SEMINARS IN ARTIFICIAL INTELLIGENCE

SOCIAL SIGNALLING

Marc Hanheide

UNIVERSITY OF LINCOLN

SAPIENZA UNIVERSITÀ DI ROMA

L-CAS

29/04/16: Social Signals

This session will focus on the ways humans and robots can communicate with one another, focusing on implicit signalling.

At the end, we shall give Riccardo a chance to present his paper from two weeks ago.

Paper	Presented by	Discussed by
4-1 Fischer, K. et al., 2013. The impact of the contingency of robot feedback on HRI. In Proceedings of the 2013 International Conference on Collaboration Technologies and Systems, CTS 2013. pp. 210–217.	Mirco Colosi	Irvin Aloise
4-3 Moon, Aj. et al., 2013. Design and Impact of Hesitation Gestures during Human-Robot Resource Conflicts. International Journal of Human-Robot Interaction (IJHR), 2(3), pp.18–40. Available at: http://hri-journal.org/index.php/HRI/article/view/49.	Ahmad irjoob	Gabriele Angeletti
3-2 Lu, D. V, Hershberger, D. & Smart, W.D., 2014. Layered costmaps for context-sensitive navigation. In Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on. pp. 709–715.	riccardo rinaldi	SALVATORE GIGLIO

SOCIAL SIGNALS CAN'T BE AVOIDED

One cannot not communicate!

frontiers in PSYCHOLOGY

ORIGINAL RESEARCH ARTICLE
published: 27 November 2013
doi: 10.3389/fpsyg.2013.00859

Toward understanding social cues and signals in human–robot interaction: effects of robot gaze and proxemic behavior

Stephen M. Fiore[1,2]*, Travis J. Wiltshire[2], Emilio J. C. Lobato[2], Florian G. Jentsch[2,3], Wesley H. Huang[4] and Benjamin Axelrod[4]

[1] Department of Philosophy, Cognitive Sciences Laboratory, Institute for Simulation and Training, University of Central Florida, Orlando, FL, USA
[2] Institute for Simulation and Training, University of Central Florida, Orlando, FL, USA
[3] Department of Psychology, University of Central Florida, Orlando, FL, USA
[4] iRobot Corporation, Bedford, MA, USA

Fiore, S.M. et al., 2013. Toward understanding social cues and signals in human-robot interaction: Effects of robot gaze and proxemic behavior. Frontiers in Psychology, 4(NOV).

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- examine how humans interpret social cues exhibited by robots.
- examine the relationship between social cues and signals as a function of the degree to which a robot is perceived as a **socially present agent**.
- An experiment in which **social cues were manipulated** on an iRobot Ava^{TM} mobile robotics platform in a hallway **navigation scenario**.
- Cues associated with the robot's **proxemic behavior** were found to **significantly affect** participant perceptions of the **robot's social presence** and **emotional state**
- Cues associated with the robot's **gaze behavior** were **not found to be significant**.
- Further, regardless of the proxemic behavior, participants attributed more social presence and emotional states to the robot over **repeated interactions than when they first interacted** with it.
- These results indicate the **importance for HRI research** to consider how social cues expressed by a robot can differentially affect perceptions of the robot's mental states and intentions.

TOWARD UNDERSTANDING SOCIAL CUES AND SIGNALS IN HUMAN-ROBOT INTERACTION: EFFECTS OF ROBOT GAZE AND PROXEMIC BEHAVIOR

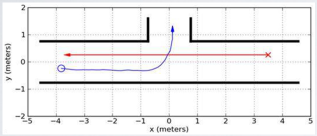

FIGURE 1 | Illustrative layout of the experimental space. Participant starting point is denoted by the red "X" and the robot starting point is denoted by the blue "O." Idealized paths to the trial end points are denoted for the participant and the robot by the red and blue lines, respectively.

Robot Specifications:
"Eye" height: approx. 1 m
Total height: approx. 1.25 m
Base width: 0.45 m

FIGURE 2 | iRobot Ava mobile robotics platform and physical specifications. Primary robot sensors are denoted by "A."

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TOWARD UNDERSTANDING SOCIAL CUES AND SIGNALS IN HUMAN-ROBOT INTERACTION: EFFECTS OF ROBOT GAZE AND PROXEMIC BEHAVIOR

Networked Minds Social Presence Inventory (NMSPI)

frontiers in PSYCHOLOGY ORIGINAL RESEARCH ARTICLE published: 27 November 2013 doi: 10.3389/fpsyg.2013.00859

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1. First order social presence: Co-presence

The following items form the measure of co-presence, the degree to which the users feel as if they are together in the same space.

Perception of self	Perception of the other
I often felt as if (my partner) and I were in the same (room) together.	I think (my partner) often felt as if we were in the same room together.
I was often aware of (my partner) in the (room).	(My partner) was often aware of me in the (room).
I hardly noticed (my partner) in the (room)	(My partner) didn't notice me in the (room).
I often felt as if we were in different places rather than together in same (room)	I think (my partner) often felt as if we were in different places rather than together in the same (room).

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Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
(1)	(2)	(3)	(4)	(5)

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2. Second order social presence: Psycho-behavioral interaction

These items seek to measure the user perception of attention, emotional contagion, and mutual understanding with their partner or participant.

Perceived psychological engagement

Perception of self	Perception of the other
Perceived attentional engagement	
I paid close attention to (my partner).	(My partner) paid close attention to me
I was easily distracted from (my partner) when other things were going on.	(My partner) was easily distracted from me when other things were going on.
I tended to ignore (my partner).	(My partner) tended to ignore me.
Perceived emotional contagion	
I was sometimes influenced by (my partner's) moods.	(My partner) was sometimes influenced by my moods.
When I was happy, (my partner) tended to be happy.	When (my partner) was happy, I tended to be happy.
When I was feeling sad (my partner) also seemed to be down.	When (my partner) was feeling sad, (my partner) I tended to be sad.
When I was feeling nervous, (my partner) also seemed to be nervous.	When (my partner) was nervous, (my partner) I tended to be nervous.
Perceived comprehension	
I was able to communicate my intentions clearly to (my	(My partner) was able to communicate their intentions

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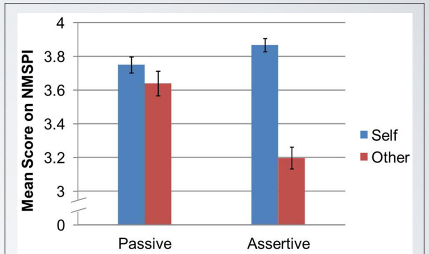

FIGURE 3 | Interaction between proxemic behavior condition and mean scores for self- and other-attributions as measured by the NMSPI.

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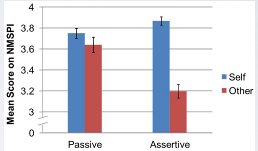


FIGURE 3 | Interaction between proxemic behavior condition and mean scores for self- and other-attributions as measured by the NMSPI.

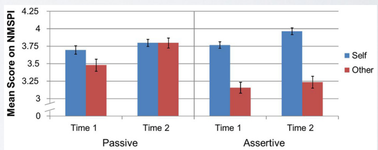
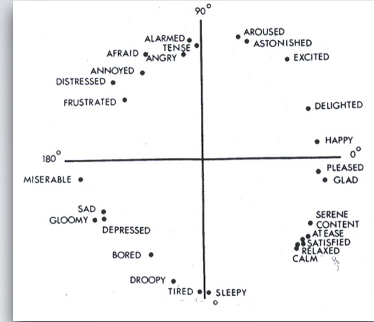


FIGURE 4 | Three-way interaction between proxemic behavior condition, time of measure, and mean scores for self- and other-attributions as measured by the NMSPI.

TOWARD UNDERSTANDING SOCIAL CUES AND SIGNALS IN HUMAN-ROBOT INTERACTION: EFFECTS OF ROBOT GAZE AND PROXEMIC BEHAVIOR



circular mood scale

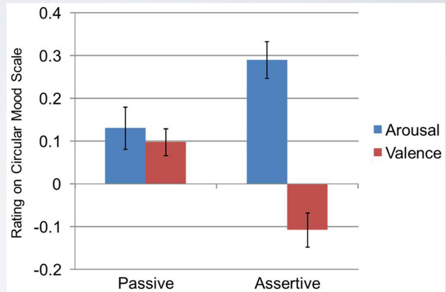
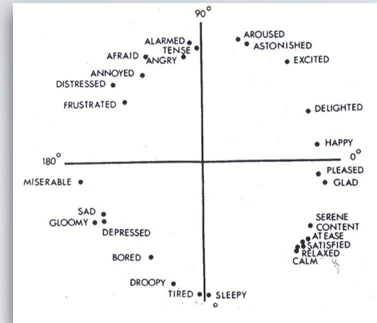
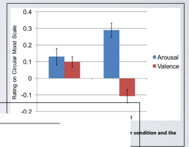


FIGURE 5 | Interaction between proxemic behavior condition and the dimensions of mood as measured by the CMS.

TOWARD UNDERSTANDING SOCIAL CUES AND SIGNALS IN HUMAN-ROBOT INTERACTION: EFFECTS OF ROBOT GAZE AND PROXEMIC BEHAVIOR



circular mood scale



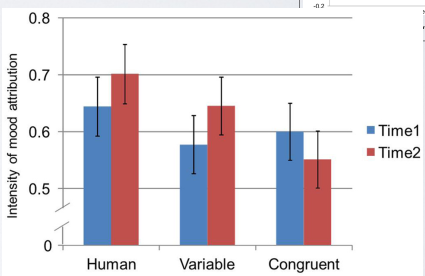


FIGURE 6 | Two-way interaction between measurement time and gaze on intensity of emotional attributions measured by the CMS.

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- There are contradicting studies (as always)
- What to learn from psychologists:
  - Use established metrics when measuring subjective qualitities
  - Perform sound statistical tests

WHAT IS HUMAN-ROBOT INTERACTION?

- How do we study HRI?
- By implementing theories:
  - verify them through controlled HRI studies
  - explore the system through explorative studies
  - make a proof of concept by achieving a learning outcome
  - ...
- There are contradicting studies (as always)
- What to learn from psychologists:
  - Use established metrics when measuring subjective qualitities
  - Perform sound statistical tests

Perceived Humanness: What do you think about the movements of the robot?

Artificial	1	2	3	4	5	Natural
Synthetic	1	2	3	4	5	Real
Inanimate	1	2	3	4	5	Living
Human-made	1	2	3	4	5	Humanlike
Mechanical Movement	1	2	3	4	5	Biological Movement
Without Definite Lifespan	1	2	3	4	5	Mortal

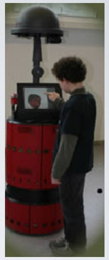
Eeriness: What are your feelings about the robot?

Reassuring	1	2	3	4	5	Eerie
Numbing	1	2	3	4	5	Freaky
Ordinary	1	2	3	4	5	Supernatural
Uninspiring	1	2	3	4	5	Spine-tingling
Boring	1	2	3	4	5	Thrilling
Predictable	1	2	3	4	5	Mortal
Bland	1	2	3	4	5	Uncanny
Unemotional	1	2	3	4	5	Hair-raising

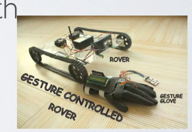
Attractiveness: What do you think of the robot's appearance?

Unattractive	1	2	3	4	5	Attractive
Ugly	1	2	3	4	5	Beautiful
Repulsive	1	2	3	4	5	Agreeable
Crude	1	2	3	4	5	Stylish
Messy	1	2	3	4	5	Sleek

INFORMATION EXCHANGE / SIGNALLING

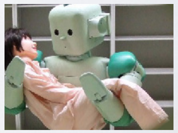


- **visual displays**, typically presented as graphical user interfaces or augmented reality interfaces
- **gestures**, including hand and facial movements and by movement-based signalling of intent
- **speech and natural language**, which include both auditory speech and text-based responses, and which frequently emphasise dialog and mixed-initiative interaction

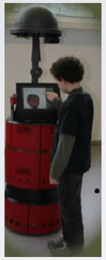


INFORMATION EXCHANGE / SIGNALLING

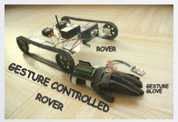
- **non-speech audio**, frequently used in alerting
- **physical interaction and haptics**, frequently used remotely in augmented reality or in teleoperation to invoke a sense of presence especially in tele-manipulation tasks and also frequently used proximately to promote emotional,
- **social, and assistive** exchanges

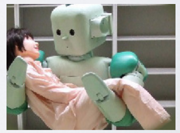


INFORMATION EXCHANGE / SIGNALLING



The modalities, specifics, flexibility, and requirements for information exchange vary a lot between tasks





NON-VERBAL COMMUNICATION (BODILY COMMUNICATION)

Argyle, M., 1988. Bodily communication 2nd ed.,

Bodily communication, or non-verbal communication (NVC), plays a central part in human social behaviour. Recent research by social psychologists and others has shown that these signals play a more important part, and function in a more intricate manner, than had previously been realized. If we want to understand human social behaviour we shall have to disentangle this non-verbal system.

We know what these non-verbal signals are:

facial expression
gaze (and pupil dilation)
gestures, and other bodily movements
posture
bodily contact
spatial behaviour
clothes, and other aspects of appearance
non-verbal vocalizations
smell

NON-VERBAL COMMUNICATION (BODILY COMMUNICATION)

Argyle, M., 1988. Bodily communication 2nd ed.,

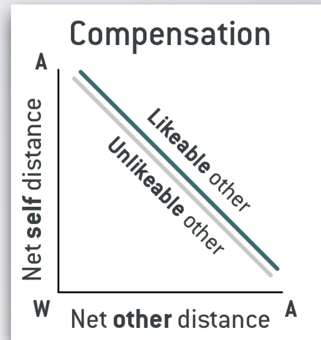
state of A → encodes → NV signal → decodes → state of B

How to generate?

How to perceive?

CLOSENESS

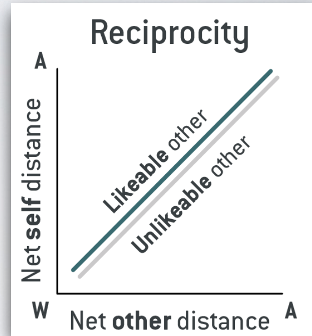
- **The Compensation Model**
- model of interpersonal distancing that suggested an *equilibrium* in the distance between two individuals
- when individuals increase their closeness (or decrease distance) with their partners, their partners *compensate* for this increase by decreasing closeness with them.
- more eye-contact => increase distance…



Mumm, J. & Mutlu, B., 2011. Human-robot proxemics. In Proceedings of the 6th international conference on Human-robot interaction - HRI '11. New York, New York, USA: ACM Press, p. 331.

CLOSENESS

- **The Reciprocity Model**
- This second model suggests that, in dyadic interaction, when one increases closeness (or decreases distancing), the other reciprocates and increases closeness to the other person
- linear increase in participants' self-disclosure when the experimenter increased disclosure



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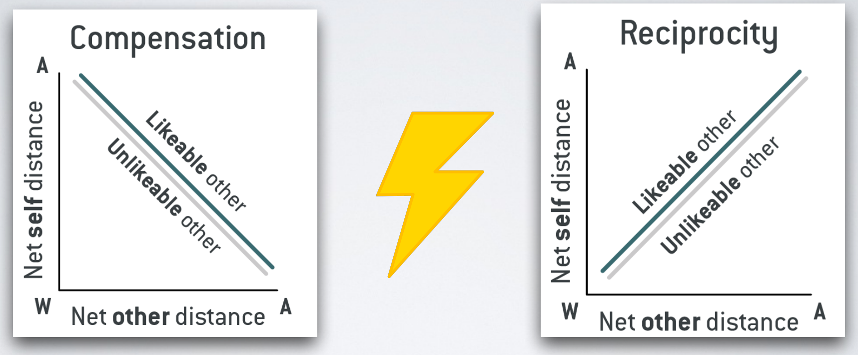

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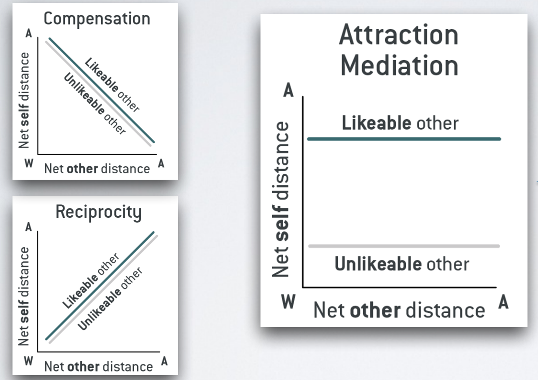
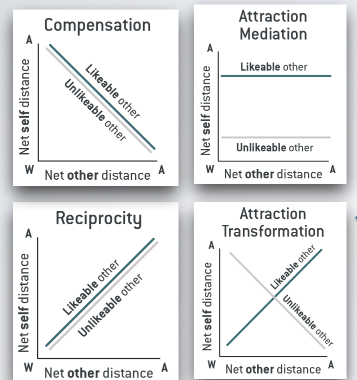


- attraction between the individuals at the onset of the interaction determines the distancing behavior.

Mumm, J. & Mutlu, B., 2011. Human-robot proxemics. In Proceedings of the 6th international conference on Human-robot interaction - HRI '11. New York, New York, USA: ACM Press, p. 331.

CLOSENESS



- incorporate the reciprocity and compensation models
- the level of attraction between individuals at the onset of the interaction affects whether individuals compensate or reciprocate.

Mumm, J. & Mutlu, B., 2011. Human-robot proxemics. In Proceedings of the 6th international conference on Human-robot interaction - HRI '11. New York, New York, USA: ACM Press, p. 331.

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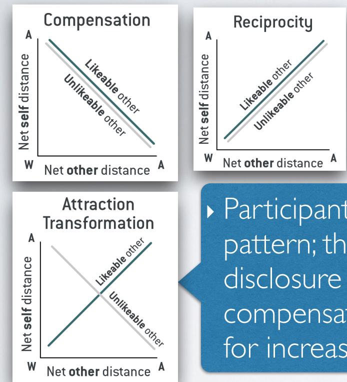


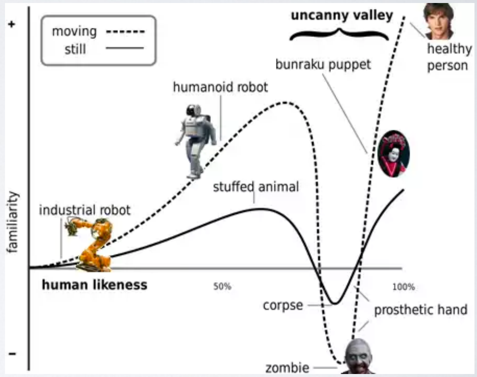
facial expression
gaze (and pupil dilation)
gestures, and other bodily movements
posture
bodily contact
spatial behaviour
clothes, and other aspects of appearance
non-verbal vocalizations
smell

- Participants' nonverbal behaviour showed a different pattern; they reciprocated the liked confederate's disclosure by increasing the amount of gaze and compensated for the disliked confederate's attempt for increasing closeness by reducing it.

EMBODIMENT

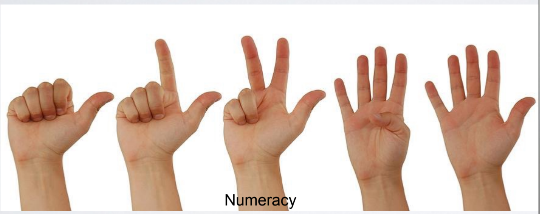
DESIGN AND HUMAN FACTORS

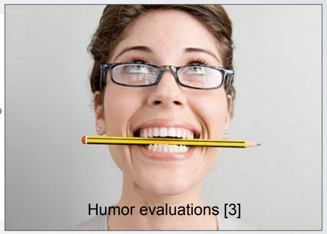
- Embodiment
- Anthropomorphism (How human-like do you want your robot to be?)
  - uncanny valley
- Appearance effects likability
- Expectations



EMBODIED COGNITION

- **Definition: The theory that psychological processes are influenced by our body, including sensory input, body morphology, and motor systems** [2]


Numeracy


Humor evaluations [3]

[2] Glenberg, A.M., 2010. Embodiment as a unifying perspective for psychology. Wiley Interdisciplinary Reviews: Cognitive Science, 1(4), pp.586-596.
[3] Strack, F., Martin, L.L. & Stepper, S., 1988. Inhibiting and facilitating conditions of the human smile: a nonobtrusive test of the facial feedback hypothesis. Journal of personality and social psychology, 54(5), p.768.

EMBODIED COGNITION: PERCEPTION

- **Affordance Theory [4]:**

The environment is perceived in terms of the potential actions that can be made, so called *affordances*.

Perception and action are inextricably linked; we think and perceive the world in behavioural terms.

Visual perception: Beer

Affordance: A receptacle holding alcoholic liquid accessible by a pinch grip near the centre followed by lifting and tipping motion

[4] Gibson, J. J. (1977). The theory of affordances. In R. Shaw & J. Bransford (Eds.), Perceiving, acting, and knowing: Toward an ecological psychology (pp. 67-82). Hillsdale, NJ: Erlbaum

EMBODIED COGNITION: NEUROPSYCHOLOGY

- Mirror Neuron System:

  Premotor neurons activate when an action is executed, and also when it is observed being performed by someone else.

  Neurobiological analogue of embodied cognition: thinking is acting and vice-versa.

  Embodied Simulation enables us to understand the meaning, intention, feeling and emotion underlying other's behaviour.

  Suggests that perception is not a static process, but instead involves our imagining of acting out the actions of others.

"Social identification, empathy, and 'we-ness' are the basic ground of our development and being." [5].

[5] Gallese, V., 2009. Mirror neurons, embodied simulation, and the neural basis of social identification. Psychoanalytic Dialogues, 19(5), pp.519-536.

EMBODIMENT IN INTERACTION

- The following definition, developed by Quick et al. [6], is defining embodiment as that which **establishes a basis for structural coupling** by creating the potential for **mutual perturbation between system and environment**. Embodiment is in this sense not solely a feature of a system in an environment, but is grounded in the relationship between the two.

A system **X** is embodied in an environment **E** if perturbatory channels exist between the two. That is, **X** is embodied in **E** if for every time **t** at which both **X** and **E** exist, some subset of **E**'s possible states have the capacity to perturb **X**'s state, and some subset of **X**'s possible states have the capacity to perturb **E**'s state.

[6] Quick, T., Dautenhahn, K., Nehaniv, C.L. and Roberts, G., 1999. On bots and bacteria: Ontology independent embodiment. In Advances in Artificial Life (pp. 339-343). Springer Berlin Heidelberg.

EMBODIMENT EXAMPLES IN ROBOTICS

- How was your Turtlebot influenced by its environment?
  - The green box/light
  - Static obstacles: walls, furniture
  - Semi-static obstacles: furniture like chairs
  - Dynamic obstacles: humans, animals
  - …
- How did it influence its environment?
  - Changing its position
  - Alter the position of dynamic obstacles: humans move aside to let it pass
  - Alter the position of semi-static obstacles: pushing chairs/the box/other robots
  - Changing the actions of humans by its mere presence
  - …

EMBODIMENT EXAMPLES IN ROBOTICS

- What difference did the embodiment make compared to the simulation?
  - Different sensor feedback
  - Changing its perception by moving
  - Different motor control
  - Different appearance of movement
  - People interacted with the robot
  - Adding auditory feedback
  - Changing limitations (WiFi)

Result: *The emergent behaviour was completely different to the simulation*

EMBODIMENT EXAMPLES IN ROBOTICS

USER'S SOCIAL SIGNALS

WHAT IF IT GOES ALL WRONG

Mirnig, N. et al., 2015. Impact of Robot Actions on Social Signals and Reaction Times in HRI Error Situations. In A. Tapus et al., eds. Int Conf Social Robotics. Lecture Notes in Computer Science. Cham: Springer International Publishing. Available at: http://link.springer.com/10.1007/978-3-319-02675-6.

WHAT IF IT GOES ALL WRONG

Mirnig, N. et al., 2015. Impact of Robot Actions on Social Signals and Reaction Times in HRI Error Situations. In A. Tapus et al., eds. Int Conf Social Robotics. Lecture Notes in Computer Science. Cham: Springer International Publishing. Available at: http://link.springer.com/10.1007/978-3-319-02675-6.

Human-robot interaction experiments featuring **error situations** are often excluded from analysis. We argue that a lot of value lies hidden in this discarded data. We analyzed a corpus of **201 videos** that show error situations in human-robot interaction experiments. The aim of our analysis was to research (a) if and which social signals the experiment participants **show in reaction to error situations**, (b) **how long** it takes the participants to react in the error situations, and (c) whether different robot actions elicit **different social signals**.

IMPACT OF ROBOT ACTIONS ON SOCIAL SIGNALS AND REACTION TIMES IN HRI ERROR SITUATIONS

(a) JAMES robot (b) JAST robot (c) IURO robot (d) RPBD robot

- analysed errors in 4 different systems:
  - JAMES (Joint Action for Multimodal Embodied Social Systems)
  - JAST2 (Joint Action Science and Technology)
  - IURO3 (Interactive Urban Robot)
  - Master thesis project RPBD (Robot Programming by Demonstration).
- developed coding scheme

IMPACT OF ROBOT ACTIONS ON SOCIAL SIGNALS AND REACTION TIMES IN HRI ERROR SITUATIONS

(a) JAMES robot (b) JAST robot (c) IURO robot (d) RPBD robot

- Coding Scheme
- error situations categorised as either *social norm violation* or *technical failure.*

RobotAction	Frequency	Percent
TaskRelatedAction	244	14.3
RepeatPreviousAction	812	47.5
RightActionGoneWrong	42	2.5
OutOfContextAction	105	6.1
Filler	216	12.6
NoReaction	291	17.0
Total	1710	100.0

IMPACT OF ROBOT ACTIONS ON SOCIAL SIGNALS AND REACTION TIMES IN HRI ERROR SITUATIONS

- Social Signals vs. No Social Signals.
  - different social signals annotated in video

RobotAction	No Signal	Signal	Chi-Square	
TaskRelatedAction	**57%**	43%	$\chi^2(1, N = 244) = 4.20$	$p = .041$
RepeatPreviousAction	**63%**	37%	$\chi^2(1, N = 812) = 57.46$	$p < .001$
RightActionGoneWrong	29%	**71%**	$\chi^2(1, N = 42) = 7.71$	$p = .005$
OutOfContextAction	47%	53%	$\chi^2(1, N = 105) = 0.47$	$p = .495$
Filler	29%	**71%**	$\chi^2(1, N = 216) = 37.50$	$p < .001$
NoReaction	31%	**69%**	$\chi^2(1, N = 291) = 40.83$	$p < .001$

IMPACT OF ROBOT ACTIONS ON SOCIAL SIGNALS AND REACTION TIMES IN HRI ERROR SITUATIONS

Table 4. Top 10 of double and triple combinations of social signals (RepeatLastS. = RepeatLastSentence; AskQuestionToExp. = AskQuestionToExperimenter; LookToExp. = LookToExperimenter; LookToGM = LookToGroupMember; MakeStatementToGM = MakeStatementToIngroupMember)

No. Double Combination	No. Triple Combination
25 LeanForward + RepeatLastS.	4 Laugh + LookDown + Smile
21 Laugh + Smile	3 LookToRobotHead + NewSentence + Smile
18 LookToExperimenter + Smile	2 LookToExp. + LookToGM + MakeStatementToGM
12 LeanForward + NewSentence	2 FunnyFace + LookToRobotHead + NewSentence
11 LookToGroupMember + Smile	2 Laugh + Smile + StepBack
10 LookToRobotHead + RepeatLastS.	2 LeanForward + LookToRobotHead + RepeatLastS.
9 AskQuestionToExp. + LookToExp.	2 LookToObject + LookToRobotHead + NewSentence
8 LookToRobotHead + NewSentence	2 Laugh + LookToGroupMember + Smile
7 NewSentence + Smile	2 LookToRobotHand + LookToRobotHead + Smile
6 RephraseLastSentence + Smile	2 LookToRobotHead + RepeatLastSentence + Tilt

IMPACT OF ROBOT ACTIONS ON SOCIAL SIGNALS AND REACTION TIMES IN HRI ERROR SITUATIONS

Table 3. Mean reaction times and standard deviation in seconds

RobotAction	N	Mean	SD
TaskRelatedAction	106	1.65	1.70
RepeatPreviousAction	298	1.15	0.86
RightActionGoneWrong	30	4.39	4.92
OutOfContextAction	56	1.71	1.96
Filler	153	1.97	4.21
NoReaction	200	1.71	1.89

NOT ONLY ABOUT PROBLEMS

- A robot could learn a lot from understanding social signals
- It can help to
  - structure tutoring
  - get reinforcement signals
  - react to errors
  - take turns, collaborate,…

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DIFFERENT KIND OF SIGNALS IN TUTORING CHILDREN AND ADULTS: "MOTIONESE"


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CONCLUSION

- Take-Home messages
  - Different social signals are present in human's responses
  - They can be quite confusing, e.g. laughter when an error occurs
  - Different types of problems elicit different signals, and some hardly any
  - It's a highly multi-modal endeavour to "read" them
- exploit their nature, but recognise them first ;-)

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SOME MODALITIES

SOCIAL SIGNALS AND EMOTIONS CAN'T BE AVOIDED

One cannot not communicate!

4-2 *(moved here due to unavailability of presenter next week)* Lang, C. et al., 2009. Feedback interpretation based on facial expressions in human-robot interaction. In RO-MAN 2009 - The 18th IEEE International Symposium on Robot and Human Interactive Communication. Toyama, Japan: IEEE, pp. 189–194.	Wilson Villa	Harold Agudelo

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SOCIAL SIGNALS AND EMOTIONS CAN'T BE AVOIDED

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EMOTIONS

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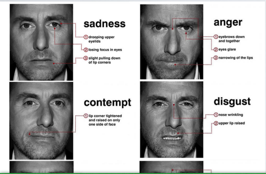
EMOTIONS



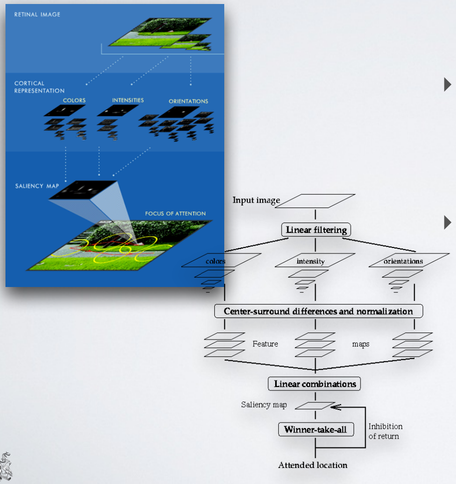
Facial Action Coding System (FACS) is a system to taxonomize human facial movements by their appearance on the face

P. Ekman and W. Friesen. Facial Action Coding System: A Technique for the Measurement of Facial Movement. Consulting Psychologists Press, Palo Alto, 1978.

Valstar, M. & Pantic, M., 2006. Fully automatic facial action unit detection and temporal analysis. CVPR workshop.

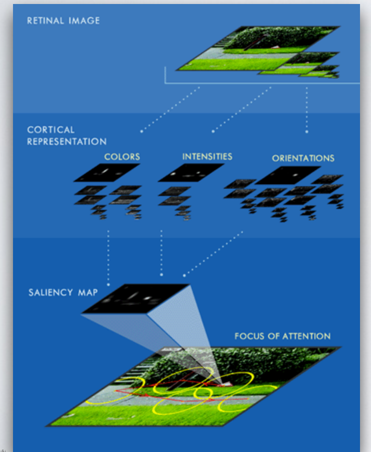
GAZE

ITTI'S & KOCH'S SALIENCY MAPS

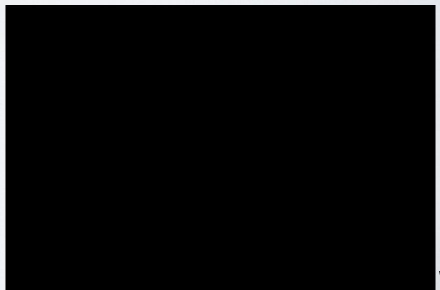


- model for the bottom-up control of visual attention in primates.
- Given an input image, this systems attempts to predict which location in the image will automatically and inconsciously your attention towards them

ITTI'S & KOCH'S SALIENCY MAPS

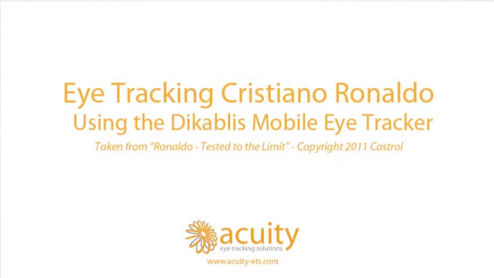


- purely static model
- extended by Nagai et al for motion cues



RECOGNISING GAZE

- Where does the human look?
- What are his likely next actions (which object to grasp)?
- What is she referring to in her utterance?



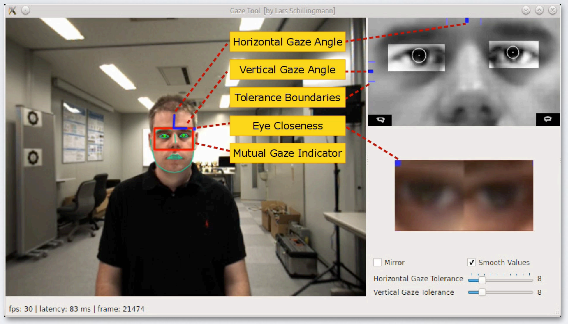
RECOGNISING GAZE

- Where does the human look?
- What are his likely next actions (which object to grasp)?
- What is she referring to in her utterance?

Image Acquisition → Face Detection and Alignment → Feature Extraction → Gaze and Lid Estimation → Hypothesis Output

Fig. 1: Pipeline architecture of the gaze detection system

YET ANOTHER GAZE DETECTOR: AN EMBODIED CALIBRATION FREE SYSTEM FOR THE ICUB ROBOT



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YET ANOTHER GAZE DETECTOR: AN EMBODIED CALIBRATION FREE SYSTEM FOR THE ICUB ROBOT

The face detection module uses the dlib library's [7] face detection and face alignment algorithms to find faces in each frame provided by the image acquisition module. The face alignment module aligns a non-rigid facial feature point model to each detected face [6].

[6] V. Kazemi and J. Sullivan, "One Millisecond Face Alignment with an Ensemble of Regression Trees," in *In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2014)*, 2014.
[7] D. E. King, "Dlib-ml: A Machine Learning Toolkit," *The Journal of Machine Learning Research*, vol. 10, pp. 1755–1758, Dec. 2009.

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YET ANOTHER GAZE DETECTOR: AN EMBODIED CALIBRATION FREE SYSTEM FOR THE ICUB ROBOT

The feature extraction module calculates features for each detected face. The features include feature points provided by the previous module. Based on this initial feature set this module estimates pupil positions and extracts histogram of oriented gradients (HOG) descriptors (dlib's HOG implementation [7]) on the eye regions.

[6] V. Kazemi and J. Sullivan, "One Millisecond Face Alignment with an Ensemble of Regression Trees," in *In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2014)*, 2014.
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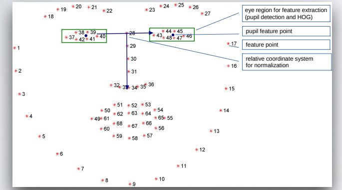

- **Positional Face Features**
- The face alignment module provides 68 feature points for each detected face.
- + two detected pupil positions
- => 70 feature points are available resulting in a 140 dimensional feature vector.
- the feature points are transformed into a relative coordinate system defined by the axis between the eye corners and the root of the nose.

The feature extraction module calculates features for each detected face. The features include feature points provided by the previous module. Based on this initial feature set this module estimates pupil positions and extracts histogram of oriented gradients (HOG) descriptors (dlib's HOG implementation [7]) on the eye regions.

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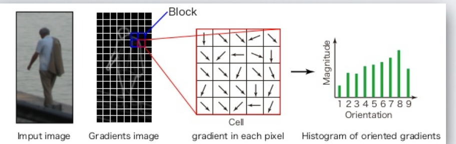

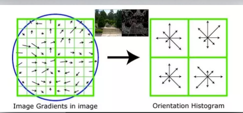

...ule calculates features for each ...lude feature points provided by ... on this initial feature set this ...ions and extracts histogram of oriented gradients (HOG) descriptors (dlib's HOG implementation [7]) on the eye regions.

- **+ HOG features** because they perform well in classifying eye closeness.
- calculate a size and orientation normalised feature vector for eye closeness:
- 1) 32x32 eye patch.
- 2) The patches are horizontally concatened.
- 3) HOG features are extracted. A cell size of 8 pixels resulting in a 372 dimensional feature vector is used.

Image Acqusition → Face Detection and Alignment → Feature Extraction → Gaze and Lid Estimation → Hypothesis Output

Fig. 1: Pipeline architecture of the gaze detection system

YET ANOTHER GAZE DETECTOR: AN EMBODIED CALIBRATION FREE SYSTEM FOR THE ICUB ROBOT

This module estimates horizontal gaze, vertical gaze, and lid closeness with epsilon insensitive support vector regression models. The models were trained on different feature subsets. Dlib's implementation of the insensitive support vector regression method is used [7].

[6] V. Kazemi and J. Sullivan, "One Millisecond Face Alignment with an Ensemble of Regression Trees," in *In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2014)*, 2014.
[7] D. E. King, "Dlib-ml: A Machine Learning Toolkit," *The Journal of Machine Learning Research*, vol. 10, pp. 1755–1758, Dec. 2009.

TABLE I: Model Optimization Results

Model	Feature Set	pca-ϵ	c	ϵ	ϵ-ins.	MSE	R^2
horiz. gaze	positional	-	1	0.1	2	33.25	0.68
horiz. gaze	HOG	-	0.1	0.5	2	36.14	0.66
horiz. gaze	HOG+pos.	-	1	0.1	1	23.40	0.78
vert. gaze	positional	-	0.1	0.5	2	41.69	0.43
vert. gaze	HOG	-	0.1	0.05	1	30.18	0.59
vert. gaze	HOG+pos.	0.8	0.1	0.5	2	27.24	0.61
lid	HOG	0.85	5	0.025	0.1	0.05	0.80
lid	HOG+pos.	0.9	5	0.05	0.1	0.048	0.80

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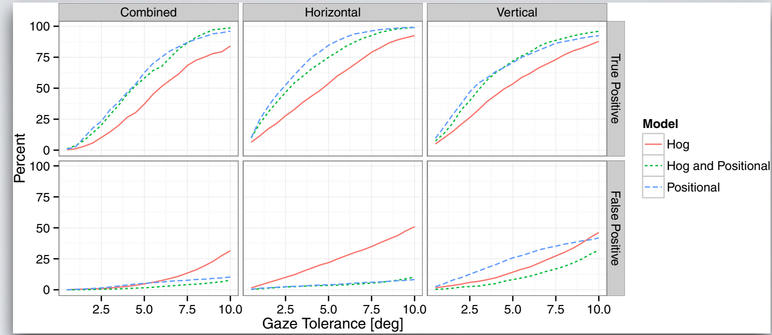
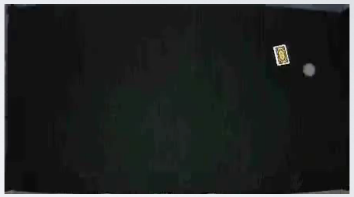


Fig. 1: Pipeline architecture of the gaze detection system

https://github.com/lschilli/gazetool

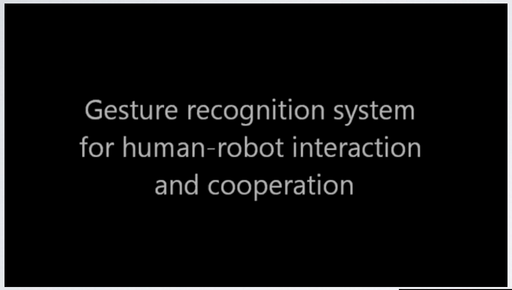
GESTURES / BODY MOTION

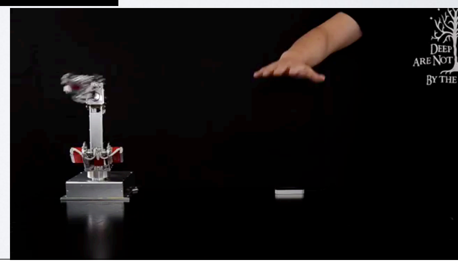
HAND TRACKING



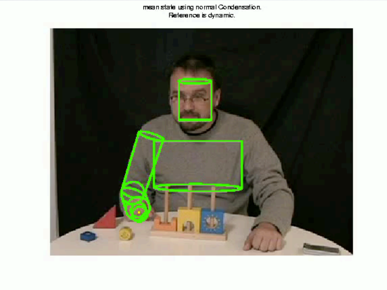
- The detector is mainly morphological, based on Convex Hulls, and also uses the skin color module from the HandVu system of Mathias Kölsch.
- The tracker is based on two main techniques: the Mixture Particles Filter from:
  - "A Boosted Particle Filter: Multitarget Detection and Tracking" by Kenji Okuma et.al;
  - The segmentation of the hands and the sleeves from the background is done using the: "Bilayer Segmentation of Live Video" of A. Criminisi et.al;

GESTURE RECOGNITION





BODY TRACKING WITH PARTICLE FILTERING



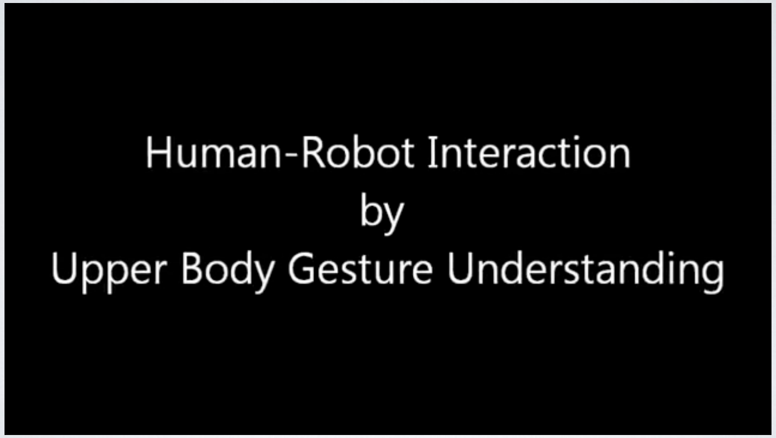
- Condensation algorithm based on face detector and skin colour models
- Used to analyse and understand actions of a human tutoring a robot

Schmidt, J., Fritsch, J. & Kwolek, B., Kernel Particle Filter for Real-Time 3D Body Tracking in Monocular Color Images. In 7th International Conference on Automatic Face and Gesture Recognition (FGR06). IEEE, pp. 567–572. Available at: http://ieeexplore.ieee.org/articleDetails.jsp?arnumber=1613079 [Accessed April 28, 2016].

DEICTIC GESTURES

- spatial references using gestures
- usually "pointing", but also others like

BODY MOTION



JOINT GAZE AND MOTION

Challenges of Human-Robot Interaction in Real-World Contexts

Half-day workshop at RO-MAN 2016, New York, August 31th

HOME PAPER SUBMISSION PROGRAM

Home

PROBLEM STATEMENT

Most Human-Robot Interaction (HRI) research is performed in the lab which offers a simplification of the real-world context to allow problem solving. However, robotic systems should eventually be tested in ecologically valid settings to determine whether and how they actually meet real-world needs. Only recently, robotic systems have become reliable and robust enough to be deployed in real-world settings, such as homes, schools, care facilities, museums and the like. And long-term acceptance research of social robots in such real-world settings is about to become a sub-field in evaluating the interactions between robots and their human users. This stresses the need for more ecologically valid research and the inclusion of the real potential end-users required to be able to gain insight into how people perceive, accept ecologically valid research is to use methods, materials and settings that approximate the real-world as much as possible. Studying HRIs in real-world contexts reveals more natural interactions and human reactions. Moreover, the robotic system can be tested within its intended use context which is unpredictable, dynamic and unstructured, something that is difficult if not impossible to simulate in the lab. Therefore, HRI research in real-world contexts offers a unique insight into the interactions between robots and their human users. However, studying HRI in real-world contexts also brings along many challenges, among other topics related to:

- Technologically with regard to the robustness and reliability of the system
- Methodologically with reference to the controllability of variables and a lack of validated measurement tool kits for the evaluation
- Contextually in relation to the social and cultural aspects of HRI

AIM OF THE WORKSHOP

The aim of this workshop is to bring together researchers from both industry and academia to discuss best practices as well as pitfalls of HRI research in real-world settings, and to provide the HRI community with guidelines to inform future developments of their robotic systems. We invite multi-disciplinary contributions from researchers and practitioners from the fields of HRI, engineering, computer sciences, fine and media arts, (interactive) design, sociology, anthropology, psychology, neurosciences, cognitive sciences, semiotics, linguistics, literary studies, history, policy, law, communication science, and cultural studies.

29/04/16: Social Signals

This session will focus on the ways humans and robots can communicate with one another, focusing on implicit signalling.

At the end, we shall give Riccardo a chance to present his paper from two weeks ago.

Paper	Presented by	Discussed by
4-1 Fischer, K. et al., 2013. The impact of the contingency of robot feedback on HRI. In Proceedings of the 2013 International Conference on Collaboration Technologies and Systems, CTS 2013. pp. 210–217.	Mirco Colosi	Irvin Aloise
4-3 Moon, Aj. et al., 2013. Design and Impact of Hesitation Gestures during Human-Robot Resource Conflicts. International Journal of Human-Robot Interaction (IJHR), 2(3), pp.18–40. Available at: http://hri-journal.org/index.php/HRI/article/view/49.	Ahmad irjoob	Gabriele Angeletti
3-2 Lu, D. V, Hershberger, D. & Smart, W.D., 2014. Layered costmaps for context-sensitive navigation. In Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on. pp. 709–715.	riccardo rinaldi	SALVATORE GIGLIO

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4-1 Fischer, K. et al., 2013. The impact of the contingency of robot feedback on HRI. In Proceedings of the 2013 International Conference on Collaboration Technologies and Systems, CTS 2013. pp. 210–217.	Mirco Colosi	Irvin Aloise
4-3 Moon, Aj. et al., 2013. Design and Impact of Hesitation Gestures during Human-Robot Resource Conflicts. International Journal of Human-Robot Interaction (IJHR), 2(3), pp.18–40. Available at: http://hri-journal.org/index.php/HRI/article/view/49.	Ahmad irjoob	Gabriele Angeletti
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