Enhancing Social HRI using Affective Communication

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August 24, 2016

Contents

Chapter 1

Introduction

Chapter 2

Literature Review

[intro paragraph]

2.1 IET and Emotional Expression in Humans

2.1.1 IET and its Impact on Human Behaviour

There are different hypotheses concerning the purpose of IET and emotional expression more generally in HHI. A functionalist approach (considering the consequences in order to determine the purpose) suggests that at the dyadic level, emotion expressions help individuals determine other's emotions, beliefs, intentions and orientation towards their relationship; and that evoking emotions in others is associated with behaviours such as avoidance, helping, affiliation and soothing [1]. An evolutionary approach (considering development over time and the link to population fitness) suggests that emotional expression evolved from being a physiological response (e.g. scrunching the nose to prevent inhalation of noxious gas) into a form of social communication, which observers evolved an ability to instantly and subconsciously decode in order to obtain information about the expresser and/or their environment [2]. Regardless of exact purpose, a consistent theme in psychology literature is the importance and subconscious nature of IET resulting from emotional expression in communication, and this is what has the greatest relevance to HRI.

There is evidence to suggest that one form of IET is social appraisal, whereby individual human judgement is influenced by the perceived judgement of others [3]. Specifically, it has been demonstrated that judgement of an everyday object differs depending on whether it is presented alongside a smiling or disgusted face [4] suggesting that emotional expression is a trigger for this form of IET. Another experiment demonstrated that even in a very dangerous situation (a simulated fire) participants surrounded by seemingly calm and unresponsive actors were slower to react than participants that were alone; it has been argued that this could be due to IET effects whereby the participants felt calmer due to the calmness of the actors and also judged the situation to be less dangerous based on their perceived lack of concern ([5] as discussed in [3]).

3

Another evidenced form of IET is emotion contagion, whereby an individual's emotional state changes based on that of their interaction partner; however, this is less well understood and more difficult to experimentally examine than social appraisal effects [3]. There is a general consensus that most emotion contagion is a form of social mimicry, however, it is disputed whether this is based on physical mimicry, in which the related emotion is generated from mimicking the physical expression; i.e. the individual smiles in response to a smile and hence feels happier [6], or whether expression is less important and actually an individual must understand and perceive the reason for another's emotional expression in order for emotion contagion to occur [7]. In contrast to the idea of simple mimicry it should also be noted that emotion contagion has been demonstrated to induce contrasting rather than matching emotions, and that this may be linked to social stature [8].

Demonstrated examples of emotion contagion highlight the impact it can have both at the individual and group level. For example, listening to neutral information spoken in an emotional way can induce similar emotions in the listener [9], and emotion contagion in a group can improve attitudes and reduce conflicts resulting in improved task performance [10]. It has even been demonstrated that emotion contagion can occur through social networks, with Facebook users producing more positive or negative posts when the amount of negative or positive emotional content in their newsfeed was reduced respectively [11]. Other interesting results include thirsty individuals pouring more or less from a drink jug if exposed to a smiling or frowning face respectively [12] or acceptance of an offer being higher for smiling and lower for frowning proposers compared to those that wore neutral expressions [13].

As such, whilst the origins and exact mechanisms of IET are not clear, the evidence presented suggests it has significant impact on HHI and can influence an individual's feelings, judgement and behaviour as well as group collaboration and effectiveness. This warrants the study of IET in HRI in order to establish whether the same effects can be observed, and if so whether they can be useful e.g. in improving things like robot effectiveness and acceptance or task performance. Key research questions include whether robot to human IET can occur and how robot emotional expressions affect human judgements and behaviour. Additionally, the number of unconfirmed hypothesise in the psychology literature suggests that HRI experiments dealing with emotion in a very controlled way might be useful as a mechanism for testing theories and contributing to psychological understanding of the role of human emotions.

2.1.2 Human Displays of Emotion

In order to design emotionally expressive robot behaviours it must first be established how emotion is expressed in humans and identify specific behaviours which might be transferable onto a robot. Specifically the robotic platform to be used for this project is Aldebaran Robotics' humanoid robot NAO[1], which means that facial expression cannot

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[1]https://www.aldebaran.com/en/cool-robots/nao

be altered and hence lies outside the scope of this project. As such, the following discussion covers emotional expression through speech and movement only. It is noted that the literature describes facial expression as a complex and important part of affective communication and so future work would be to extend this investigation to include that.

The study of emotion recognition in point light displays generated from dance and acting performances has demonstrated that movement alone can express emotion even if the semantic purpose of that movement is unknown (e.g. [14], [15], [16]). Laban Movement Analysis (LMA), a multidisciplinary tool for movement analysis considering parameters such as weight, space and time, has become a standard method for parameterising movement in order to further study such effects [17]. As such, instructions on how to perform a certain emotion, as might be explained to dancers or actors, typically utilise LMA (e.g. [18]). Similarly, it is widely accepted that emotion can be portrayed through neutral speech [9] or across languages [19] and similar to LMA, this can be quantitatively described by variation in parameters such as pitch, speed and quality (e.g. [20], [21]).

The reviewed literature therefore suggests that emotion can theoretically be expressed through any movement or speech, regardless of semantic content. This is particularly relevant for roboticists because it means that emotional expression can be added to communication or task execution without changing the robot's functional behaviour. Furthermore the study of emotion in movement and voice lends credibility to the idea of a parameterisation framework for generating emotional expressions, particularly in a robot such as the NAO with no capability for facial expression.

2.2   IET and Emotional Expression in Robots

Giving robots the capability to display emotional expressions has been a recurrent theme in social robotics since the field's infancy [22]. Recent demonstrations include robots whose emotional state and hence behaviour is adaptive based on such things at its 'personality' [23] or whether it is winning or losing at a game [24]. Whilst adaptive emotional expression is certainly an area of further work for this project, the initial concern is simply the generation of pre-determined emotions which can be displayed through generic functional behaviours through adjusting vocal and movement parameters as discussed above. Examples of a parameter based emotion framework have already been demonstrated (e.g. [25], [26], [27]) and used to successfully generate emotional expressions in a range of robots including the NAO ([26] and [27]).

Masuda and Koto's system uses the six main parameters of LMA; space, time, weight, inclination, height and area, which are set based on previous analysis of observed movement emotion classification from a pilot experiment [28]. Implemented on a humanoid robot the resulting motion had an average emotion recognition rate greater than 60% [25]. Lim et al.'s framework for adding emotion to gesturing uses only four parameters: speed, intensity, regularity and extent, which are set based on a mapping from the same features measured in an actor's speech sample. Implemented on a NAO the resulting motion had an emotion recognition rate of above 60% and, when combined

with the original speech sample, lead to improved recognition rates for the emotions of happiness and sadness compared to speech alone [26]. Xu et al.'s framework uses a combination of general motion and pose parameters (e.g. speed, decay rate, stroke curves) as well as gesture specific ones (e.g. palm up or down). In addition, the head is utilised as an effector which can be set in different poses. Parameter settings were then derived by averaging the results of an experiment in which participants were asked to set them in order to achieve specific emotional expressions on a NAO [27]. A later experiment demonstrated that different arousal and valence states can be recognised based on these parameters; however, no results for specific emotion recognition were described [29].

Considering these three models, Lim et al.'s is the most simple and yet achieved very similar recognition rates to Masuda and Koto's system. In addition the idea of setting gesture parameters based on feature matching to speech samples is attractive for generating natural looking behaviour. How well this feature mapping would work on artificially generated speech as opposed to actor samples is not clear because the effectiveness of the whole system is dependent on how well the provided speech sample portrays emotion (an option in some text to speech engines e.g. CereVoice[2]). However, if the parameter values could be set in a different way, the concept of having a small number of generic parameters that map directly onto both speech and motion could form the basis of a simple yet powerful framework for easily generating complete emotional expressions. Xu et al.'s method of essentially crowd-sourcing parameter settings for different emotions may offer such an option.

Of these three models only Xu et al. went on to evaluate the impact of their generated emotional expression on HRI, specifically attempting to demonstrate whether robot to human IET occurred, for which they did find some evidence [30]. The experimental design of Xu et al.'s study, as well as others concerned with affective communication and HRI, are discussed in the following section.

2.3 Experimentally Evaluating the Impact of Robot Affect

Previous studies documenting the impact of affective robot behaviour have typically produced only qualitative data. For example, Tielman et al. demonstrated an adaptive emotion model implemented on a NAO used to play a quiz game with children; by using questionnaires they determined that children found emotional expression to be a positive trait for a robot [24]. Similarly, a long term study documenting the use of a humanoid game playing robot in an elderly care home found, also by questionnaire, that users rated emotional expression to be one of their favourite robot traits [31]. Clearly such qualitative results are important and can offer a valuable insight into HRI, especially surrounding how well 'liked' the robot is which is arguably some measure of the robot's effectiveness itself; however, examples from the psychology literature suggest that it should also be possible to produce more quantitative results which demonstrate the measured impact

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[2]https://www.cereproc.com/en/products/sdk

of affective communication, e.g. around the performance of a task [10] or reaction to an event [5].

In a rare example of quantitative study considering robot to human IET, Xu et al. demonstrated that participants performed better in a harder task when working with a robot displaying a negative rather than positive 'mood'; they then used this result to argue that emotion contagion had occurred because of a hypothesised psychological phenomenon that humans undertake certain types of task better when in a negative mood [30]. Finding further inspiration for evaluation methods and experiment design requires the consideration of HRI studies that do not specifically consider affective communication but do measure the impact of different robot behaviours. Two such studies are outlined below.

Chidambaram et al. used a desert survival HRI task to demonstrate how both vocal and nonverbal robot cues affected their robot's persuasiveness [32]. They used a range of conditions considering variation or lack thereof in body movement (proximity, gaze and gesturing) and voice (pitch). Their evaluation measures combined subjective surveys of perceived persuasiveness and objective measures of compliance (i.e. actual persuasiveness). This had the advantage of allowing a valuable comparison between actual and perceived persuasion to be made in the discussion.

Nakagawa et al. used a monotonous task with a robot companion to determine the effect of robot touch on motivation [33]. Participants were asked to undertake a monotonous task for as long as they liked; the base condition had the robot companion only talking to the participant, the two other conditions involved the robot also being passively touched by or actively touching the participant while they worked. The time spent undertaking the task was measured for each condition to give a quantitative measure of the impact. Similar to the work of Chidambaram et al., subjective feedback measures were also used to collect information on the participants' perception but in this case considering robot perception generally rather than specifically its use in motivation.

In summary there are very few previous HRI studies that deal specifically with the impact of affective communication; however, additional inspiration for quantitative measurements can be drawn from other HRI studies. How best to demonstrate the impact of affective communication is one of the key research questions considered in this project; the aim is to generate insightful data that offers some quantitative measure of impact but also captures more qualitative information to allow for interesting discussion. Considering this aim alongside the example experiments discussed here highlights human/robot task performance, human emotional state and subjective participant opinions as key measures for evaluation.

Chapter 3

Research Methodology

[intro paragraph]

3.1 Generating Emotional Expressions on NAO

[Intro paragraph on wanting to be able to make functional gestures emotional rather than expressing emotion through specific emotive movements]

- nao limitations - no facial expression so had to be done via movement and speech only

- previous emotional display on NAO focused on gesture modification - Lim and Xu work

3.1.1 Gesture Modification: SIRE Framework

Application of Lim's SIRE framework to any gesture Use of Choregraphe (as opposed to...?)

Pseudo-code for the SIRE framework: Each gesture consists of moving from base pose to the extended pose and back again. For each gesture the following key parameters were defined:

- pMin : a minimum amplitude version of the gesture described in the Cartesian co-ordinate set $[x, y, z, \alpha, \beta, \gamma]$

- pMax : maximum amplitude version of the gesture described in the Cartesian coordinate set $[x, y, z, \alpha, \beta, \gamma]$

- tExt : time for extension gesture based on average from an actor video

- tPos : time extended posture is held based on average from an actor video

- tRet : time for return gesture based on average from an actor video

- tMin : minimum time required to execute gesture (for safe operation)

- rMax : maximum time offset for irregular movements (such that gesture is still clear)

Speed & Intensity

Speed of the movement is adjusted by modifying the extension and return times passed to the path planner, tExt and tRet. The maximum times described above are multiplied by $(1 - S)$ where S is the speed parameter, i.e. as speed is increased the gesture time is reduced. A maximum operator is used to compare the adjusted time with the specified minimum to ensure the movement is not too fast.

Intensity is applied by further reducing the extension time, t_1, in the same way as speed, by multiplication with $(1 - I)$ where I is the intensity parameter. This gives the appearance of essentially accelerating gesture extension with no change to the return movement.

$$t_1 = max[(1 - S) * (1 - I) * tExt, tmin] \tag{3.1}$$

$$t_2 = max[(1 - S) * tRet, tmin] \tag{3.2}$$

Regularity

Regularity is applied by introducing a temporal delay, dt, defined based on $(1 - R)$ where R is the regularity parameter, between execution of the left and right arm movements in gestures which utilise both arms. Doing anything with head movements (as in Lim's original)?? Perhaps not as may be confusing given task requires movement copying - explain if this is the case.

$$dt = (1 - R) * rMax \tag{3.3}$$

$$t(rightArm) = t(leftArm) + dt \tag{3.4}$$

Extent

Extent is applied by adjusting the size of the gesture between the minimum and maximum, by adding a proportion of the difference between them (set by the extent value E) to the minimum.

$$p = p_{min} + E * (p_{max} - p_{min}) \tag{3.5}$$

Positive and negative SIRE values initially set based on general design principles identified by Xu et al [27] and specific values found by Lim (cite her thesis); neutral just set as all 0.5 (medium) apart from regularity which is 1.

As interaction activity is to copy gestures for a workout, regularity was not applied as could be confusing; explain this is ok because Lim's thesis showed that SIE was enough to show happiness and sadness.

Setting Initial SIRE Values

Talk about original method of extracting from voice - something for future work and making autonomous/live (although robots now exist that supposedly monitor your emotion live).

Generic design principles identified:

	Positive	Negative
Speed	high	low
Intensity	high	low
Regularity	high	high
Extent	high	low

Actual initial values used:

	Positive	Negative	Neutral
Speed	0.8	0.1	0.5
Intensity	0.8	0.1	0.5
Regularity	1.0	1.0	1.0
Extent	0.8	0.1	0.5

3.1.2 Speech Generation

Cereproc/Cerevoice; emotion tags

3.1.3 Choregraphe

Controlling NAO - both voice and speech, how timing was set etc.

3.2 Testing & Validation of Emotion Expression

Recognition experiments: Voice Only,Gesture Only, Voice + Gesture. 15 participants.

Voice: overall recognition about 60 %, a lot higher than chance (a third) happy and sad easy to recognise, but neutral was significantly misclassified as happy. Reasons could be participants wanting to pick an emotion, or neutral voice could just seem slightly happy. Need to see how this compares to gestures and then gestures + voice combined.

Give pretesting results here including the extremity thing.

3.3 Human Robot Interaction Experiment Design

3.3.1 Interaction Activity & Context

- need monotonous/repetitive task to test whether motivation/performance improves inspired by Nakagawa et al. [33].

- wanted to build on work of Xu et al which used imitation game - good way of getting participants to focus on the robot's gestures indirectly

- however one possible issue with use of a game based interaction when looking for emotional impact is the actual emotional impact of doing well/badly in the game (find a ref for this)

- so instead, inspired by mataric's work on the use of robots in encouraging physical exercise and therapy compliance (especially the one where the robot does a gesture which the participant has to copy!), decided to contextualise the gesture imitation as a workout rather than a game

- this also means results will be particularly relevant to the field of assisted living robots

In designing the HRI activity

- centred around a monotonous task to be voluntarily completed by the participant

- require the participant to closely watch the robots behaviour

- emotionally neutral

3.3.2 Hypotheses

H1 Participants in the happy condition will demonstrate a more positive emotional state, compared to those in the neutral condition, after interacting with the robot, (i.e. emotion contagion will occur)

H2 Emotion recognition in valenced conditions - do I need to test this in final experiment given will have gone through sire pre testing? Or is it still helpful to see what participants think robot emotional state is?

H3 Emotion expression will have an impact on human task performance/motivation and enjoyment

H4 Emotion expression will have an impact on robot perception (based on Chidambaram et al [32])

3.3.3 Measures

Feature of Interest	Related Measures	Relevant Hypotheses
Emotion Contagion	Word completion task	H1
	SAM survey (robot and self)	H2
Impact on HRI	Number of exercise rounds voluntarily completed	H3
	Enjoyment Likert scale	H3
	Reason for stopping Likert scale	H3
	Perceived usefulness Likert scale	H4
	Selected Godspeed Questions	H4

Word Completion Test

Something about design of word completion activity and reason for using that as a mood measure compared to other mood measures.

3.3.4 Experimental Procedure

- participants briefed and given a demo of what to expect, then once robot was seen to be working correctly and giving instructions experimenter left the room before exercise started

- IMPORTANT - participants were told that exercise could be stopped at any time and it was up to them how much they wanted to complete

- directly after the interaction participants completed an online survey ordered as follows: word completion test, q's on enjoyment/good exercise instructor, bored/tiredness, manipulation and own emotion check

- 60 participants, 20 per condition

  A total of 62 participants were recruited for the experiment with the data for XX being retained; one participant's data was discarded due to a fire alarm disrupting the experiment... Each participant was assigned randomly to one of the three conditions resulting in 20 participants per condition (or 21 for one of them if keep p61's data??).

  Participants were first asked to read through an experiment information sheet which contained... [note no information about emotion or that exercise rounds would be noted down at this point] and to sign a consent form. A demo was then given to show the participants what to expect and how to interact with the robot [touch to continue used due to lack of confidence in speech recognition]. Again it was pointed out to the participants that the number of exercise rounds was voluntary and they could stop at any time. Once the robot was seen to be working correctly, the experimenter left the room until the exercise session was complete

(either because the participant stopped or the maximum number of rounds was reached.)

[robot programme diagram from previous]

Chapter 4

Results

Chi squared for word completion because ... and list results

Anova for voluntary rounds, emotional robot state (is it worth doing that in chi squared to match sire pre-test though?), self state and all likert q's because... and list results

Chapter 5

Discussion

5.1 Emotion Recognition in Robot Gesture and Voice

– perceived extremity increased by use of gestures - relevant to telepresence etc

– why was emotion recognised correctly in pre test but not exercise experiment? Relative difference?

5.2 Robot to Human Emotion Contagion

5.3 Impact of Affective Communication on HRI

Chapter 6

Conclusions

6.1   Further Work

Bibliography

[1] Dacher Keltner and Jonathan Haidt. Social functions of emotions at four levels of analysis. *Cognition & Emotion*, 13(5):505–521, 1999.

[2] Azim F Shariff and Jessica L Tracy. What are emotion expressions for? *Current Directions in Psychological Science*, 20(6):395–399, 2011.

[3] Brian Parkinson. Interpersonal emotion transfer: Contagion and social appraisal. *Social and Personality Psychology Compass*, 5(7):428–439, 2011.

[4] Andrew P Bayliss, Alexandra Frischen, Mark J Fenske, and Steven P Tipper. Affective evaluations of objects are influenced by observed gaze direction and emotional expression. *Cognition*, 104(3):644–653, 2007.

[5] Bibb Latane and John M Darley. Group inhibition of bystander intervention in emergencies. *Journal of personality and social psychology*, 10(3):215, 1968.

[6] Fritz Strack, Leonard L Martin, and Sabine Stepper. Inhibiting and facilitating conditions of the human smile: a nonobtrusive test of the facial feedback hypothesis. *Journal of personality and social psychology*, 54(5):768, 1988.

[7] Marco Tamietto, Lorys Castelli, Sergio Vighetti, Paola Perozzo, Giuliano Geminiani, Lawrence Weiskrantz, and Beatrice de Gelder. Unseen facial and bodily expressions trigger fast emotional reactions. *Proceedings of the National Academy of Sciences*, 106(42):17661–17666, 2009.

[8] Larissa Z Tiedens and Alison R Fragale. Power moves: complementarity in dominant and submissive nonverbal behavior. *Journal of personality and social psychology*, 84(3):558, 2003.

[9] Roland Neumann and Fritz Strack. Mood contagion: the automatic transfer of mood between persons. *Journal of personality and social psychology*, 79(2):211, 2000.

[10] Sigal G Barsade. The ripple effect: Emotional contagion and its influence on group behavior. *Administrative Science Quarterly*, 47(4):644–675, 2002.

[11] Adam DI Kramer, Jamie E Guillory, and Jeffrey T Hancock. Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, 111(24):8788–8790, 2014.

[12] Piotr Winkielman, Kent C Berridge, and Julia L Wilbarger. Unconscious affective reactions to masked happy versus angry faces influence consumption behavior and judgments of value. *Personality and Social Psychology Bulletin*, 31(1):121–135, 2005.

[13] Patrick Mussel, Anja S Göritz, and Johannes Hewig. The value of a smile: Facial expression affects ultimatum-game responses. *Judgment and Decision Making*, 8(3):381, 2013.

[14] Winand H Dittrich, Tom Troscianko, Stephen EG Lea, and Dawn Morgan. Perception of emotion from dynamic point-light displays represented in dance. *Perception*, 25(6):727–738, 1996.

[15] Frank E Pollick, Helena M Paterson, Armin Bruderlin, and Anthony J Sanford. Perceiving affect from arm movement. *Cognition*, 82(2):B51–B61, 2001.

[16] Anthony P Atkinson, Winand H Dittrich, Andrew J Gemmell, and Andrew W Young. Emotion perception from dynamic and static body expressions in point-light and full-light displays. *Perception*, 33(6):717–746, 2004.

[17] Rudolf Laban. *The Mastery of Movement*. Dance Books Ltd, 2011.

[18] Jean Newlove. *Laban for actors and dancers: putting Laban's movement theory into practice: a step-by-step guide*. Theatre Arts Books, 1993.

[19] Klaus R Scherer. A cross-cultural investigation of emotion inferences from voice and speech: implications for speech technology. In *INTERSPEECH*, pages 379–382, 2000.

[20] Klaus R Scherer. Vocal affect expression: a review and a model for future research. *Psychological bulletin*, 99(2):143, 1986.

[21] Roddy Cowie, Ellen Douglas-Cowie, Nicolas Tsapatsoulis, George Votsis, Stefanos Kollias, Winfried Fellenz, and John G Taylor. Emotion recognition in human-computer interaction. *Signal Processing Magazine, IEEE*, 18(1):32–80, 2001.

[22] Cynthia Breazeal and Brian Scassellati. How to build robots that make friends and influence people. In *Intelligent Robots and Systems, 1999. IROS'99. Proceedings. 1999 IEEE/RSJ International Conference on*, volume 2, pages 858–863. IEEE, 1999.

[23] Jong-Chan Park, Hyoung-Rock Kim, Young-Min Kim, and Dong-Soo Kwon. Robot's individual emotion generation model and action coloring according to the robot's personality. In *Robot and Human Interactive Communication, 2009. RO-MAN 2009. The 18th IEEE International Symposium on*, pages 257–262. IEEE, 2009.

[24] Myrthe Tielman, Mark Neerincx, John-Jules Meyer, and Rosemarijn Looije. Adaptive emotional expression in robot-child interaction. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, pages 407–414. ACM, 2014.

[25] Megumi Masuda and Shohei Kato. Motion rendering system for emotion expression of human form robots based on laban movement analysis. In *RO-MAN, 2010 IEEE*, pages 324–329. IEEE, 2010.

[26] Angelica Lim, Tetsuya Ogata, and Hiroshi G Okuno. Converting emotional voice to motion for robot telepresence. In *Humanoid Robots (Humanoids), 2011 11th IEEE-RAS International Conference on*, pages 472–479. IEEE, 2011.

[27] Junchao Xu, Joost Broekens, Koen Hindriks, and Mark A Neerincx. Mood expression through parameterized functional behavior of robots. In *RO-MAN, 2013 IEEE*, pages 533–540. IEEE, 2013.

[28] Megumi Masuda, Shohei Kato, and Hidenori Itoh. Emotion detection from body motion of human form robot based on laban movement analysis. In *Principles of Practice in Multi-Agent Systems*, pages 322–334. Springer, 2009.

[29] Junchao Xu, Joost Broekens, Koen Hindriks, and Mark A Neerincx. *Bodily mood expression: Recognize moods from functional behaviors of humanoid robots*. Springer, 2013.

[30] Junchao Xu, Joost Broekens, Koen Hindriks, and Mark A Neerincx. Robot mood is contagious: effects of robot body language in the imitation game. In *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*, pages 973–980. International Foundation for Autonomous Agents and Multiagent Systems, 2014.

[31] Wing-Yue Geoffrey Louie, Derek McColl, and Goldie Nejat. Playing a memory game with a socially assistive robot: A case study at a long-term care facility. In *RO-MAN, 2012 IEEE*, pages 345–350. IEEE, 2012.

[32] Vijay Chidambaram, Yueh-Hsuan Chiang, and Bilge Mutlu. Designing persuasive robots: how robots might persuade people using vocal and nonverbal cues. In *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*, pages 293–300. ACM, 2012.

[33] Kayako Nakagawa, Masahiro Shiomi, Kazuhiko Shinozawa, Reo Matsumura, Hiroshi Ishiguro, and Norihiro Hagita. Effect of robot's active touch on people's motivation. In *Human-Robot Interaction (HRI), 2011 6th ACM/IEEE International Conference on*, pages 465–472. IEEE, 2011.