Robot Mood is Contagious: Effects of Robot Body Language in the Imitation Game

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ABSTRACT
Mood contagion is an automatic mechanism that induces a congruent mood state by means of the observation of another person's emotional expression. In this paper, we address the question whether robot mood displayed during an imitation game can (a) be recognized by participants and (b) produce contagion effects. Robot mood was displayed by applying a generic framework for mood expression using body language. By modulating the set of available behavior parameters in this framework for controlling pose and motion dynamics, the gestures performed by the humanoid robot NAO were adjusted to display either a positive or negative mood. In the study performed, we varied both mood as well as task difficulty. Our results show that participants are able to differentiate between positive and negative robot mood. Moreover, self-reported mood matches the mood of the robot in the easy task condition. Additional evidence for mood contagion is provided by the fact that we were able to replicate an expected effect of negative mood on task performance: in the negative mood condition participants performed better on difficult tasks than in the positive mood condition, even though participants' self-reported mood did not match that of the robot.

Categories and Subject Descriptors
I.2.9 [**Artificial Intelligence**]: Robotics – *Commercial robots and applications.* H.1.2 [**Models and Principles**]: User/Machine Systems – *Human factors*. H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – *Evaluation/methodology*.

Keywords
Mood Expression, Nonverbal Cues, Behavioral Cues, Body Language, Social Robots, Human Robot Interaction (HRI).

1. INTRODUCTION
To participate in emotion-based interaction, robots must be able to communicate their affective state to others [1]. In human-robot interaction (HRI), expressive body language of a robot facilitates human understanding of a robot's behavior, rationale, and motives, and is known to increase the perception of a robot as trustworthy, reliable, and life-like [2]. Bodily affective expression is in particular important for humanoid robots that lack facial features such as NAO, ASIMO, and QRIO. In this paper, we study the use of body language for expressing mood.

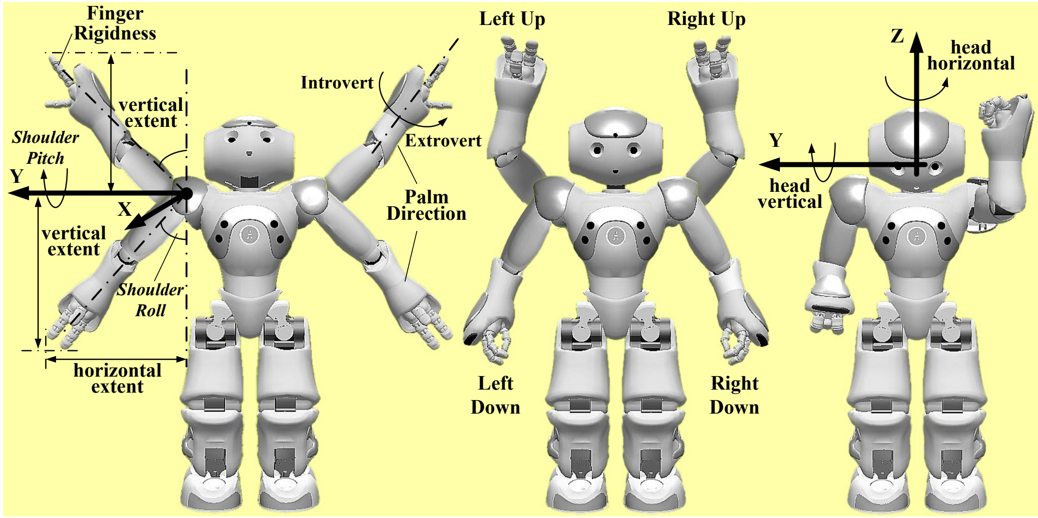
Appears in: *Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France.*

One reason to focus on mood is that mood is a more long-lasting affective state and an individual is at any given time in a more or less positive or negative mood. Integrating mood into the body language of a robot therefore may provide a robot with an interesting alternative and more stable channel for communicating affective information than by means of explicit emotion expression. This may also contribute to the believability, reliability, and lifelike quality of a robot. Our main research questions are whether people, while interacting with a robot, can recognize mood from robot behaviors that are modulated to express positive or negative mood and what the effects of robot mood on someone who is interacting with that robot are. Further, it is well known that mood can transfer between persons and has specific effects on behavior [3] and it is useful to gain insights into the effects and possible transfer of mood from a robot to an individual.

Another reason for investigating the design and expression of robot mood is that mood typically is a more integral part of ongoing behavior whereas emotions are more often expressed by explicit gestures that, for a brief period of time, interrupt functional behavior. For example, raising arms akimbo to display anger [4]; covering eyes by the robot's hands to display fear [5]; and raising both hands can be used to display the emotion of happiness [6]. Explicit gestures like these, however, cannot be used when a robot is, for example, carrying a box that requires the use of both arms and hands. For the expression of mood, a rather different model is needed that allows for the expression of affective state that is integrated into ongoing (functional) behavior of a robot in a more or less continuous fashion. In this paper, we extend previous work reported in [7], [8], [9] on a parameterized behavior model for expressing mood. The model is adapted here to enable the continuous display of mood in an interactive game.

The remainder of this paper is organized as follows. Section 2 discusses related work. In Section 3, the mood expression model and the interactive game we used in our study are introduced. In Section 4, we formulate our main research questions and hypotheses. Section 5 discusses the experimental setup and Section 6 presents the results. In Section 7, we discuss these results and the paper is concluded in Section 8.

2. RELATED WORK
Affect expression of robots contributes in many ways to human-robot interaction applications. A long-term field study showed that facial expression of robot mood influenced the way and the time that people interact with a robot [10]. Emotional behaviors made elderly participants perceive a robot as more empathic during their conversation [11]. Emotional gestures improved participants' perception of expressivity of a NAO robot during a story-telling scenario [12]. In a personal assistant application for



(a) positive mood **(b) neutral mood** **(c) negative mood**

Figure 1. Modulated gestures for the imitation game: figure (a) shows the four elementary gestures modulated for a positive mood; figure (b) shows the four mirrored elementary gestures for a neutral mood; figure (c) shows the slope-right gesture modulated for a negative mood. Pose parameters (amplitude-vertical, amplitude-horizontal, palm-direction, and finger-rigidness) are annotated on the figure.

children [13], robot emotion expression was shown to improve the effectiveness of the robot when used as companion, educator, and motivator. In an application of a robot companion that is capable to play chess with children [14], robot emotion expression that varied with the state of the game was used to help children better understand the game state. A preliminary evaluation also suggested that the emotional behavior of the robot improved children's perception of the game. In another study [15], this robot responded empathically to children's affective states. Results suggest that the robot's empathic behaviors enhance children's attitude towards the robot. Adaptive multimodal expression was studied with children using a quiz game [16]. Expressive behaviors were selected based on events in the environment and internal parameters. The study showed positive effects of the adaptive expression on children and the children's preference for bodily expression. Robots equipped with minimally expressive abilities were developed to help children with autism with their social abilities [17]. Facial and bodily expressions of the robot were used to help children learn to recognize these expressions and use their own expressions by imitating the expressions of the robot. These robot expressions were found to attract children, improve and maintain engagement of the interaction, and evoke emotional responses [18]. Affect expression also influences users that interact with virtual agents (see [19] for a review).

The affective states of a robot or a virtual agent can be expressed nonverbally by poses and movements of facial and body components. Facial expressions have been used in embodiments such as Kismet [20], iCat [21], Greta [22], and Max [23], while bodily expression has been used for ROMAN [4], NAO [5], [24], KOBIAN [6], Greta [22], and Max [23]. Experimental evaluations showed that people are capable of recognizing these expressions in general. Wallbott [25] investigated whether body movements, body posture, gestures, or the quantity and quality of movement in general allow us to differentiate between emotions. This study found that qualities of movement (movement activity, spatial extension, and movement dynamics) and other features of body motion can indicate both the quality of an emotion as well as its quantity. Furthermore, [4], [6] showed that bodily expression combined with facial expression may significantly enhance the recognition of a robot's emotion expression.

Bodily expression can be generated by directly simulating human static postures and movements as done in, e.g., [6], [24]. A more generic approach for generating expressive behaviors, however, is to modify the appearance of a behavior via the modulation of parameters associated with that behavior. Laban movement analysis (LMA) [26] models body movements using four major components: body, space, effort, and shape, characterized by a broad range of parameters. Based on LMA, Chi et al. [27] developed the EMOTE framework that uses post-processing of pre-generated behaviors to generate expressive gestures for virtual agents. The model developed by Pelachaud et al. [22] modifies gestures before generating actual movements. This model distinguishes spatial, temporal, fluidity, power, overall activation, and repetition aspects of behavior. It has been applied to the Greta virtual agent [28] and the NAO robot [12] for communicating intentions and emotions.

In previous work, a parameterized behavior model for expressing mood using body language while performing (functional) behaviors was proposed [7]. We have adapted this parameterized behavior model for this work. The model is based on a set of generic parameters that are associated with specific body parts and that are inherently part of related body movements. These parameters subsequently are modulated in order to express various moods. This model allows us to integrate mood into functional behaviors in a manner that does not interfere with the functions of these behaviors. The model was validated by evaluating whether users could recognize robot mood in a recognition experiment. The results obtained showed that participants who were asked to rate valence and arousal were able to differentiate between five valence levels and at least four levels of arousal [9].

In this paper, we ask the question whether a robot's mood can be transferred from robot to human. Some evidence that supports this has been found by Tsai et al. [29] who showed that even still images of virtual characters can induce mood. Their study also

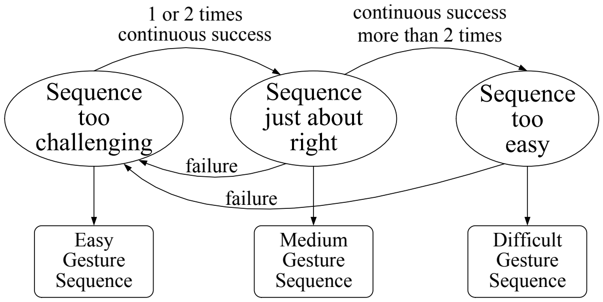


Figure 2. Item selection strategy.

revealed an interaction effect between cognitive load and contagion in a strategic game: the contagion effect was reduced by the mobilization of more cognitive resources required for the decision-making task. The application of robot bodily expression in an HRI scenario and its effects on the interaction, however, are still largely unexplored. To investigate these effects, in the study reported in this paper bodily mood expression has been used that can be displayed simultaneously with functional behaviors. In particular, we address the question whether these body expressions can produce a well-known psychological effect — emotional contagion (in our case robot mood transferred to humans) — during human robot interaction.

3. EXPRESSING MOOD IN A GAME

In order to study the effects of robot mood in an interaction scenario rather than a setting where participants are explicitly asked to recognize mood, we have used a gesture-based game in this study and we have applied the mood expression model to these gestures. The aim of our work is to design robot mood expressions for interactive settings like these that can be distinguished by users, have a (positive) effect on user's mood, and have a (positive) effect on a user's task performance. Instead of explicitly asking a user to recognize mood we asked users to play a simple imitation game and investigated the effects of expressing robot mood on the mood of users and their task performance while playing that game.

3.1 Imitation Game

The interaction scenario we used in this study is an imitation game, in which the humanoid robot NAO performs a sequence of gestures that are shown to a human player who is asked to imitate the gestures in the same order. Eight gestures were used to form the sequences in the game; single left arm pointing to left of robot in upward direction, left arm pointing left and downward, right arm pointing right and upward, and right arm pointing right and downward (see Figure 1b). The left and right arm movements were also performed at the same time, resulting in four more gestures: both up, both down, slope left (left up right down), and slope right (right up left down). The left and right were mirrored between participants and the robot. For example, when the robot performs a left-arm gesture, the participant should perform a right-arm gesture with the same up or down direction.

The classification of participants' gestures into one of the eight types of gestures was done by one of the experimenters. Using this input, the robot system evaluated whether the participant's gestures correctly replicated its own gestures in the right order and provided feedback by means of speech. The feedback text was selected randomly from a predefined list of sentences, e.g., "Yes, those were the right gestures" for a correct imitation, or "No, those were not the right moves" for an incorrect imitation.

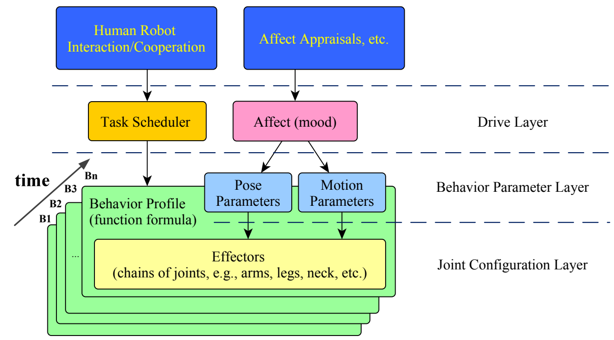


Figure 3. General Parameterized Behavior Model.

To make the game more entertaining and keep the human player engaged, the system chose a gesture sequence (item) of a slightly different item difficulty for each turn. The selection strategy is illustrated in Figure 2. The robot system kept track of how many times a participant imitated a gesture sequence correctly, and based on this information the system estimated whether the item difficulty was too easy, just about right, or too challenging for a participant. This estimate then was sent to a rating system (a component of the robot system) based on the Glicko rating system [30] for selecting the next sequence from a list of predefined gesture sequences with different ratings. The selection of a sequence depends on not only the rating of the sequence but also the current rating of the participant, representing the participant's game skills (for more details see [30]). For example, the rating of a sequence should be higher than the current rating of the participant. The selection was based on the strategy illustrated in Figure 2 aimed at choosing a sequence for each specific participant in a certain game state that would keep the participant engaged and motivated. The participant rating was initialized to a rating that corresponds to an average performance rating and then adapted to account for the fact that an easy game or a difficult game was started. After each turn this rating was updated by the rating system using only the input whether a participant correctly or incorrectly imitated a gesture sequence. The ratings of gesture sequences were derived from previously played games.

3.2 Mood Expression Model

To enable a robot to express a long-lasting affect state such as mood, even during task execution, we adapted a previously developed model for integrating affect expression with functional behaviors (e.g., task behaviors, communicative gestures, and walking). In this model, behaviors are parameterized (see Figure 3), and by varying behavior parameters different moods can be expressed. The set of parameters is generic and can be used to modulate behavior parameters of arbitrary behaviors. Example parameters include the speed of movement and the amplitude of a movement. A parameter may also be associated with a particular body part of the robot (e.g., head, hand palm, and finger). For a specific behavior, one only needs to specify which parameters should be varied to express mood while performing that behavior. Moreover, by varying these parameters the "style" of executing a particular functional behavior can be modified without changing the particular function of that behavior. The style thus can be selected such that a range of affective states can be expressed, and affect can be displayed throughout a series of behaviors.

One of our goals of the study we performed is to apply and evaluate this model in a more interactive scenario as a step towards the application of this mood expression model in real-life

Table 1. Design principles for mood expression

Parameters		Valence	Arousal
Amplitude	large	positive	/
	small	negative	/
Palm Direction	extrovert	positive	/
	introvert	negative	/
Finger Rigidness	straight	positive	/
	bent	negative	/
Motion Speed	fast	positive	active
	slow	negative	passive
Hold Time	short	positive	active
	long	negative	passive
Head Vertical	raised	positive	active
	lowered	negative	passive
Head Horizontal	follow arm[1]	positive	/
	look forward	negative	/

[1] look forward when two arms act.

application context. To this end, we used the imitation game introduced above. The robot gestures used in this game were adapted using the design principles (Table 1) gained from previous studies [7], [8], [9] in order to express robot mood while the robot is playing the game, i.e., performing various gesture sequences that are to be imitated.

The robot arm movements are the primary relevant movements for the imitation game. Three pose parameters, amplitude, palm-direction, and finger-rigidness, were used for the arm. The amplitude relates to three aspects: vertical extent, horizontal extent, and arm extension; these are controlled individually by the joints shoulder-pitch, shoulder-roll, and elbow-roll (see Figure 1a). We also used two pose parameters for head movement (see Figure 1c). Two motion parameters, motion-speed and hold-time, were used to modulate the motion dynamics. Decay-speed was used in [7] to control the speed of movements when robot actuators return to its initial poses. In this study, we used motion-speed as decay-speed because decay-speed was found to correlate with motion-speed in [8]. The design principles for mood expression used to control these parameters have been evaluated in a recognition experiment in a laboratory setting in a previous study [9]. In that study, it was also found that the parameters for motion-speed, hold-time, and head-vertical correlate with arousal (Table 1). The modulated game gestures thus do not only display the valence of the robot mood but also the arousal. The resulting gestures for positive and negative moods are illustrated in Figure 1a, c. A video clip of the gestures used in this study and gestures modulated by mood on a continuous scale is available online.[1]

4. RESEARCH QUESTIONS AND HYPOTHESES

The main questions addressed in this study are (a) whether participants can differentiate between positive and negative robot mood expressed in gestures during an interaction scenario, rather than in a pure recognition task, and (b) whether mood expressed by a robot induces mood contagion effects in human observers.

Because it is known from psychology that cognitive load should not influence the recognition accuracy of emotion [31], and as we in the long term aim at a model that is able to generate robot moods that are recognized by observers in a similar fashion as mood expressed by humans, we need to show that our recognition results do not depend on the difficulty of the interaction task. A second reason to vary the difficulty of the task is that we want to be able to replicate mood effects on task performance [32], [33], [34], [35], [36], as a behavioral measure for mood contagion (in addition to self-reported mood).

As a result, in this study we looked at the effect of robot mood (positive versus negative) and task difficulty (difficult sequences to imitate versus easy sequences) on three dependent constructs: observed robot mood (self-reported valence and arousal), observer mood (self-reported valence and arousal), and task performance (percentage of correct imitation sequences). We formulated the following hypotheses:

H1. Robot behavior influences how participants rate perceived robot mood: participants rate robot mood more positive when the robot behavior is modulated to display positive mood than when the behavior is modulated to display negative mood. This effect should not be dependent on the easy and difficult task conditions.

H2. Participants' affective states are influenced by the robot mood: participants' affective self-reports are more positive in the positive robot mood condition than the negative robot mood condition.

H3. Participants' task performance is better in the negative robot mood condition than in the positive robot mood condition.

The latter hypothesis needs some explanation. If robot mood influences participant mood, then we should be able to observe mood effects on task performance. The imitation game is a detail-oriented game in need of bottom-up attention because the goal is to watch and repeat robot movements exactly. It is well known that orientation towards details and bottom-up attention is favored in neutral-to-negative mood states, as opposed to creative and out of the box thinking in positive mood states [34], [35], [36]. Therefore, if mood contagion happens, we would expect to see higher task performance in the negative mood condition than in the positive mood condition.

5. EXPERIMENTAL SETUP

We used a mixed model 2x2 design with game difficulty (easy / difficult) as a between-subject factor and robot mood (positive / negative) as a within-subject factor. Each participant plays with the robot in only one game difficulty condition (easy or difficult) and in both robot mood conditions (positive/active and negative/passive) in two sessions. Each session took between 6 and 10 minutes and involved 10 imitations. The game difficulty was manipulated by restricting the items that the rating system could select by the item ratings (see Section 3.1): for an easy game condition, the item ratings ranged from 300 to 1500; for a difficult game condition, the item ratings ranged from 1501 to 2800. Mood was manipulated by controlling behavioral parameters as explained in Section 3.2. Task difficulty was manipulated by the length of the sequence and the variation of the gestures in the sequence. Participants were randomly assigned to the two groups (Table 2). The order of the mood conditions was counter-balanced. After the two sessions, participants were asked to report the perceived robot mood as well as their own mood

Table 2. Experiment conditions and participant groups

Game Difficulty	Robot Mood	
	Negative/Passive	Positive/Active
Easy	Group A	Group A
Difficult	Group B	Group B

[1] http://ii.tudelft.nl/SocioCognitiveRobotics/index.php/ImitatGameMood

using Self-Assessment Manikins [37]. Participants' game performance was assessed by the percentage of correct imitations during each session (the score of the participant for that session).

5.1 Materials

A Wizard-of-Oz method (Figure 4) was used in this experiment for the recognition of the participants' gestures. An operator was sitting in the room next door to the experiment room. He could see and hear the participants via a webcam and microphone. His task was to recognize the correctness of the participants' response. The operator classified all gestures made by the participants. Procedural instructions on how to classify were given to the operator: each gesture had to be classified as one of the eight gestures the robot displayed, and in the event that the operator could not classify a gesture he was told to ignore that gesture and continue. The operator had been trained before the experiment to minimize the chance that he made mistakes during the operation.

A screen (Figure 4) was placed on the wall just behind the robot so that participants knew that the "robot" could see their gestures. Participants were told that the screen was used for facilitating the recognition of gestures by the robot, while in fact this was the operator's view. A grey NAO robot (NaoQi version 1.14; head version 4.0; body version 3.3) was used with LED lights switched off. The robot provided oral feedback on the participant's imitation performance by indicating whether a sequence of gestures performed by the participant correctly reproduced the gestures performed by the robot. The robot accompanied its gestures with speech (e.g., "Left up." "Both down."). The robot voice and texts were affect neutral. That is, phrases such as "Excellent!" or "Very good!" were avoided. The robot (58cm tall) was placed on a desk (Figure 4) to ensure that participants could see the robot by facing the robot and looking straight ahead.

5.2 Participants

36 students (25 males and 11 females) whose ages range from 19 to 41 (*Mean* = 26.6, *SD* = 4.1) were recruited from the Delft University of Technology for this experiment. They were from nine different countries, but most of them are Dutch (N=13) or Chinese (N=13). A pre-experiment questionnaire confirmed that the participants had little expertise on the design of gestures or behaviors for robots or virtual agents. As compensation, each participant received a gift after the experiment. Participants were encouraged to obtain a high score: they were told beforehand that the winner would receive a prize.

5.3 Procedure

Before the experiment, each participant was asked to fill in demographics and a general questionnaire about previous experiences with robots. Participants were told that the robot was autonomous (as is common in a Wizard-of-Oz setup). Participants were told to pay attention to the game in general, and we did not emphasize mood or behavior to try to eliminate a demand effect (participants rating what they think we want them to feel / see). Participants were asked to act slowly to ensure that the robot could recognize their gestures. In addition, participants were told that they did not need to mimic the exact movements of the robot, but to imitate the correct direction (of four possible directions). They were asked to not make any other gestures to avoid misrecognition. They were informed that the experiment contains two sessions with different experiment conditions.

The robot started the interaction when the participant was ready, which was indicated by a thumbs-up gesture of the participant. After the participant finished an imitation (sequence of movements), the robot told whether it was correct or not, and the score of the participant was updated in the system but not shown to the participant. Then the robot started the next turn and performed the next gesture sequence. Each session contained 10 turns. There was no break between the two sessions, but participants were clearly informed about the session switch.

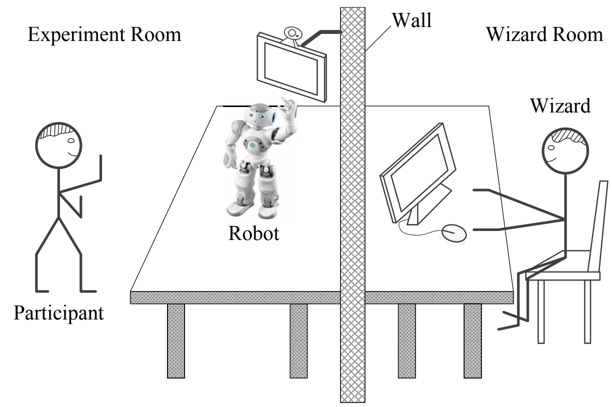


Figure 4. **The Wiz-of-Oz setting: the wizard recognized the gestures of the participant and input into the system; the system selected next gesture sequence and the robot generated the mood-modified gestures automatically.**

After the two sessions, participants filled in the post-experiment questionnaires and SAM affect self-report. The experiment took about 30 minutes on average. After the experiment, participants were fully debriefed, and each participant signed a consent form.

6. RESULTS

6.1 Manipulation check

Task difficulty was effectively manipulated. An independent sample t test showed that the difference in correctness is significant between the easy (*Mean* = 72%, *SD* = 10%), and difficult (*Mean* = 33%, *SD* = 18%) conditions ($t(34)=8.121$, $p<0.001$). In addition, we asked participants to rate to what extent they thought the game is challenging on a 5-point Likert scales (-2 to 2) after the experiment. Participants in the difficult-game group considered the game more challenging than those in the easy-game group ($t(34)=2.428$, $p<0.05$).

6.2 Participants consistently differentiate between positive and negative robot mood

Participants were able to distinguish between positive and negative robot mood and this distinction was consistent across the two task difficulty conditions, as evidenced by a mixed MANOVA with robot mood and difficulty as independent factors and perceived valence and arousal of the robot mood as dependent variable. This analysis (see Figure 5) shows that robot mood had a significant effect on participants' robot mood perception: $F(2,33)=23.597$, $p<0.001$, $\eta^2=0.588$. The perceived valence and arousal were significantly different between positive and negative conditions: $F(2,33)=27.008$, $p<0.001$, $\eta^2=0.443$ for the valence; $F(2,33)=44.222$, $p<0.001$, $\eta^2=0.565$ for the arousal. In addition, task difficulty did not influence mood perception significantly ($F(2,33)=1.589$, $p=0.219$, $\eta^2=0.088$). These results directly support our first hypothesis (H1). Moreover, participants rated the positive robot mood as positive (one sample t-test on valence measure, $t(35)=8.620$, $p<0.001$), and active during the interaction (one sample t-test on arousal $t(35)=8.544$, $p<0.001$), and rated the negative robot mood as passive (one sample t-test testing on

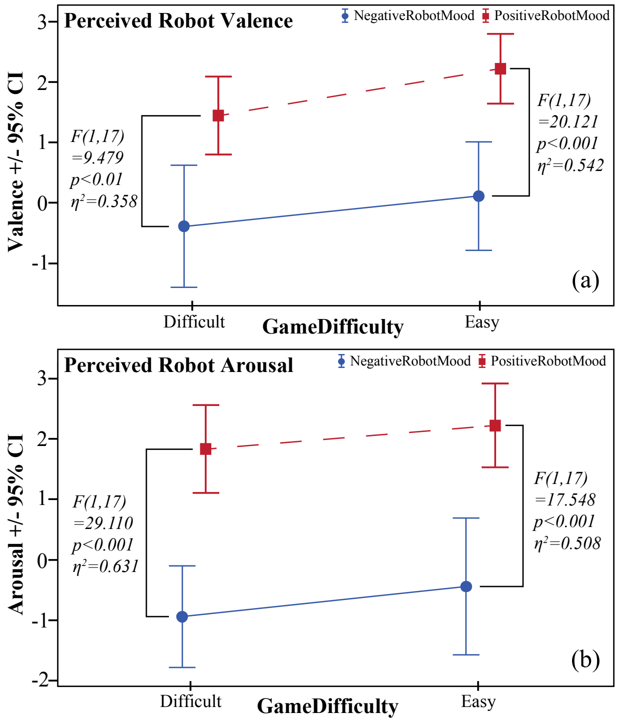


Figure 5. The participants' perceived valence and arousal of the robot mood during the interaction.

arousal $t(35)$=-2.086, p<0.05) but they did not rate it significantly more negative than neutral ($t(35)$=-0.435, p=0.666). This further supports our first hypothesis (H1), as it shows that arousal manipulation was in the right direction for both positive and negative, and that valence of the positive mood was also perceived as being more positive than neutral.

6.3 Participants' mood depends on robot mood

Participants' affective states were influenced by the robot mood in the expected directions, supporting our second hypothesis (H2) that robot mood has a contagion effect on human observers. A mixed MANOVA with robot mood and difficulty as independent factors and self-reported participant mood valence and arousal as dependent variables showed that both mood ($F(2,33)$=8.379, p=0.011, η^2=0.337) and task difficulty ($F(2,33)$=4.397, p<0.05, η^2=0.210) influenced participants' self-reported mood. Post hoc analyses showed that participant arousal ($F(1,17)$=20.302, p<0.001, η^2=0.544) and participant valence ($F(1,17)$=10.000, p<0.01, η^2=0.370) were significantly influenced in the easy task condition, but not in the difficult task condition (see Figure 6). This suggests that we were able to measure mood contagion effects with self-reported mood only for the easy task. In the difficult task, no contagion effect seems to be present.

6.4 Task performance depends on robot mood

Finally, participants' game performances were influenced by the robot mood (H3). A mixed ANOVA showed that participants' scores (percentage of correct imitations) were significantly ($F(1)$=7.335, p=0.011, η^2=0.177) different when the robot showed a negative mood. Post-hoc tests showed that participants' scores were significantly different between the robot mood conditions for the difficult game condition only ($F(1,17)$=6.608, p<0.05, η^2=0.280), but not for the easy game condition (see Figure 7). The direction of the mood effect on task performance is exactly as one

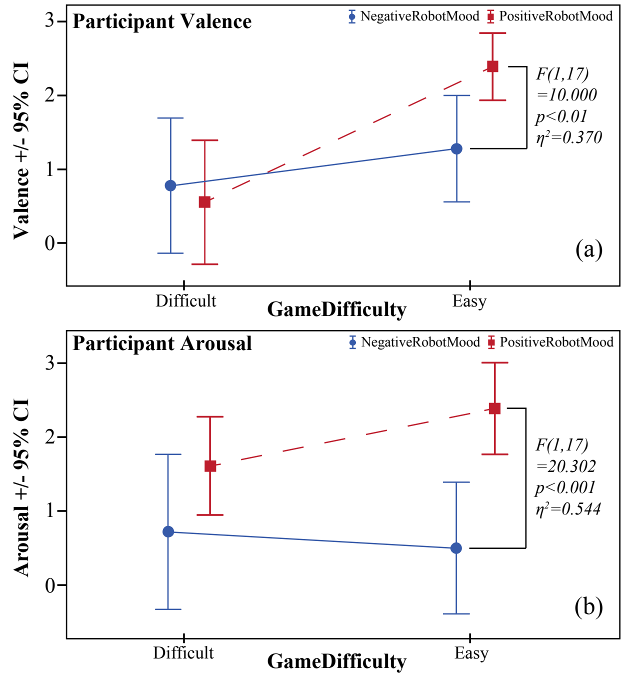


Figure 6. The participants' affective states.

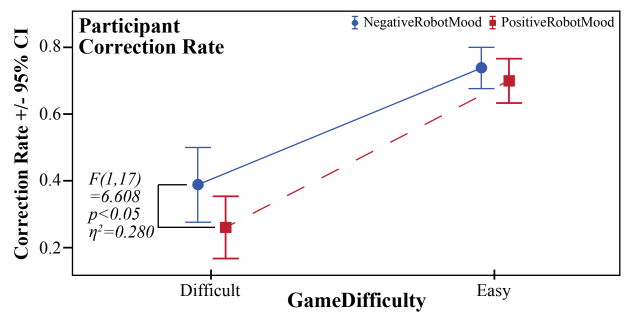


Figure 7. The participants' game performance.

would expect based psychological research [34], [35], [36]: a neutral-to-negative mood state favors orientation towards details and bottom-up attention as opposed to a positive mood state. This type of processing is needed to perform well on the imitation task.

7. DISCUSSION

First and foremost, this study showed that our model for bodily mood expression of a humanoid robot successfully generalized to the behaviors needed in the imitation game: we applied the parameter modulation principles obtained in [7] to the imitation gestures directly (see Section 3.2); and results show that participants distinguish between positive and negative robot mood, even when they were faced with a high task load. Moreover, the recognition of the valence and arousal is consistent with the findings in [9]: modulating these behavior parameters varied both valence and arousal in the same direction. We would like to stress that this is an important contribution to the ability of appearance-constrained robots lacking facial expression capabilities to express affective signals. Further, this is an important step towards the expression of affect during task execution of a robot, something humans do automatically (e.g., walking in a sad, happy, or angry way looks very different).

Our aim in this study has been to use bodily mood expression that does not interfere with the behavioral functions of body movements and to study the effects of mood expression. This has been achieved by using a parameterized behavior model, but this does not necessarily mean that no additional effects besides the mood expression in an interaction scenario have been introduced. More specifically, effects on the game itself may have been introduced: mood expression potentially influenced game difficulty. For example, the use of head movements for expressing mood was reported by one participant as something that distracted attention and thus made it more difficult for that participant to remember the exact sequence. Another participant reported that the slow speed of the gestures in the negative mood condition increased the duration of the sequence, and consequently, increased the time that the participant needed to remember the sequence. Even so, participants consistently rated the difficult game as more challenging than the easy game, and participants actually performed better in the negative mood condition.

We asked participants to report their own mood only after the two sessions, because we wanted to avoid introducing a demand effect in the second session. This may have influenced the self-reported mood because of mood decay effects or because of the different robot mood in the second session. In a mixed MANOVA we found a significant interaction effect between mood condition and mood order on self-reported valence and arousal ($F(2,33)=3.507$, $p<0.05$, $\eta^2=0.175$), primarily caused by a decay in self-reported arousal for the mood condition that was presented first. This shows that presentation of the second session indeed diminishes the self-reported contagion effect of the first session.

Participants' assessment of the robot mood is a comprehensive affective appraisal over all aspects on display including robot body movements, the robot's speech, game events, etc. In line with this the attribution of a mood was explained differently by different participants even though only body language was varied in both sessions (see Section 5). Some participants thought the robot mood changed because of their performance within a session. For example, one participant said "the robot's mood was negative because I always made mistakes." Additional evidence that robot mood was consciously recognized by participants is provided by the fact that a participant indicated that the robot was happy because the robot did not display a negative mood even when she made many mistakes. Some participants also said they recognized mood by means of the voice of the robot even though no changes were made to the robot's voice between the two sessions. This also indicates that participants were consciously aware that the robot mood changed.

In this study, the bodily expression of robot mood produced contagion effect on the participants: 1) explicitly, participants' self-reported valence and arousal was significantly influenced by the robot mood under the easy game condition; and 2) implicitly, participants' game performance was significantly influenced by the robot mood under the difficult game condition, suggesting that participants' true mood might be influenced by the robot mood during task execution even though they did not report it after the task. We have no clear explanation for the absence of an influence on self-reported mood in the difficult condition, apart from the following two. Tsai et al. [29] proposed that the contagion effect of a virtual character still image was hindered by the occupation of cognitive resources by decision-making. It could be the case that in our study self-reported mood was somehow hindered by cognitive load. Another alternative explanation is that the participant's mood in the difficult task was more negative by default, because the task was difficult. The fact that the participant's negative mood was not rated even more negative could thus be due to a floor effect as one does typically not get into a very bad mood due to a game in an experiment. Hence, no effect of negative mood induction due to the robot mood was measured. The same sort of explanation would hold for why we did not find an effect of robot mood on participants' task performance in the easy task. Here we probably had a ceiling effect: the easy imitation game is so easy, that no matter what your own mood is, you can do it almost perfectly. Finally, we cannot completely rule out alternative explanations for our findings that would argue, e.g., that participants were entertained more in the positive condition and for this reason somehow performed worse. Even so, explanations like these would still suggest some kind of mood transfer would have happened.

8. CONCLUSION AND FUTURE WORK

This study shows that it is feasible to use parameterized behavior to express a robot's mood in an actual HRI interaction scenario. Results show that people are clearly able to distinguish between positive and negative robot mood. Our results also suggest that mood contagion takes place between the robot and the human. We have evidence for this contagion effect in the following two forms: 1) participants self-reported mood matches that of the robot mood, and 2) participants' task performance is lower in the positive robot mood condition compared to the negative robot mood condition replicating a well-known mood-cognition effect.

To the best of our knowledge, this study is one of the very few in which the robot mood expressed by bodily expression is clearly distinguished by participants and the robot mood has an effect on participants, which we interpreted as mood contagion. Our study is unique in that a) robot mood expression was evaluated and investigated in a real HRI scenario, b) mood expression was realized by integrating robot body language into functional behaviors required by a task, and c) the participants were not primed to pay attention to any form of affective expression.

One additional interesting aspect that we found in our study is that participants attributed the robot mood to various factors that were not manipulated. In a complex interaction scenario such as the imitation game, participants may believe that the affective state of a robot is shaped by the events that happen during the game, the objects present in the interaction scenario, or, for example, by the (performance of) participants themselves. It is interesting to explore this conscious attribution of mood and its causes to a robot in more detail in future work. Moreover, the self-reports on mood are subjective; we will annotate the video records using an event-based coding scheme to get more reliable results.

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