the case of a necessity to modulate emotions' arousal more evident differences are needed.

The findings of this exploratory study will be used to further investigate whether robots can express emotions that intrinsically represent their current state in real-world scenarios.

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