Embodied social robots trigger gaze following in real-time HRI

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Abstract— **When interacting with others, we use information from gestures, facial expressions and gaze direction to make inferences about what others think, feel or intend to do. Gaze direction also triggers shifts of attention to gazed-at locations and establishes joint attention between gazer and observer. The ability to follow gaze develops early in life and is a prerequisite for more complex social-cognitive processes like action perception, mentalizing and language acquisition. It has been shown that robot gaze induces similar gaze following effects in observers as human gaze, with positive effects on attitudes and performance in human-robot interaction. However, so far most studies have used images or videos in controlled laboratory settings to investigate gaze following in human-robot interaction rather than realistic social embodied robot platforms. The current experiment shows that gaze following can be observed in real-time interactions with embodied social robot platforms. The implications of this finding for human-robot interaction are discussed.**

I. Introduction and Background

Bodily signals like gaze direction or gestures are important signals in social interactions that inform us about the social relevance of observed behavior and influence how we react towards others. A crucial part of this process concerns the degree to which others are believed to be intentional agents with internal states like beliefs, emotions or action goals [1]. Perceiving intentionality in the behavior of others is a prerequisite for developing a Theory-of-Mind and allows us to make inferences about the internal states of others [2]. For instance, perceiving a fearful expression on another person's face, triggers the inference that he/she is currently anxious or stressed, and seeing another person gaze at an apple triggers the thought that he/she must be hungry and intends to eat the food by grasping it.

While reasoning about the internal states of others happens automatically in human-human interactions, robots trigger social inference processes only when they are believed to show intentional behavior [3]–[5]. Previous research has shown that in order to be perceived as intentional agent, robots need to appear similar to humans, which can be accomplished by equipping them with human-like appearance or behaviors [6]–[8]. Once robots are perceived as intentional

Fig. 1. Full test setup showing the Meka anthropomorphic head, two smart bulbs, a custom user touch interface, and the participant. This image shows one light being activated and the participant pressing the corresponding button on the user interface.

beings, social relevance is ascribed to their actions, and human interaction partners show more positive attitudes towards them [3]–[10]. For example, it was found that robots showing human gestures like nodding or shrugging, trigger more positive emotional reactions in human observers and are trusted more than robots that only show mechanistic gestures [11]. Robots that trigger perceptions of intentionality also induce social facilitation effects in human interaction partners [12]–[15] and have a positive effect on performance during joint human-robot tasks in general [16]–[20].

One feature that particularly triggers perceptions of intentionality is the implementation of human gaze behavior in embodied robot platforms [21]–[25], and virtual avatars [26]–[28]. Robots shifting their eye gaze during social interactions as opposed to robots whose eyes do not move are perceived as more enjoyable [29], and robots that conjointly attend to where human interaction partners are looking are rated as more competent than robots that do not engage in joint attention [30]. Robots that use gaze cues to communicate also foster recollection in memory tasks [31], and facilitate communication between human and robot partner by enabling turn-taking [21]–[23]. Robots reacting to human input by shifting gaze in a coherent fashion also positively affect the reported physical and emotional closeness between human and robot [32], and their gaze behavior is more likely judged as intentional rather than random [33].

From a psychological perspective, observing changes in gaze direction triggers shifts of the observers attention to

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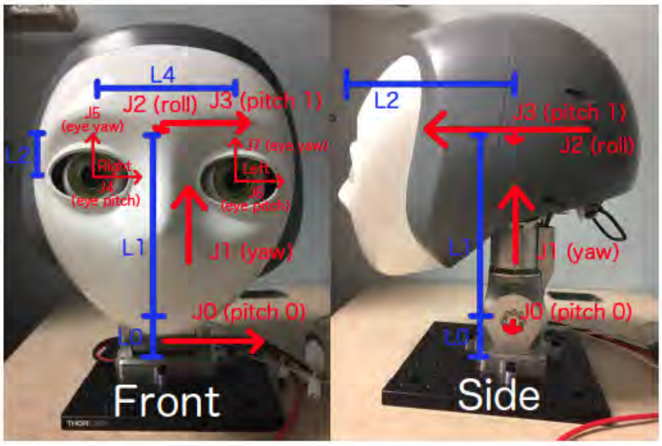

Fig. 2. Meka S2 anthropomorphic humanoid head kinematic chain. Front view shown in LEFT image, side view shown in RIGHT image. Neck: Serial kinematic chain (botto to top): pitch, yaw, roll, pitch. Eyes (left and right) have two independent DOF, pitch and yaw. Positive direction is denoted by the right hand rule.

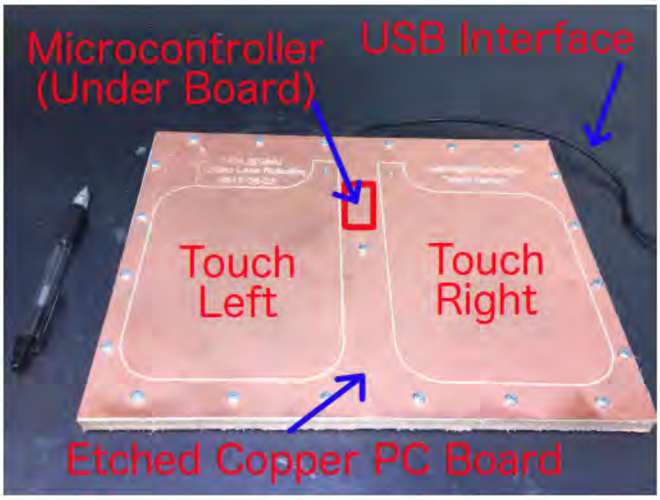

Fig. 3. Self-calibrating capacitive touch interface with two large buttons for user interface. A standard ballpoint pen is included in the picture for a scale reference.

the gazed-at location, and allows two interaction partners to conjointly attend to the same location, object or event [34]. Joint attention is needed to coordinate actions of multiple interaction partners in time and space, is a prerequisite for developing a functioning theory-of-mind, and is necessary for making inferences about the internal states of others [35]. Joint attention is investigated in computer experiments, where a face is presented on a screen that gazes straight ahead, and then changes gaze direction to the left or right side of the screen, which triggers shifts of the observers attention to the gazed-at location [34]. The change in gaze direction, or gaze cue, is followed by the presentation of a target item (dot, letter), which either appears at the cued location (valid trial) or an uncued location (invalid trial). Participants are instructed to respond as fast and accurately as possible to the target by pressing designated keys on a standard keyboard. Since observing gaze cues shifts attention to the gazed-at location, reaction times to targets presented at the cued location are usually faster than reaction times to targets presented at an uncued location (gaze-cueing effect: [34]).

For the most part, gaze signals sent by robot agents induce similar effects in observers as human gaze signals [36]–[39]. For instance, robots that establish mutual gaze with human partners receive more favorable evaluations [40], and participants spend more time on interactions with them [41] compared to robots who do not show mutual gaze. Robot gaze can be interpreted with the same spatial accuracy as human gaze, although this effect depends on the morphology of the robot eye (extent to which robot eye is covered by eyelids; [5]). Robot gaze signals seem to be so natural to human observers that adults readily follow the gaze of robot images in highly controlled computer experiments [4]–[6], and even ten-month old infants follow the line of sight of a robot to gazed-at locations [42]. Despite these similarities, differences in processing human versus robot gaze become apparent when looking at the cognitive process in detail. For example, Yu and colleagues looked at the dynamics of attentional orienting and found that participants spent significantly more time looking at robot faces than human faces in a gaze-based object naming task, indicating that there is concern whether the robot is able to attend to relevant objects [43]. Admoni and Scassellati showed that while humans automatically follow the gaze of human agents, attending to where a robot agent is looking can more easily be suppressed [6], which suggests that human gaze is processed in different neural pathways than robot gaze. Similarly, eye tracking in 12-month-old infants revealed anticipatory gaze shifts and enhanced processing of looked-at objects in response to human but not robot gaze cues [44], [45].

While there is evidence that robots induce gaze following effects in highly controlled laboratory settings, it has not been examined whether embodied, physical robots can also induce comparable effects in real-time human-robot interaction. On the one hand, one could hypothesize that gaze following might be stronger in real-time interactions with robots since beneficial effects of physical embodiment over virtual environments are vastly reported in human-robot interaction [46]–[48]. On the other hand, one could speculate that real-time interactions with embodied robots might have negative effects on gaze following due to issues with mechanistic motion patterns or timing of the robot head [46]–[48]. In terms of gaze following, it is possible that embodiment increases the social relevance of robot gaze behavior with positive effects on how strongly participants follow its gaze. However, it is also possible that unrealistic motion patterns and timing of robot eye movements lead to a break down in gaze following. The current study investigates whether gaze following can be induced in real-time human-robot interaction or whether its observation is specific to highly controlled laboratory settings.

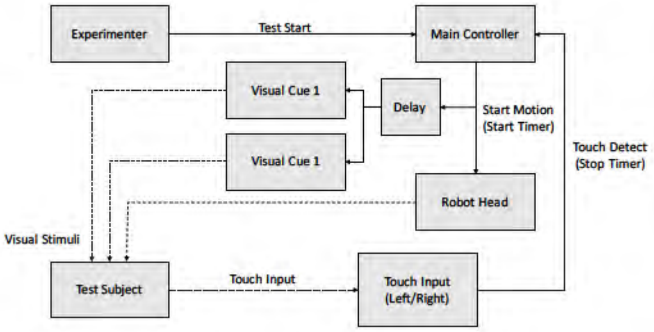

Fig. 4. Full test setup including the Meka head, two smart bulbs, a custom user touch interface, and a sub-millisecond accuracy timer.

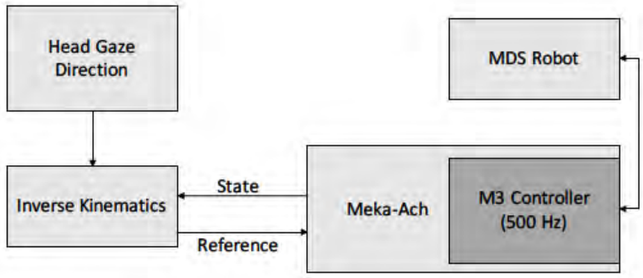

Fig. 5. Diagram of the Meka-Ach process based control system.

II. Methods and Materials

A. Participants

Seventeen participants were recruited for the experiment using the participant management website SONA Systems and local campus advertisement at George Mason University. Two participants had to be excluded due to technical problems with the setup and one because of prolonged reaction times (about twice as long as the remaining subjects), leading to a final sample size of fourteen participants (six females, 8 males, age: 24.6, SD: 3.9, one left handed). Testing time was about twenty minutes. All participants reported normal to corrected-to-normal vision and gave informed consent. Participant data was stored and analyzed anonymously according to IRB guidelines.

B. Apparatus and Stimuli

The test setup consists of the S2 humanoid robot head made by Meka Robotics, two networked and programmable light bulbs (smart bulbs), a custom user touch interface, and a sub-millisecond accuracy timer (Figures 1,2,3 and 4).

1) Robot Head: The Meka head has 8 degrees of freedom: four degrees of freedom in the neck in a serial formation (order of neck joints from bottom of the neck up: pitch, yaw, roll, pitch), and two degrees of freedom (pitch, yaw) for each eye (left, right). The eyes are attached to the face which is at the end of the neck's kinematic chain; see Figure 2.

2) Meka-Ach Middleware: The middleware used to control the Meka head is an extension of the Hubo-Ach system used for the Hubo (KHR-4), Hubo 2+, DRC-Hubo, and DRC-Hubo+ models [49], [50]. Accordingly the middleware is called Meka-Ach. Meka-Ach is a multi-process based real-time control system that uses high-speed and low-latency shared memory channels with networking capabilities. When running a controller over the network Meka-Ach uses an unencrypted UDP to help reduce latency. When real-time control is not required an encrypted SSH tunnel is used. Meka-Ach talks with the shared memory of the Mekabot M3 software running at 500 hz. Meka-Ach is made by the authors and is still in pre-Alpha stages of development. It is not officially released. When released, Meka-Ach will be under the BSD Open Source license designation; see Figure 5.

3) Human Interface: The experiment requires the participant to indicate by key-press whether the light on the left or right is turned on: if the light on the left is on, the left key is pressed; if the light on the right is on, the right key is pressed. A self-calibrating capacitive touch interface with two large buttons was developed for this purpose. The touch interface was created using a custom etched copper PCB board. A real-time capable microcontroller is used to monitor the capacitive interface. This part of the system is event based. When a touch is detected a "touch" message is sent over a standard serial (USB-Serial) interface to the host computer at 115200 baud. This message states that a touch has been detected and which side it was detected at. If no touch is detected no message is sent. The system calibrates itself by reading 10,000 capacitive values from each sensor (right and left) on power up and sets the triggering threshold to 1.5 times that value.

4) Target Stimuli: The experiment requires two lights that are able to be turned on and off with millisecond precision. Two A19 compatible smart lights were used. The smart lights are connected on a dedicated 2.4 ghz wireless network. A on/off message is created using a *Node.js* implementation and sent over TCP/IP. To allow for consistant communications latency each light is placed 1.5 m from the antenna in identical orientations. The resulting latency (denoted by t_l) was recorded to be 1.032 ms with a 0.217 ms standard deviation. This latency is taken into account when recording the reaction time of the test subject.

5) Head Motion: The head looks at either the left or right bulb based on pre-programmed joint space values. These values are pre-determined by the use of the head's sparse reachable map and Inverse Jacobian Inverse Kinematics method [51]. The input to the inverse kinematic solver is the location of the object desired to be looked at by the robot. The location of the object is in reference to the base of the robot's head. The resulting joint space values are recorded and used for each given motion. Figure 5 shows the kinematic structure of the Meka head. Linear interpolation between joint space values is used when a work-space step input is given. The time of the linear interpolation is 0.25 sec and is updated at a rate of 500 hz.

6) Reaction Time Recording: System clock time is recorded twice every trial, first when the smart light turns on (t_{c0}) and second when a message from the capacitive touch interface is received. The test subject reaction time t_c additionally takes into account the light activation latency t_l and is calculated by:

$$t_c = (t_{c1} - t_{c0}) - t_l \quad (1)$$

C. Design and Procedure

At the beginning of the experiment, participants received written instructions, and gave informed consent. They were instructed to perform a joint attention task that required them to respond as fast and accurately as possible to a change in color of one of two lights in front of them. Responses to changes in color had to be given by pressing a button on their left for the light on the left and a button on their right for the light on the right (i.e., localization task). Participants were also told that before the color change occurred, Meka would perform an eye movement from initially looking at them to looking at one of the two lights, either the one that was looked at by Meka or the one on the opposite side. Participants were instructed to respond as soon as they noticed the change in color, and the time it took participants to react to the change in color was measured as dependent variable. As soon as participants had given their response by key press, Meka would move back to her original position and the participant could initiate a new trial by establishing direct eye contact with Meka.

Figure 6 illustrates the sequence of events on a given trial. At the beginning of each trial, Meka established mutual gaze with the participant to signal their readiness to start the trial. 250 ms after establishment of mutual gaze, Meka changed her gaze direction to either the left or right light on the table in front of her (including a slight head movement). After a stimulus-onset asynchrony (SOA) of 200 ms the light at the gazed-cued location or the uncued location changed its color. Mekas posture and the color of the light remained unchanged until a response was given or a time out of 5000 ms was reached, whichever appeared first. At the end of the trial, Meka moved back to neutral position, and participants prepared for the beginning of the next trial.

The experiment was composed of 80 trials: 40 valid trials, and 40 invalid trials. Gaze direction (left, right), and target side (left, right) were selected pseudo-randomly and every combination appeared with equal frequency. Gaze validity was calculated based on the combination of gaze direction and target location: on valid trials, the target appeared where Meka was looking (i.e., gaze to the left, target on the left), while on invalid trials the target appeared opposite of where Meka was looking (i.e., gaze to the left, target on the right). No information about the reliability of Mekas gaze behavior was disclosed to the participants at any time during the experiment.

D. Analysis

Reaction time data was analyzed using R 3.2.4. Misses and incorrect responses, as well as reaction times deviating by more than +/- 2.5 SD from the individual participants means were removed prior to analyses, totaling 2.67% of all trials. The remaining data was analyzed in two steps: First, average reaction times for valid trials and invalid trials were calculated for each participant. Second, average reaction times for valid and invalid trials were compared using a t-test, with a significant difference in reaction times between valid and invalid trials being evidence for the presence of a gaze following effect.

III. Results

Results of the analysis of the reaction time data are shown in Figure 7. The test revealed a significant difference between valid and invalid trials ($t(13) = 4.00$, $p = 0.002$, $\eta^2_{partial} = 0.533$, $d = 1.069$), with shorter reaction times for valid ($M = 500ms$) than invalid trials ($M = 525ms$), providing evidence for the presence of a gaze following effect.

IV. Discussion

The goal of the experiment was to examine whether gaze following in human-robot interaction is specific to controlled laboratory settings or whether it can also be observed in real-time interactions with physically embodied robots. To address this issue, we adapted a computer-based gaze following protocol [34] to real-time interactions with the embodied humanoid robot head Meka. Participants had to perform a localization task, where they had to indicate by key press as fast and accurately as possible whether a light on the left or the right side of the table changed its color. Crucially, the light that changed its color was either cued or uncued by Meka's gaze. Reaction time to the target was measured as dependent variable and differences in reaction times between cued and uncued trials were calculated to determine whether gaze following effects were measurable.

Reaction times on cued trials were significantly shorter than reaction times on uncued trials, showing that the observation of gaze following effects is not specific to controlled laboratory settings but generalizes to real-time interactions with physically embodied robots. With 25 ms, the observed effect is slightly larger than gaze following effects normally observed in laboratory experiments (i.e., 15 ms, [3]–[5]). This enhanced gaze following effect could either be due Meka's physical embodiment or the fact that in addition to eye movements, Meka also performed head movements, potentially providing a second directional cue. The results are in line with previous studies showing that gaze following is not specific to human-human interaction, but can also be observed in real-time human-robot interaction [36]–[39].

There are two limitations to the current study that should be addressed in future research on real-time gaze following. First, the experiment cannot quantify the degree to which robot gaze triggered shifts of attention in human observers since gaze and head cues were presented at the same time. Because of that, it cannot be determined if gaze following is stronger in real-time interactions with embodied robots than in laboratory settings. Future studies need to address this limitation by manipulating head and gaze cues separately and comparing the effect they induce to gaze-cueing effects observed in laboratory experiments. Second, due to practical

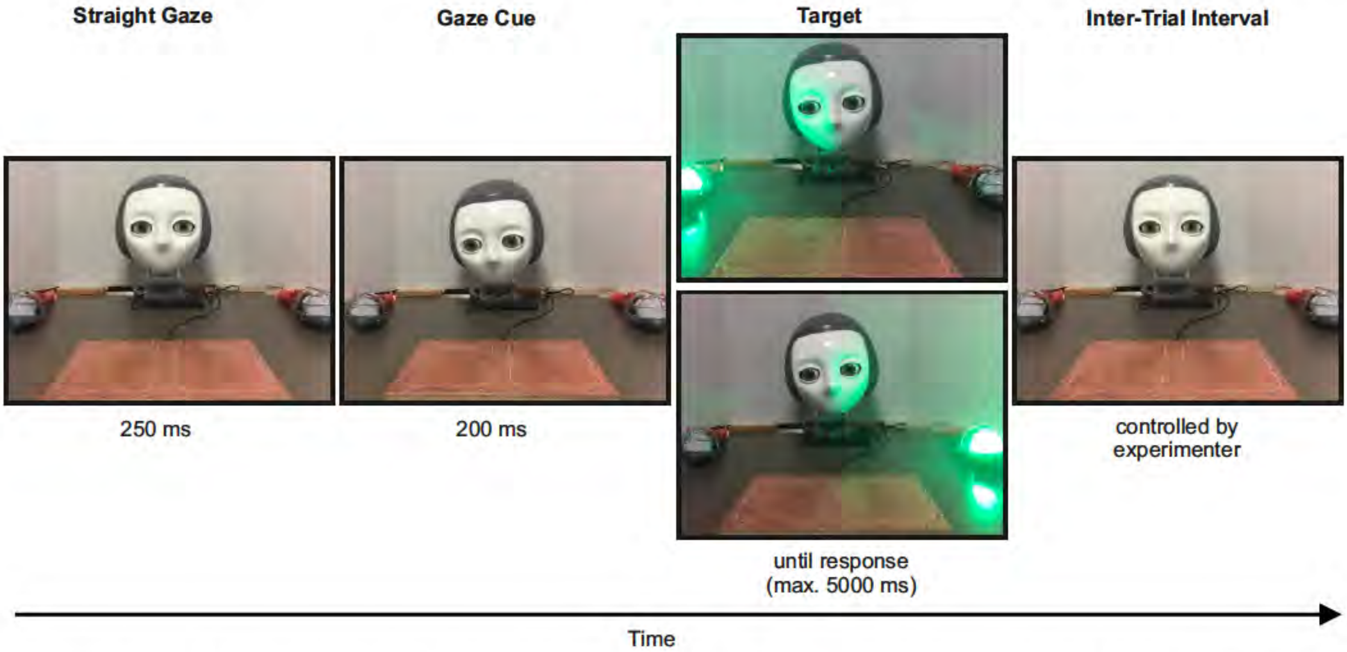

Fig. 6. Trial Sequence: Meka first established direct eye contact with the participant and then shifted her gaze to either the light on the left or the right side of the table. Afterwards, either the light that was looked at by Meka changed its color or the other light.The task was to respond to the change in color as fast and accurately as possible by pressing the key on the left for the left light or the key on the right for the right light. At the end of the trial, Meka would return back to neutral position and establish eye contact again to start a new trial.

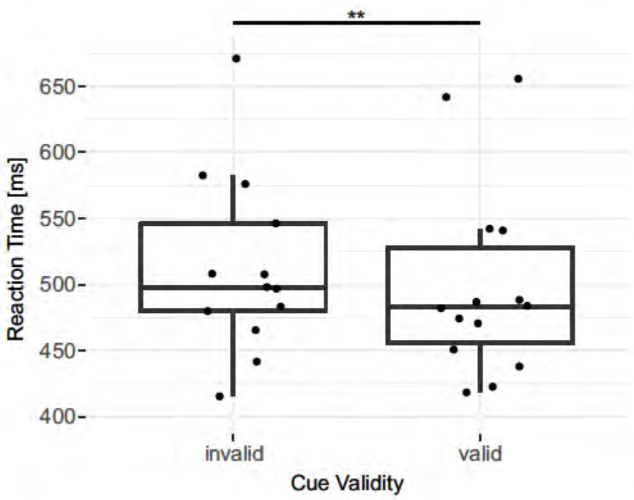

Fig. 7. Results of the analysis of the gaze-cueing effects: Horizontal boxplot lines represent 25th, 50th, and 75th percentile. Whiskers extend to data points no further than 1.5*IQR (interquartile range; the distance between 25th and 75th percentile). Individual data points are plotted on top of the boxplot. ** p ¡ .01.

reasons, data was collected in a relatively noisy environment with a high amount of people passing by, which could potentially increase the noise in our data. Gaze cueing has mostly been investigated in well controlled laboratory settings [3]–[6] and while our current setting should have increased external validity compared to those studies, the different environments make it hard to compare effect sizes between studies.

The results show that humans ascribe social relevance to robot gaze and readily establish joint attention with them in interactive scenarios. In consequence, robots can use their gaze when working with humans on joint tasks to resolve ambiguity and shift their interaction partner's attention to relevant locations and objects. Furthermore, since gaze direction allows inferences about the internal states of others, robot gaze can be used to better predict robot behavior and make human-robot interaction more efficient and productive.

REFERENCES

[1] H. M. Gray, K. Gray, and D. M. Wegner, Dimensions of mind perception, Science, vol. 315, no. 5812, pp. 619619, 2007.
[2] R. Adolphs, Cognitive neuroscience: Cognitive neuroscience of human social behaviour, Nat. Rev. Neurosci., vol. 4, no. 3, pp. 165178, 2003.
[3] C. zdem, E. Wiese, A. Wykowska, H. Mller, M. Brass, and F. Van Overwalle, Believing androidsfMRI activation in the right temporo-parietal junction is modulated by ascribing intentions to non-human agents, Soc. Neurosci., pp. 112, 2016.
[4] A. Wykowska, E. Wiese, A. Prosser, and H. J. Mller, Beliefs about the minds of others influence how we process sensory information, PLoS One, vol. 9, no. 4, p. e94339, 2014.
[5] E. Wiese, A. Wykowska, J. Zwickel, and H. J. Mller, I See What You Mean: How Attentional Selection Is Shaped by Ascribing Intentions to Others, PLoS ONE, vol. 7, no. 9, p. e45391, 2012.
[6] H. Admoni and B. Scassellati, Robot Gaze Is Different From Human Gaze: Evidence that robot gaze does not cue reflexive attention, in Proceedings of the Gaze in Human-Robot Interaction Workshop, Boston, MA, 2012.
[7] C. E. Looser and T. Wheatley, The tipping point of animacy: How, when, and where we perceive life in a face, Psychol. Sci., vol. 21, no. 12, pp. 18541862, 2010.
[8] A. Waytz, K. Gray, N. Epley, and D. M. Wegner, Causes and consequences of mind perception, Trends Cogn. Sci., vol. 14, no. 8, pp. 383388, 2010.
[9] S. Kiesler, A. Powers, S. R. Fussell, and C. Torrey, Anthropomorphic interactions with a robot and robotlike agent, Soc. Cogn., vol. 26, no. 2, pp. 169181, 2008.

[10] C. K. Morewedge, Negativity bias in attribution of external agency., J. Exp. Psychol. Gen., vol. 138, no. 4, p. 535, 2009.
[11] E. J. Carter, M. N. Mistry, G. P. K. Carr, B. A. Kelly, and J. K. Hodgins, Playing catch with robots: Incorporating social gestures into physical interactions, in The 23rd IEEE International Symposium on Robot and Human Interactive Communication, 2014, pp. 231236.
[12] N. Riether, F. Hegel, B. Wrede, and G. Horstmann, Social facilitation with social robots, in Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction, 2012, pp. 4148.
[13] C. Bartneck, Interacting with an embodied emotional character, in Proceedings of the 2003 international conference on Designing pleasurable products and interfaces, 2003, pp. 5560.
[14] S. Park and R. Catrambone, Social Facilitation Effects of Virtual Humans, Hum. Factors J. Hum. Factors Ergon. Soc., vol. 49, no. 6, pp. 10541060, 2007.
[15] S. Woods, K. Dautenhahn, and C. Kaouri, Is someone watching me?-consideration of social facilitation effects in human-robot interaction experiments, in Computational Intelligence in Robotics and Automation, 2005. CIRA 2005. Proceedings. 2005 IEEE International Symposium on, 2005, pp. 5360.
[16] A. Waytz, J. Heafner, and N. Epley, The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle, J. Exp. Soc. Psychol., vol. 52, pp. 113117, 2014.
[17] R. Pak, N. Fink, M. Price, B. Bass, and L. Sturre, Decision support aids with anthropomorphic characteristics influence trust and performance in younger and older adults, Ergonomics, vol. 55, no. 9, pp. 10591072, 2012.
[18] R. Looije, M. A. Neerincx, and F. Cnossen, Persuasive robotic assistant for health self-management of older adults: Design and evaluation of social behaviors, Int. J. Hum.-Comput. Stud., vol. 68, no. 6, pp. 386397, 2010.
[19] C. Breazeal, C. D. Kidd, A. L. Thomaz, G. Hoffman, and M. Berlin, Effects of nonverbal communication on efficiency and robustness in human-robot teamwork, in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005, pp. 708713.
[20] N. Caruana, G. McArthur, A. Woolgar, and J. Brock, Simulating social interactions for the experimental investigation of joint attention, Neurosci. Biobehav. Rev., 2016.
[21] B. Mutlu, T. Kanda, J. Forlizzi, J. Hodgins, and H. Ishiguro, Conversational gaze mechanisms for humanlike robots, ACM Trans. Interact. Intell. Syst., vol. 1, no. 2, pp. 133, 2012.
[22] A. Yamazaki, K. Yamazaki, M. Burdelski, Y. Kuno, and M. Fukushima, Coordination of verbal and non-verbal actions in human-robot interaction at museums and exhibitions, J. Pragmat., vol. 42, no. 9, pp. 23982414, 2010.
[23] M. Bennewitz, F. Faber, D. Joho, M. Schreiber, and S. Behnke, Towards a humanoid museum guide robot that interacts with multiple persons, in 5th IEEE-RAS International Conference on Humanoid Robots, 2005, pp. 418423.
[24] C. L. Sidner, C. D. Kidd, C. Lee, and N. Lesh, Where to look: a study of human-robot engagement, in Proceedings of the 9th international conference on Intelligent user interfaces, 2004, pp. 7884.
[25] J. G. Trafton, M. D. Bugajska, B. R. Fransen, and R. M. Ratwani, Integrating vision and audition within a cognitive architecture to track conversations, 2008, p. 201.
[26] N. Pfeiffer-Lessmann, T. Pfeiffer, and I. Wachsmuth, An operational model of joint attention-timing of gaze patterns in interactions between humans and a virtual human, in Proceedings of the 34th annual conference of the Cognitive Science Society, 2012.
[27] J. Cassell, Embodied conversational interface agents, Commun. ACM, vol. 43, no. 4, pp. 7078, 2000.
[28] E. Gu and N. Badler, Visual attention and eye gaze during multiparty conversations with distractions, in Intelligent Virtual Agents, Marina Del Rey, CA, 2006, pp. 193204.
[29] T. Kanda, H. Ishiguro, and T. Ishida, Psychological analysis on human-robot interaction, in Robotics and Automation, 2001. Proceedings 2001 ICRA. IEEE International Conference on, 2001, vol. 4, pp. 41664173.
[30] C.-M. Huang and A. L. Thomaz, Effects of responding to, initiating and ensuring joint attention in human-robot interaction, in 20th IEEE international symposium on robot and human interactive communication, Atlanta, GA, 2011, pp. 6571.v.
[31] B. Mutlu, J. Forlizzi, and J. Hodgins, A Storytelling Robot: Modeling and Evaluation of Human-like Gaze Behavior, in 6th IEEE-RAS International Conference on Humanoid Robots, 2006, pp. 518523.
[32] J. Mumm and B. Mutlu, Human-robot proxemics: physical and psychological distancing in human-robot interaction, in Proceedings of the 6th international conference on Human-robot interaction, 2011, pp. 331338.
[33] Y. Yoshikawa, K. Shinozawa, H. Ishiguro, N. Hagita, and T. Miyamoto, The effects of responsive eye movement and blinking behavior in a communication robot, in Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on, 2006, pp. 45644569.
[34] C. K. Friesen and A. Kingstone, The eyes have it! Reflexive orienting is triggered by nonpredictive gaze, Psychon. Bull. Rev., vol. 5, no. 3, pp. 490495, 1998.
[35] C. D. Frith and U. Frith, How we predict what other people are going to do, Brain Res., vol. 1079, no. 1, pp. 3646, 2006.
[36] T. Chaminade and M. M. Okka, Comparing the effect of humanoid and human face for the spatial orientation of attention, Front. Neurorobotics, vol. 7, no. 12, 2013.
[37] M. Staudte and M. W. Crocker, Visual attention in spoken human-robot interaction, in Proceedings of the 4th ACM/IEEE international conference on Human robot interaction, 2009, pp. 7784.
[38] J.-D. Boucher et al., I reach faster when I see you look: gaze effects in humanhuman and humanrobot face-to-face cooperation, Front. Neurorobotics, vol. 6, 2012.
[39] H. Kozima and H. Yano, A robot that learns to communicate with human caregivers, in Proceedings of the First International Workshop on Epigenetic Robotics, 2001, pp. 4752.
[40] T. Yonezawa, H. Yamazoe, A. Utsumi, and S. Abe, Gaze-communicative behavior of stuffed-toy robot with joint attention and eye contact based on ambient gaze-tracking, in Proceedings of the 9th international conference on Multimodal interfaces, 2007, pp. 140145.
[41] A. Ito, S. Hayakawa, and T. Terada, Why robots need body for mind communication - an attempt of eye-contact between human and robot, 2004, pp. 473478.
[42] J. R. Movellan and J. S. Watson, The development of gaze following as a Bayesian systems identification problem, in Development and Learning, 2002. Proceedings. The 2nd International Conference on, 2002, pp. 3440.
[43] C. Yu, P. Schermerhorn, and M. Scheutz, Adaptive eye gaze patterns in interactions with human and artificial agents, ACM Trans. Interact. Intell. Syst. TiiS, vol. 1, no. 2, p. 13, 2012.
[44] Y. Okumura, Y. Kanakogi, T. Kanda, H. Ishiguro, and S. Itakura, Infants understand the referential nature of human gaze but not robot gaze, J. Exp. Child Psychol., vol. 116, no. 1, pp. 8695, 2013.
[45] Y. Okumura, Y. Kanakogi, T. Kanda, H. Ishiguro, and S. Itakura, The power of human gaze on infant learning, Cognition, vol. 128, no. 2, pp. 127133, 2013.
[46] W. A. Bainbridge, J. W. Hart, E. S. Kim, and B. Scassellati, The benefits of interactions with physically present robots over video-displayed agents, Int. J. Soc. Robot., vol. 3, no. 1, pp. 4152, 2011.
[47] A. Powers, S. Kiesler, S. Fussell, and C. Torrey, Comparing a computer agent with a humanoid robot, in Proceedings of the ACM/IEEE International Conference on Human-robot Interaction, Arlington, Virginia, USA, 2007, pp. 145152.
[48] J. Kennedy, P. Baxter, and T. Belpaeme, Comparing robot embodiments in a guided discovery learning interaction with children, Int. J. Soc. Robot., vol. 7, no. 2, pp. 293308, 2015.
[49] N. Dantam, D. Lofaro, A. Hereid, P. Oh, A. Ames, and M. Stilman, "The ach library: A new framework for real-time communication," *Robotics Automation Magazine, IEEE*, vol. 22, no. 1, pp. 76–85, March 2015.
[50] D. Lofaro, "Unied algorithmic framework for high degree of freedom complex systems and humanoid robots," in *Ph.D. dissertation, Drexel University, College of Engineering, Electrical and Computer Engineering Department*, May 2013.
[51] D. Lofaro, R. Ellenberg, P. Oh, and J. Oh, "Humanoid throwing: Design of collision-free trajectories with sparse reachable maps," in *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, Oct 2012, pp. 1519–1524.