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Bi-directional navigation intent communication using spatial augmented reality and eye-tracking glasses for improved safety in human–robot interaction☆

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ABSTRACT

Safety, legibility and efficiency are essential for autonomous mobile robots that interact with humans. A key factor in this respect is bi-directional communication of navigation intent, which we focus on in this article with a particular view on industrial logistic applications. In the direction robot-to-human, we study how a robot can communicate its navigation intent using Spatial Augmented Reality (SAR) such that humans can intuitively understand the robot's intention and feel safe in the vicinity of robots. We conducted experiments with an autonomous forklift that projects various patterns on the shared floor space to convey its navigation intentions. We analyzed trajectories and eye gaze patterns of humans while interacting with an autonomous forklift and carried out stimulated recall interviews (SRI) in order to identify desirable features for projection of robot intentions. In the direction human-to-robot, we argue that robots in human co-habited environments need human-aware task and motion planning to support safety and efficiency, ideally responding to people's motion intentions as soon as they can be inferred from human cues. Eye gaze can convey information about intentions beyond what can be inferred from the trajectory and head pose of a person. Hence, we propose eye-tracking glasses as safety equipment in industrial environments shared by humans and robots. In this work, we investigate the possibility of human-to-robot implicit intention transference solely from eye gaze data and evaluate how the observed eye gaze patterns of the participants relate to their navigation decisions. We again analyzed trajectories and eye gaze patterns of humans while interacting with an autonomous forklift for clues that could reveal direction intent. Our analysis shows that people primarily gazed on that side of the robot they ultimately decided to pass by. We discuss implications of these results and relate to a control approach that uses human gaze for early obstacle avoidance.

1. Introduction

In their interaction, humans rely on implicit and explicit, verbal and non-verbal cues to communicate [1,2]. These forms of human-human communication are used for understanding each other, establishing trust, predicting future actions and making corresponding decisions, thus contributing to safe, legible and efficient interactions. Accordingly, in human–robot interaction (HRI), it is desirable to have bi-directional communication between humans and robots, especially to improve safety in potentially dangerous industrial environments.

Safety consideration in HRI include two key underlying aspects: general safety and perceived safety. General safety in HRI is hoped to be achieved by following safety measures[1] when designing robots to prevent any physical injuries to humans. An example of such safety measures is that mobile robots need to maintain a safe distance and speed in the vicinity of humans. In order to allow for safe, yet efficient interactions, human intention prediction capabilities are essential for robots. More elusive is the aspect of *perceived safety*, which in HRI is defined as a human's perception of the level of danger when interacting with a robot, and the humans' level of comfort during the interaction [3]. To

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improve perceived safety, in a scenario where a robot coexists in a workspace with humans, it is desirable for the robot to communicate its intentions in a clearly understandable manner. Improvement in perceived safety is expected to increase the acceptability of robots as reliable co-workers.

In this work, our specific focus is on communication and recognition of motion intentions. We consider the exemplary and highly relevant use case of autonomous transport vehicles used in material handling systems and flexible manufacturing systems. Automatic Guided Vehicles (AGV) have been increasingly introduced over the last few decades. Initially, they have been using pre-defined paths laid out on the floor for navigation, which made it straightforward for human workers to predict their future actions. The improved levels of autonomy, developed over the last decade, allow AGVs to be more versatile and efficient. This poses safety issues which were not present in classical industrial plants [4] leading to two challenges with respect to safety which are addressed in this work.

The first challenge is that freely moving behavior of robots can appear unpredictable to humans leading to the disapproval of autonomous AGVs. Within a shared spatial environment, humans and robots form a system whose activities include internal intention formulation, intention communication, perception, intention recognition, actions, and reactions [5]. One way to communicate motion intention explored in this article is by using Spatial Augmented Reality (SAR) to project trajectory intentions on shared floor space [6–10]. In comparison to our previous work on SAR intention communication [6,7], we present in this article experiments with a new experimental design that models real-world situations in industrial warehouses. In these experiments, we used upgraded SAR hardware (to improve legibility of the projected intentions on the shared floor space) and eye-tracking glasses, and investigate a new communication pattern.

The second challenge addressed in this work is that robots should interact with humans in a legible way and cooperatively navigate to support safety and efficiency. Robots in human co-habited environments should be aware of people's navigation intentions for, e.g., human-aware task and motion planning, and therefore require a means to infer navigation intentions from observable human cues. In public spaces, an airport, for example, a robot can typically deduce human intentions only with its onboard sensors, e.g., by using RGB-D cameras for trajectory and human head pose estimation [11]. In industrial environments, however, it is possible to issue regulations that require human workers to wear special safety equipment, e.g., safety vests or, as we suggest in this paper, safety eye-tracking glasses. Eye gaze can convey information about intentions beyond trajectory and head pose of a person [12]. Thus, we propose as novel safety equipment eye-tracking glasses, which robots have access to for implicit *human intention transference*. Especially in safety-critical, co-habited workplaces, e.g., warehouses or distribution centers with autonomous forklift trucks, this could reduce the number of accidents and enable more efficient operation. In our study, we investigated the possibility to recognize human navigation intent implicitly expressed through gaze patterns. We set out with the hypothesis that navigational intent can be identified at least to some extent and in some situations from gaze patterns. We analyzed gaze patterns in relation to navigational decisions during human–robot encounters and found that people primarily gazed on that side of the robot they ultimately decided to pass by. We discuss implications of these results and relate to a control approach that uses human eye gaze for early obstacle avoidance. We introduced the concept of using eye-tracking glasses for implicit intention recognition in [13]. In this article we further explore this idea and present an extended evaluation (see Section 4) of trajectories and gaze patterns as well as stimulated recall interviews with the participants (SRI) [14].

In summary, the key contributions of our work are

1 Development and implementation of a Spatial Augmented Reality (SAR) based intention communication system for mobile robots that projects motion intentions on the shared floor space. We present and use a substantial hardware upgrade to increase the visibility of projected intentions, which was important for the study conducted in the chosen more realistic experimental setup.
2 Experimental evaluation of the SAR intention communication system; analysis of eye-tracking and trajectory data from human–robot interaction experiments in which the participants encountered a forklift truck in a realistic experimental setup.
3 Analysis of participants' attention and trajectory selection during their encounters with the forklift truck through stimulated recall interviews - with gaze-overlaid videos as stimulus.
4 The proposition of a method for implicit intention transfer using eye-tracking glasses that robots can access when interacting with a person.
5 Evaluation of eye-tracking based implicit intention transfer for recognition of directional navigation intent.

This paper is structured as follows: Section 2 gives an overview of relevant literature related to intention communication, eye-tracking, implicit intention recognition using eye-tracking, stimulated recall interviews and their application in human–robot interaction. Section 3 describes the hardware and software setup of the SAR based intention communication system, as well as eye-tracking and laser scanner based people tracking, which was needed to analyze the observed trajectories. Section 4 describes the design of the human–robot interaction experiments in which human participants encountered a robot with which they had to negotiate their trajectory. Section 5 describes an implicit intention transference system based on eye-tracking and presents a control approach for early obstacle avoidance using eye gaze in HRI. In Section 6, results from the experiments pertaining to intention communication and implicit navigation intention recognition are presented and discussed. Section 7 concludes the paper and briefly outlines directions for future work.

2. Related work

2.1. Intention communication

The importance of how people position themselves in social encounters has been studied decades ago by Hall [15]. Hall coined the term proxemics to describe physical and psychological distancing between two humans. During a simple task such as walking, humans communicate their motion intentions using different types of cues such as gazes, gestures and by adapting their trajectories according to communicated patterns of motion [16]. It is desirable that robots which operate in environments shared with humans conform to human expectations such that common human interaction patterns do not have to be adapted drastically. Safe and seamless modes of human–robot interaction, which allow humans and robots to occupy the same area, makes many tasks amenable to automation, including collaborative assembly and material handling [17]. Along a similar line, Vitor et al. [18] explored the IEEE ontology for robotics and automation for heterogeneous agent interaction (ORA) [19] through a use case scenario involving HRI. They emphasized the importance of sharing spatial information in HRI and suggested that, in order to achieve a given goal involving HRI, humans and robots should effectively communicate and share their knowledge about the world.

Turnwald et al. [20] focused on understanding the underlying principles of human-human encounters and showed that humans are not only reacting to the current situation but constantly predicting the trajectories of other humans to plan their trajectories. Thus, it can be expected that being able to predict the trajectory of a robot plays a key role for humans in planning their trajectory. Takayama et al. [10] claim that a robot showing its intention reassures humans of their interpretations of robot behavior, thus making the robot more appealing and approachable. This property of a robot is called legibility, which was defined by Dautenhahn et al. [21] and Alami et al. [22] as the ability of a robot to make its actions and behavior understandable and predictable to humans.

In the context of improving the predictability and legibility of a mobile robot, several researchers outline the benefits of revealing the intentions of the robot. Kruse et al. [23] and Lichtenthaler et al. [24] investigated the importance of legibility particularly pertaining to navigation behavior in a mobile robot. Lichtenthaler et al. [24] defined the mobile robot's behavior as legible if a human can infer the next actions, goals, and intentions of the robot with high accuracy and confidence and the robot behavior fulfills the expectations of the human interaction partner. Mangold et al. [25] estimated that humans receive about 85–90% of the information through their visual system and considering this, it is an obvious choice to convey a robot's trajectory intentions in a visual way.

May et al. [26] investigated pass-by situations where a human and a robot navigate through a corridor trying to circumvent each other within given spatial constraints. Similar to this work, the robot indicated its navigation intent. However, instead of SAR, head orientation and visual light indicators (like "blinkers" used in automobiles) were used. May et al. [26] evaluated perceived comfort and ambiguity of the signal with a five-point Likert-scale and the minimum distance to the robot during the interaction. One of the limitations of their work is the small size of the number of participants ($N = 10$). However, the results show a significant improvement in perceived comfort and larger minimum distances maintained by participants when the robot indicated its navigation intent.

Based on the theory of joint attention in HRI, using head orientation to communicate navigation intent of a robot provides a natural way of communicating to humans. However, such a communication modality is restricted to robots with anthropomorphic features, which are absent in industrial vehicles such as AGVs, forklifts, etc. Visual light indicators are a familiar mode of communicating navigation intent to humans which is already used in industrial vehicles. However, this modality has a limitation in terms of expressing detailed navigation information such as future trajectory and context-dependent information. For mobile robots intended to cohabit and collaborate with humans in industrial scenarios, being able to express detailed information in an intuitive manner may be very important, especially considering growing autonomous capabilities. Hence, we propose SAR as a suitable communication modality for mobile robots in industrial logistics scenarios. By using SAR, a mobile robot can communicate detailed navigation information such as its future trajectory, safe and unsafe regions or context-dependent information such as ongoing tasks, warning messages, etc. Coovert et al. [8], Matsumaru et al. [9], Leutart et al. [27], Lee et al. [28], Park et al. [29] and also we in our prior work [6,7] used SAR to reveal a robot's future intentions with encouraging results. In the experiments from our prior work, participants encountered a robot in two conditions, one with *SAR projection ON* and one with *SAR projection OFF*. The response of participants was compared on a seven-point Likert scale for five key attributes: communication, reliability, predictability, transparency, situation awareness. An average rise of 59% on Likert scale ratings was identified for the *SAR projections ON* condition [6]. We also found that the ability of the robot to communicate its future trajectory intentions has contributed to increased trust towards the robot [7]. Participants chose to veer-off from their path earlier in an encounter with the robot, when the robot communicated its future trajectory intentions on the shared floor space, implying that humans planned their path well in advance leading to safer trajectories.

Regarding the hardware setup, the work of Coovert et al. [8] and Matsumaru et al. [9] is similar to ours. They also used a projector mounted on the mobile robot to display the mobile robot's future motion intention on the floor and conducted experiments with human subjects. However, in their experiments, humans did not interact with the robot directly during the experiment. Instead, the participants were asked as bystanders whether they would have interpreted the projected intentions correctly. Key conclusions were that conveying intentions using arrows was easily understood by humans without prior training, made the robot appear more intelligible and gained human's confidence in the robot pertaining to its movements.

Watanabe et al. [30] used SAR for navigation intention communication of a robotic wheelchair and evaluated "human" and "human–robot group" interactions using Likert scale questionnaires and trajectory analysis. Their experimental scenario consisted of a person sitting on the robotic wheelchair as a passenger and the other person as a walking pedestrian engaging in a straight encounter in a corridor setting. Their results show that humans preferred having navigational intention communication and presenting navigational intention lead to smoother human trajectories. Very recently, Moondeep et al. [31] have conducted a study similar to this and our earlier work [6,7] where humans were asked to interact with a robot in various encounters. They had used SAR in combination with an audio channel for navigation intent communication. Their results indicate that using SAR had a more positive impact on the participants perceived ratings when the angle of encounter with the robot was becoming sharper. However, their experiments were conducted in lab settings using a basic robot platform in their experiments similar to the experiments conducted by Coovert et al. [8] and Matsumaru et al. [9]. We have used an Automatic Guided Vehicle built on a custom industrial forklift and conducted experiments that reflect typical encounters in industrial environments and with participants that were directly engaged in the interaction with the robot. As mentioned in the discussion of the limitations of their work [31], perceived feelings in such studies could be impacted by the physical appearance and traits of the robot. Compared to [31], the participants in our study were more diverse and had an equal gender ratio. A further important difference in our work, when compared to related works [8,9,26,30,31] is the evaluation method that uses eye-tracking data along with stimulated recall interviews to get a deeper insight into human behavior during HRI [14,32].

So far, SAR based intention communication systems were primarily evaluated using Likert scale questionnaires. As May et al. [26], Watanabe et al. [30] and Moondeep et al. [31], we additionally analyzed the trajectories of the participants in our prior work [6,7]. In this article, we use a more realistic experimental setup, collected substantially more experimental data, and improved the evaluation by additionally analyzing eye-tracking data and carrying out stimulated recall interviews [14].

2.2. Eye-tracking

Eye-tracking is a sensor technology to measure where the eyes of a human are focused on. It is used in an increasing number of application areas [33], primarily since it comes with the promise that it gives access to mental processes. This belief is expressed in the eye-mind hypothesis [34], which posits that eye gaze is tightly linked to attention and cognitive processes. The eye-mind hypothesis [35] particularly refers to fixations (periods in which the gaze point remains within a small area over a prolonged period of 200 ms up to seconds [33]) and states that there is no relevant delay between what is fixated and what is being processed cognitively. Although this assumption has to be used with care [36,37], it is often applied in the interpretation of eye-tracking data.

The most relevant works pertaining to our application of using eye-tracking in HRI research, particularly in human and mobile robot encounters, have been carried out by Baldauf et al. [38], Patla and Vickers [39], and Hayhoe et al. [40] who studied the relationship between spatial attention of humans and how they planned their future movements. The main conclusion in [38–40] is that the attentional resources of a human are concurrently deployed to multiple locations which are relevant for the following actions. Baldauf et al. [38] also showed that "more attentional resources are allocated to regions immediately following the movement goal, and to those parts that require more precise motor control". We also observed this in our experimental data and discuss this interesting point further in Section 6.1.3.

Directly related to the way we use eye-tracking for evaluation is the work by Patla and Vickers [39] who conducted experiments with participants approaching and stepping over obstacles of varying height while wearing eye-tracking glasses. They analyzed the spatiotemporal gaze patterns and observed that the participants did not fixate on the obstacles as they were stepping over but did plan in advance as they were approaching an obstacle. Hayhoe [40] studied look-ahead fixations, which are fixations that lead to action several seconds later. They also found that the human vision system acts proactively in gathering information ahead of time for future movements. Thus, a mobile robot projecting its future trajectory intentions as described in Section 3.3 is expected to accommodate the proactive nature of the human visual system by supplying information in advance.

2.3. Implicit intention recognition using eye-tracking

It was demonstrated that eye gaze is linked, in time and location, to momentary task requirements, e.g., [39,41–43]. Patla and Vikers [39,42] report that people fixate points on which they will step approximately one second before reaching them (footprint fixation). These findings support our hypothesis that navigational intent can be inferred from gaze patterns.

A first key step in human-to-robot implicit navigation intent transference is the recognition of navigation intent. Huang et al. [44], Admoni et al. [45], Li and Zhang [46] and Castellanos et al. [47] address the similar problem of recognizing human intent in a collaborative manipulation setting in which a robot arm could respond to recognized intentions. Another recent work by Li and Zhang [48] also investigates inference of intentions from gaze data to command a mobile service robot. In comparison to [44–48], our work considers a scenario where both human and robot are mobile. In this article, we study human navigational behavior in a human–robot interaction scenario and investigate the corresponding gaze patterns.

2.4. Stimulated recall interviews

In our previous work [6,7], we analyzed human motion trajectories to determine how a mobile robot projecting its intentions influences human behavior. However, the participants' reasons behind the observed behavior could not be inferred unambiguously in this way. Stimulated recall interviews (SRI) with gaze-overlaid videos as stimulus are a way to get a deeper insight into the underlying processes [14,32]. In our SRIs, the participants are shown the gaze-overlaid video of their encounters with the robot and they are then asked to describe and explain their thoughts in the situation shown.

Hansen [49] points out that gaze-overlaid videos appear to be a stronger stimulus for SRIs than "normal" videos: In his study, Hansen conducted retrospective interviews and observed a significant increase in comments from the participants when gaze-overlaid recordings were used as compared to a normal video-recording. Hansen also points out that the participants rather recall their actual thoughts than "(re-)invent" them when watching the video.

Based on the understanding that SRIs with gaze videos are an appropriate method to obtain a deep understanding of underlying mental processes, we use SRIs in this article in order to gain insight in (1) participants' understanding of the projected patterns; (2) how the different projected patterns ("arrow", "blinking arrow", "line", and "nothing") influenced the participants' perception of the robot's intentions, and (3) how the different projected patterns influenced the participants' decision making when meeting and passing by the robot.

3. Intention communication from robot to human

For intention communication from the robot to a human, we developed a Spatial Augmented Reality (SAR) based intention communication system on a mobile robot that can convey the robot's motion intentions by projecting patterns on the shared floor space. Our previous work [6,7] indicated that this form of intention communication can improve comfort levels and perceived safety in human–robot encounters and can lead to humans choosing safer paths around the robot. In comparison to [6,7] the SAR based intention communication system was upgraded and new projection patterns were considered. The hardware and software setup of this system is described in the following sub-sections.

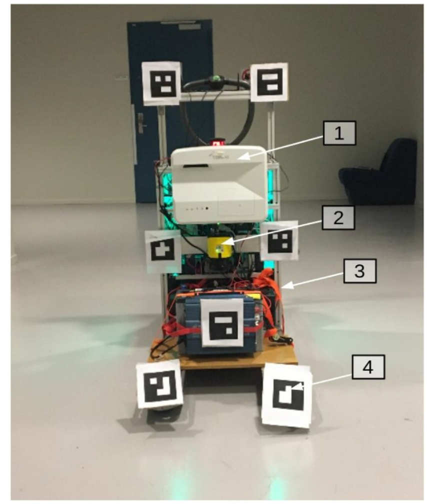


Fig. 1. The platform used for our experiments: A standard short throw projector (Optoma X320UST) (1) is mounted on a retrofitted Linde CitiTruck AGV (3). The projector is used to project the intention of the vehicle on the ground plane in front of the truck. Two SICK S300 scanners are mounted in front (2) and back to ensure safety for participants and for tracking the participant motion during the experiment. Label (4) represents the fiducial markers placed on the robot for eye-tracking data analysis.

3.1. Robotic platform

The robotic platform we use is built based on a manually operated forklift which is equipped with motorized forks and a drive wheel (see Fig. 1). The forklift has subsequently been retrofitted with a steering mechanism and a commercial AGV control system. The latter is used to interface the original drive mechanism, as well as the steering servo. To assure safe operation, the vehicle is equipped with two SICK S300 safety laser scanners[2] respectively facing in forward and backward directions. The laser scanners are also used to track people when they interact with the robot. The speed of the robot during the interactions described in this work was set to 0.6 m/s.

3.2. Spatial augmented reality system

Ideally, the coverage of the projected floor space should enclose the area around the vehicle and be sufficiently large to allow displaying the intention of the vehicle over a time horizon of at least 3 s. It is, however, hard to realize full coverage of the whole 360 ° around the robot. So, we selected the most important cone in the forward direction, which is sufficient as the robot drives only forward in our experiments and the projected area was always between the person and the robot during the encounters.

In the experiments performed in this work, we used a short throw projector, Optoma X320UST, with 4000 ANSI lumens. This is an upgrade from our earlier setup [6] where we used a standard projector

[2] http://www.sick.com/ .

Optoma ML 750 with 700 ANSI lumens. In both cases, the projector was mounted pointing in the direction of the forks as shown in Fig. 1. The motivation behind this upgrade was to increase the visibility of projected intentions in brightly lit environments like warehouses and also to increase the FOV so that the projected patterns are larger and clearly visible from a distance.

The projector is connected to an onboard computer which renders images using an available pose estimate of the vehicle's location together with information regarding the current mission. The navigation system is detailed in [50] and is briefly described below. During the experiments, the robot followed paths which are generated by using a two-step approach which combines a lattice-based motion planner and a smoothing operation. These paths are pre-computed and not modified during the trials. The path generated by the lattice-based motion planner is used as the initial path in an optimization framework, which subsequently minimizes the amount of turning and driving. The smoothed path is then used to generate a trajectory (in which constraints on maximum accelerations and velocities are fulfilled). The trajectory describes the vehicle state $s = (x, y, \theta, \phi)$, consisting of the vehicle pose (x, y, θ) and steering angle ϕ. The control variables u comprise forward velocity and change in steering angle $u = (v, \omega)$ as the forklift base is equipped with a combined steer and drive wheel. The generated trajectory is finally tracked by a model predictive controller (MPC).

3.2.1. Calibration of the spatial augmented reality system

The projected images are rendered with the GLUT framework, using the reference frame provided by the navigation system. This allows us to render the image to be projected by updating the pose of a virtual camera (in the GLUT framework) using the localization estimate of the AGV along with extrinsic calibration parameters (*i. e.*, the pose of the projector/virtual camera expressed in an AGV-fixed coordinate frame).

The calibration approach is summarized below, for further details we refer the interested reader to [6]. There are two main components involved in drawing the pattern on the floor. First, the procedure to render the image, which is dependent on the location and the parameters (*e. g.* focal length) of the virtual camera. Second, the used projector also contains a set of parameters, such as the focal length of the projector, which needs to be estimated. Therefore, the pattern generated on the floor will depend on two sets of parameters, one set from the virtual camera (used to render the image in the GLUT framework) and one set from the projector.

Rather than estimating all parameters separately we perform a calibration step which involves determining only 7 parameters – 6 containing the pose of the virtual camera (x, y, z, roll, pitch, yaw) and a scale parameter s that is used to tune the aspect ratio of the projected image. Note that we assume that the projector only has very small distortions in the projected image (i.e., we assume that a straight line will be projected as a straight line) and that no distortion parameters need to be estimated.

To perform the calibration, an evenly spaced 2D grid with a fixed size of 0.15×0.15 m is used. This grid is then projected onto the floor using the known origin of the common reference frame and the calibration parameters. A grid was selected since it facilitates to manually measure lengths on the floor, to check that there is no distortion in the projected area, for example, to verify that all lines are parallel. The calibration procedure requires to adjust the roll and pitch parameter so that the grid angles are orthogonal and lines are parallel, to adjust the scale parameter s so that the cells are square, to adjust the height z so that the size of the cells is correct, and to adjust x, y so as to align the origin with the point between the two fixed wheels at the forks (the origin of the AGV reference frame). The calibrated projector should then replicate the 2D grid pattern on the floor without any distortions (i.e., properly aligned, with the correct size, orthogonal angles and parallel lines).

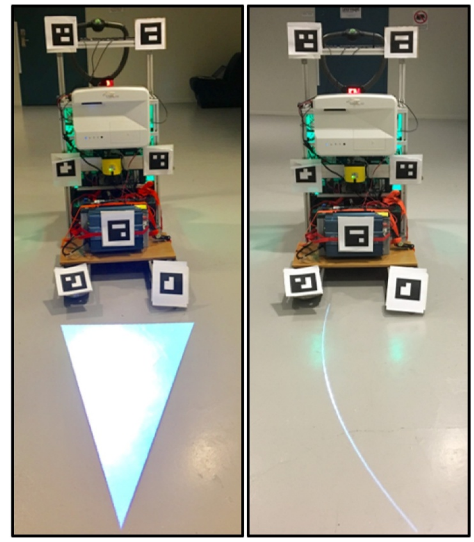


Fig. 2. AGV communicating its future trajectory intentions. Four patterns were defined to be used in the experiments - 1. Line (Right), 2. Arrow (Left), 3. Blinking Arrow (Arrow that blinks at 1 Hz) and 4. Nothing.

3.3. Communicated intentions

During the experiments, every participant encountered the robot 4 times, each time with a different pattern being projected on the shared floor space. The four chosen patterns, shown in Fig. 2, were:

(A) Line (indicating the path the robot intended for the next 5 s)
(B) Arrow (indicating the current driving direction of the robot)
(C) Blinking Arrow (Arrow mentioned in (B) blinking with 1 Hz)
(D) Nothing (baseline condition)

Patterns A, B, and C were selected since it can be assumed that they can convey the future trajectory of the mobile robot in an intuitive manner. They are not intended to replicate the way in which people communicate their intentions, but rather to explore the additional possibilities a robot has. Pattern A represents an equivalent to the projection already used in our previous experiments [6], which depicts the future trajectory over a time horizon of 5 s while patterns B and C communicate less detailed information using an arrow pointing along the instantaneous movement direction.

An arrow was chosen for several reasons. Bertamini et al. [51] provide evidence that angles attract attention and work by Bar and Neta [52] suggests that the human brain can detect sharp features very fast since they signal potential danger. Larson et al. [53] showed that a triangle with a downward-pointing vertex is recognized more rapidly than the identical shape with an upward-pointing vertex. Also, Matsui et al. [54] used arrows to indicate the intention of their robot and concluded that their system was found intelligible by humans. Furthermore, people are used to arrows indicating directions in everyday life. Accordingly, we believe that using an arrow to communicate the future path of a robot is a good choice. In order to observe the baseline behavior when encountering a robot, the last condition D is Nothing at all. During the experiments, the order of the patterns in which the participants encountered the robot was varied in a balanced Latin square pattern to avoid learning effects.

4. Experimental evaluation

Significant improvements have been made in this work regarding the evaluation method and experimental design compared to our previous work [6,7]. We propose an extended evaluation method for evaluating HRI scenarios using trajectory data, eye-tracking data along with SRIs (see Fig. 3).

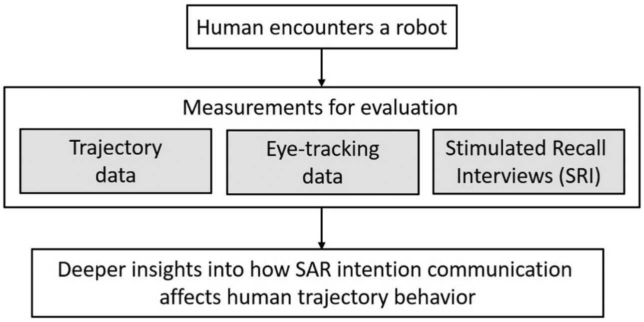


Fig. 3. Outline of the experimental evaluation.

4.1. Eye-tracking data

For acquiring eye gaze data we used a mobile eye-tracking headset from Pupil labs [55]. It is equipped with a high-speed world camera with a resolution of 1920 × 1080, recording at a frame rate of 30 fps and two infrared spectrum eye cameras with a resolution of 640 × 480, operating at a frame rate of 120 fps. Scene capturing was done using the open source software Pupil Capture. Categorization and analysis were done using the open source software Pupil Player [55]. Fiducial markers were attached to the robot in different places in order to define the areas of interest, thus, enabling an automatic categorization of the detected eye gaze fixations.

4.1.1. Eye-tracker calibration

Considering the mobile nature of the experiment, manual marker calibration [55] was used. In this calibration method, a printed marker is held at different positions in the field of view of the participant who is asked to focus on the center of the marker. With this calibration method, it was possible to calibrate on greater distances than with screen-based calibration and also to cover a greater field of view. In our calibration, the participant stood approximately 2 m away from the marker, which was moved and held at 12 different positions (4 horizontal rows with 3 positions per row). The accuracy of the calibration was tested by asking participants to focus on the center of the marker and observing the tracked gaze position on the computer screen.

4.1.2. Areas of interest

During the experiment, we are primarily interested in finding out how the participant's attention was distributed, especially when it was on the robot or on the projection. Hence, two areas of interest – AOI-R (for robot) and AOI-P (for projection) – were defined as shown in Fig. 4.

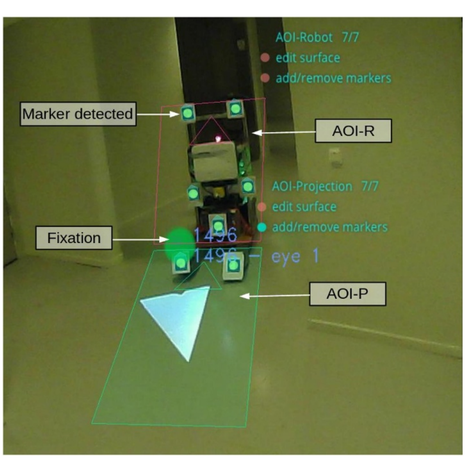


Fig. 4. The defined Areas of Interest - AOI-R ("R" for robot) and AOI-P ("P" for projection) as they are being tracked using the fiducial markers attached to the robot. Fiducial marker detections and fixation can also be seen in the figure.

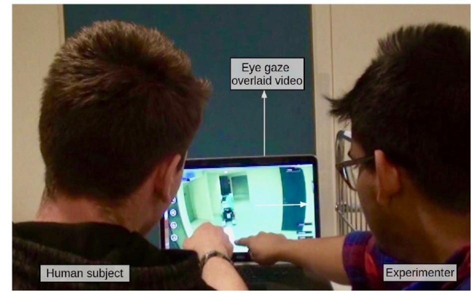


Fig. 5. Stimulated recall interview in process. The participant and the experimenter can be seen discussing a fixation. (A written informed consent has been taken from the participant before using this image. This image is published with permission from the copyright holder).

Fiducial markers attached to the robot allow tracking these surfaces and extracting the corresponding fixation data. Fixations were extracted using the Pupil Player software following the recommendation of Blignaut [56] to use threshold values suggested by Holmqvist et al. [33]: a minimum duration of 150 ms and a minimum dispersion of 1°.

4.2. Trajectory data

A SICK S300 laser scanner was mounted on the AGV as shown in Fig. 1. It recorded data that allowed to extract the trajectory data of the participant with respect to the trajectory of the robot during the experiments.

4.3. Design of stimulated recall interviews

To study how the participants' understand the projected patterns and how they make decisions (Section 2.3) we conducted SRIs. For this purpose, we used gaze-overlaid videos produced with the Pupil Player software [55].

The gaze-overlaid video was then jointly viewed by the participant and the experimenter as shown in Fig. 5. An example video from the experiments can be viewed at https://youtu.be/Mh9wGPkGNCM.

Initially, the experimenter explained how to identify the gaze point in the gaze-overlaid video. After this explanation, the participants were asked to comment on their eye gaze movements while perusing the video. The experimenter also asked questions during the SRI, addressing the participants' understanding of the projected patterns and their interpretations of the robot intentions, as well as their decision making. The questions are described in detail below.

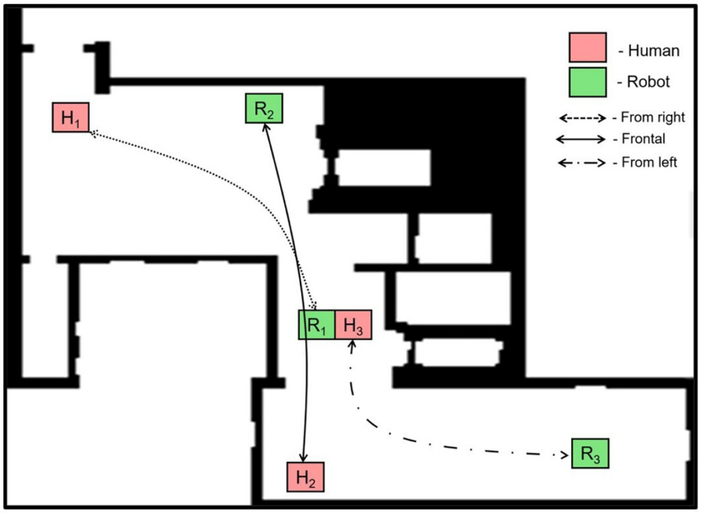
4.3.1. Questions concerning the understanding of the projected patterns

The experimenter asked the participants (1) if they could clearly see the projected patterns and (2) how they interpreted it. These questions were repeated for every projected pattern. The experimenter further asked (3) whether the participants found the patterns necessary or in any sense disturbing.

To determine how the participants interacted with the projected patterns, the experimenter asked (4) how the participants were perceiving the patterns, whether (5) they felt a tendency to not step on the projected pattern, (6) why they were looking at the robot or the projection or elsewhere, and (7) the participants' perception of the robots' behavior, in particular, whether they experienced a different behavior in each trial and (in case they did) why.

4.3.2. Questions about the participants' decision making

The second set of questions relates to the participants' navigation behavior. The experimenter asked (8) in which way certain fixations (which were selected depending on the situation by the experimenter) were relevant for planning their trajectory, (9) the participants' strategy in encountering the robot, and (10) whether the participants



Task	Human	Robot	Encounter
1	Position $H_1 \rightarrow$Position R_1	Position $R_1 \rightarrow$Position H_1	From right
2	Position $H_2 \rightarrow$Position R_2	Position $R_2 \rightarrow$Position H_2	Frontal
3	Position $H_3 \rightarrow$Position R_3	Position $R_3 \rightarrow$Position H_3	From left

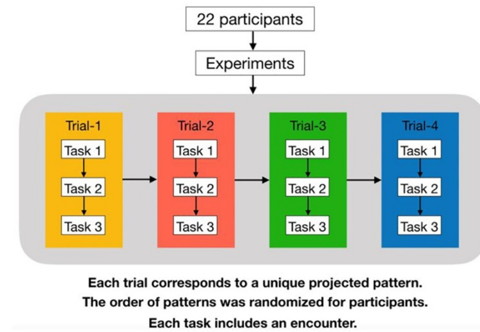


Fig. 6. Experimental design: During the experiment, the participants (denoted by H_i) were asked to move from H_i to R_i and the small forklift robot (denoted by R_i) moved from R_i to H_i. This is shown in the basement layout plan and the table on the top-right panel.

experienced the projected patterns as providing useful information for planning their path and making decisions.

4.3.3. Analysis of the stimulated recall interviews

All SRIs were recorded using a video camera (with the consent of the participants). The recordings were then systematically analyzed as follows.

Step-1 – Summarizing the information: All video recordings were watched and summarized. This was not merely converting the audio to text format, but also looking at the respective video frames to note the observations in order to get a complete picture for further analysis.

Step-2 – Classifying into categories: The information collected in Step-1 was categorized in a second step based on the two categories mentioned above (understanding of the projected patterns, and decision making). Additionally, on a more general level, we analyzed whether the participants had an overall, general strategy (spanning all patterns), or favored a specific pattern.

4.4. Experimental design

The setup of our experiments is shown in Fig. 6. This setup was chosen since it necessitates tight encounter situations between the human and the robot that reflect typical encounters in industrial environments. We define an encounter as *a sequence in which a human and a robot are getting closer to each other in space while the human can perceive the robot*. This means that the human's behavior can be influenced by the robot during an encounter. In our experiments, the robot was moving with a constant speed of 0.6 m/s.

Every participant was asked to move as shown in Fig. 6. Each experiment was divided into four trials with each trial corresponding to a unique projection pattern. The order of patterns was randomized to counterbalance learning effects. Each trial consisted of three tasks and each task included an encounter between the participant and the robot. The robot was always following a predefined path. The robot's path was designed so that it was necessary for the human to veer-off from the shortest path to the right or left in order to pass the robot and reach the given destination. This corresponds to typical real-life encounters in industrial environments. A video visualizing the predefined paths traversed by the robot can be found at https://youtu.be/je0mROu6PdQ.

The distances at which the robot was first perceived by the human were approximately 8 m, 14 m and 11 m for Task 1, Task 2 and Task 3, respectively. During the experiments, an emergency brake was activated that would stop the robot if a participant came too close (less than 0.3 m). This situation did not happen in our experiments, however.

The experimental procedure in detail was as follows: First, the participants were greeted and introduced to the experiment. They were then asked to fill out a general questionnaire and sign the consent form. Next, the inactive robot without projection was shown to familiarize the participants with the platform. This was done to make the first trial more comparable to the following trials. The experimenter then explained what the participant was supposed to do and what the robot will do during the tasks and walked them through the experimental environment, see Fig. 6. The participants were informed about safety considerations during their encounters with the robot.

After the participant confirmed that he/she understood, the eye-tracking glasses were set up. This typically included adjusting the eye cameras such that the pupil was robustly detected. Furthermore, the eye tracker needed to be calibrated as explained in Section 4.1.1.

The actual experiment then started by activating the recording of the eye-tracking data. The participants started walking to their first destination on a verbal signal from the experimenter. In the same way, the remaining tasks and trials were initiated by a verbal signal.

After all trials, the Stimulated Recall Interview was conducted. The whole experiment took approximately 55–75 min, of which the introduction and setup took about 20–30 min, the actual trial took 20–30 min and the interview about 15 min.

An ethics approval was not required for our study as per institutional guidelines and the Swedish Ethical Review Act (SFS number: 2003:460). Written informed consent was obtained from all participants. Due to the relatively low weight of the robots used in this study and the safety precautions taken, there was no risk to harm participants in the experiments.

5. Implicit intention transference from human to robot

Robots that operate in human co-habited environments such as airports [11] need human-aware task and motion planning. As in [11] detection and tracking of humans is often done by using RGB-D cameras and laser range scanners mounted on the robot. The RGB-D cameras are also used to identify human intentions through head pose estimation [11]. We believe that eye gaze can convey information about human intentions beyond trajectory and head pose of a person. Especially in safety-critical workplaces, such as warehouses or distribution centers, for example, an employer could require the workers to wear eye-tracking glasses - similar to the requirement to wear safety vests nowadays - to improve safety and enable smoother and more efficient

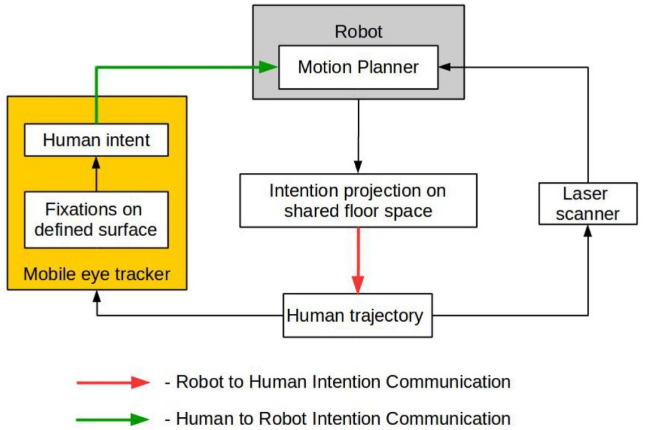


Fig. 7. Concept of a system with implicit intention transference and SAR intention projection. Implicit intention transference and SAR intention projection are evaluated in this article but not the entire closed-loop system shown.

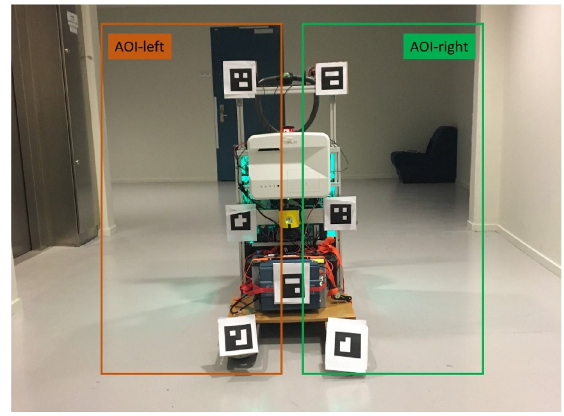


Fig. 8. Robot platform used for the experiments and the pre-defined areas of interest (AOI): AOI-left (Orange) and AOI-right (Green). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

operation of human and robot workers.

Safe and efficient human–robot interaction in industrial settings will benefit from robots that are able to respond to expressions of human motion intentions as soon as they can be inferred from human eye gaze. In this article, we investigate the applicability of the idea of Implicit Intention Transference through eye-tracking glasses in the case of a specific human navigational behavior (deciding whether to veer-off to the left or the right) in a specific scenario. We see this as a first step that contributes towards the future development of eye gaze intent predictors that can be integrated into task and motion planners used in robots. Based on our results regarding the detection of the intended veer-off direction, we propose in Section 5.2 a control approach that uses implicit intention transference. The concept of a system, that combines the two main contributions of this work, Implicit Intention Transference and SAR intention projection on the shared floor space, is shown in Fig. 7. We like to note, however, that an evaluation of the entire closed loop system visualized in Fig. 7 is out of the scope of this article.

5.1. Recognition of human navigation intent

In the experiments described in the Section 4.4, each participant had 12 encounters with the robot, corresponding to 12 decisions whether to pass the robot to the left or the right. During the encounters, the robot projected its navigational intent on the shared floor space using four different patterns: Line, Arrow, Blinking Arrow, and Nothing. We are primarily interested in finding how the gaze patterns of the participants were distributed on the left and right side of the robot in relation to their implicit navigation decisions. Hence, two areas of interest: AOI-left and AOI-right were defined as shown in Fig. 8. The dimensions of AOI-left and AOI-right were chosen after manually checking the gaze-overlaid videos so that the defined AOIs captured most of the relevant gaze points around the robot at the encountered distances. We investigate the distribution of gaze points rather than fixations [57] to avoid issues with fixation detectors [33].

5.2. Control approach for early obstacle avoidance using eye gaze

The principle of bilateral communication and interaction [5] in Fig. 9 describes human–robot interaction when the intentions of a human co-worker to move towards a certain goal are recognized by a robot. Human and robot are driven by their individual goals from which desired trajectories x_{H_d} (estimated from human's gaze) and x_{R_d} (obtained from the robot's internal and external sensors) and possible intersections are computed. x_{H_d} and x_{R_d} include both positions and orientations. For robots, it may also be possible to use motion or task primitives as reported for articulated robots in [58,59]. Actions and reactions in this scheme act to achieve desired states $x_{H_d}(t_i)$ and $x_{R_d}(t_i)$ in the shared environment. The interaction of the two agents leads to observable states $x_H(t_i)$ and $x_R(t_i)$ at time t_i. Let the human intention become apparent at the beginning or at an early part of the trajectory $x_H(t_k|k = 1,...,m)$. The variable m is the time horizon that is available to the robot to recognize the human intention. Trajectory information is communicated to the robot with a delay T_{d_H}. Then the robot starts the intention recognition and begins to plan/compute a reaction $x_{R_d}(t_i)$. The intention to react is realized as a part of the trajectory of the robot $x_R(t_k|k = j,...,n)$ where $(n - j)$ is the corresponding time horizon during which the human tries to recognize the robot's motion intention.

We assume that the robot can measure its own position and orientation as well as the position of the human. The robot further has a view on the scenario by an onboard camera (scene camera). The intended goal of the human is determined with the eye-tracking device and the scene camera. The eye-tracking device sends significant parameters (focal length of the camera, camera geometry, fixations or gaze points) the robot, which calculates the orientation angle towards the current goal of the human. The required robot actions are then planned and performed using the information about $x_{H_d}(t_i)$ and $x_{R_d}(t_i)$. Crucial information is the intersection point of two planned trajectories which can be straightforwardly computed geometrically [60]. This can be seen in Fig. 10 which shows the relationship between the intersection point (crossing), the positions/orientations of the robot and human and the distances and angles related to the coordinate systems of the human and the robot. This computation helps the robot to plan trajectories early enough to avoid collisions with humans.

6. Results and discussion

Altogether 27 experiments were conducted with one participant each. Of these, 22 experiments were completed successfully. The rest of them had to be discarded due to technical failures during the experiments. Of the successful 22 experiments, the participants had a 1:1 gender ratio with a mean age of 28.45 years and a standard deviation of 6.47 years. Three of the participants had previous experience with robots though not with the same robot used in our experiments. The participants had diverse backgrounds pertaining to their country of origin, study, and work. Two of the participants had a background in computer science. The rest of the participants had backgrounds in chemistry, biology, mathematics, social sciences, film production, nursing, and economics. Four of the participants were left-handed. Every participant has done 4 trials in varying order, with 3 tasks in each trial as shown in Fig. 6. The following sub-sections present and discuss,

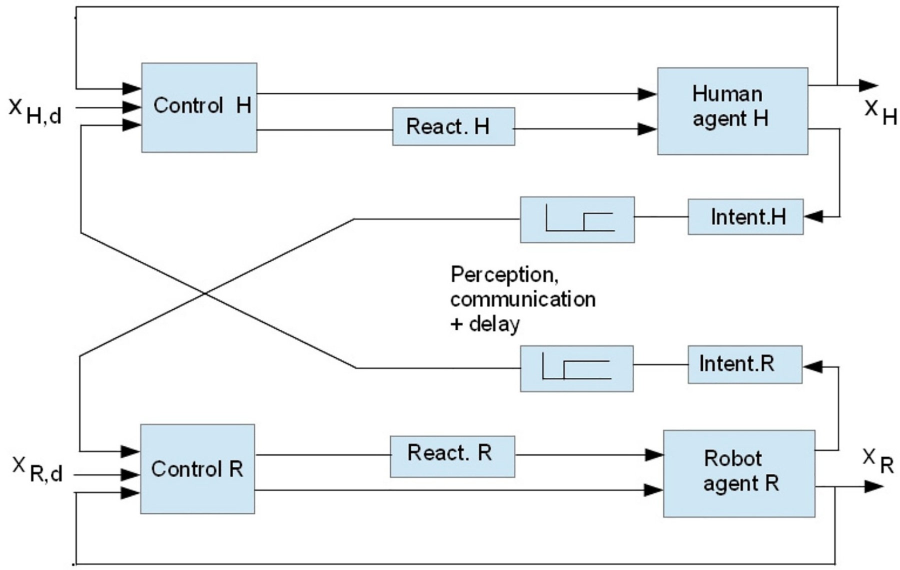


Fig. 9. Human–robot interaction block scheme that includes mutual intention recognition with a certain time delay.

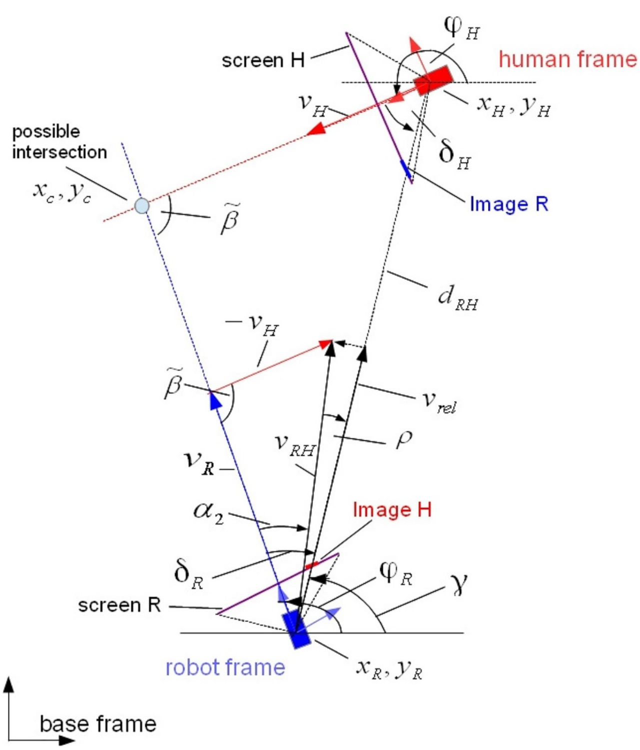


Fig. 10. Human–robot scenario.

first, the results pertaining to intention communication from robot to human – i.e., the evaluation of eye-tracking and trajectory data as well as SRIs (Section 6.1), and, second, the results about implicit navigation intention recognition (Section 6.2).

6.1. Intention communication from robot-to-human

6.1.1. Analysis of eye-tracking data

We analyzed eye gaze data to study to how human attention was distributed between the robot (AOI-R) and the area in which the intention was projected (AOI-P), conditioned on the type of projected pattern. Fixations from all trials including all participants were extracted and a boxplot of the number of fixations on each AOI with respect to the projected pattern and for all conditions is presented in Fig. 11. Please note that in the case of no intention projection ("Nothing"), the projection area of interest AOI-P is the same area as in the other conditions, i.e. where a projection would have been. For the definition of AOI-P see Section 4.1.2 and Fig. 4.

To identify which projection pattern had the most significant effect on human attention, percentage of fixations on AOI-P with respect to each projected pattern was compared by carrying out one-way analysis of variance (ANOVA) test. To identify which two groups had a statistically significant difference, we conducted post-hoc Tukey's honest significant difference (HSD) test. In order to test for possible effects of the order in which trials were carried out, we also ran an ANOVA test after grouping the data by trial number. The results are presented and discussed below.

Influence of projection pattern on the number of fixations on AOI-P: The ANOVA result, $F(3, 84) = 2.94$, $p = 0.038$, indicates that the projected pattern had a significant effect on the number of fixations on AOI-P. The post-hoc test showed a significant difference between the projection patterns "Blink" and "Nothing". A possible explanation can be found in the SRIs (see Section 6.1.3) where participants said that *the "Blink" pattern immediately caught their attention and they looked at the pattern every time the arrow appeared*. The participants also mentioned that *they felt they did not have to look repeatedly at other projections, which were intuitive and allowed to grasp the information immediately*. This can possibly explain why there is no significant difference between "Line", "Arrow", and "Blink" with respect to the number of fixations on AOI-P.

Projection vs. no-projection condition: To identify how the projection of any of the patterns used in this study influenced the number of fixations on AOI-P compared to the condition no-projection ("Nothing"), we carried out a *t*-test, comparing the average number of fixations on AOI-P for patterns A, B, C to the average number of fixations on AOI-P for pattern D. This test rejects the null hypothesis with $p = 0.0092$, indicating that projecting intentions in any form (pattern A, B or C) attracted fixations.

Influence of projection pattern on the number of fixations on AOI-R: The ANOVA result for the number of fixations on AOI-R, $F(3, 84) = 2.33$, $p = 0.0805$, indicates that the projected pattern did not have a significant effect on the number of fixations on the robot (AOI-R). This could imply that the projections were not found to be distracting.

Influence of trial order on the number of fixations on AOI-P and AOI-R: The ANOVA tests grouped by trial number indicate that the

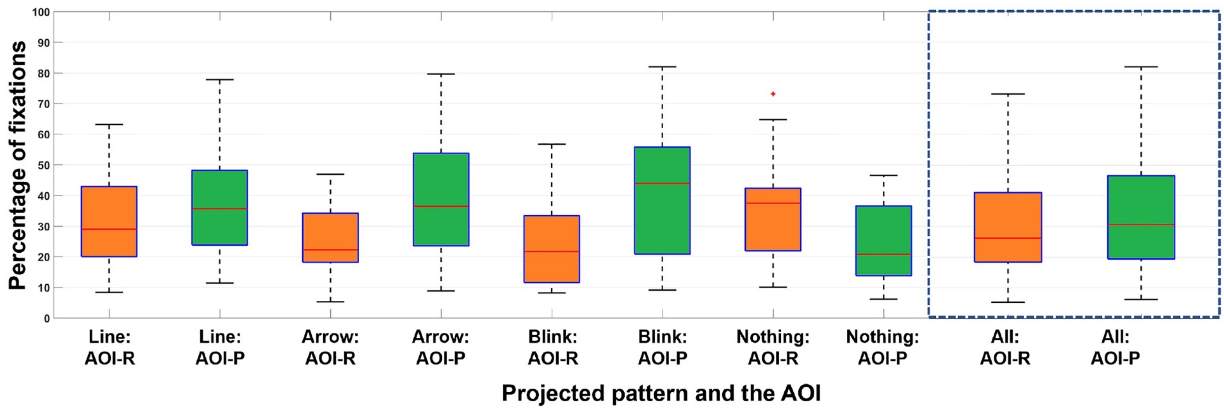


Fig. 11. Boxplot of the number of fixations on the robot (AOI-R) and projection (AOI-P) with respect to the projected pattern and for all conditions (in the dotted box).

order of the trials did not have a significant effect, neither for the number of fixations on AOI-P ($F(3, 84) = 0.76$, $p = 0.522$) nor for the number of fixations on AOI-R ($F(3, 84) = 0.88$, $p = 0.637$). This suggests that the participants did not experience a significant learning effect over subsequent trials in our experiments.

6.1.2. Analysis of trajectory data

A key parameter that we use in our trajectory analysis is veer-off distance, defined as *the distance between the robot and the point at which the participant starts to deflect from their original trajectory while approaching the robot in order to pass it*, see Fig. 12. With this operationalization, we try to capture the distance at which the human makes a decision to pass the robot to the left or the right. The veer-off distances have been extracted from the laser scanner data using standard ROS tools. A boxplot of the veer-off distances with respect to the projected pattern is presented in Fig. 13. To determine how the projected pattern influenced the veer-off distances, we carried out statistical tests as described below.

Influence of projection pattern on veer-off distance: We carried out another one-way ANOVA test to determine how the projected patterns influenced the veer-off distances of the participants. The result, $F(3, 84) = 25.9$, $p = 5.84e - 12$, indicates that the projected pattern, in fact, had a significant effect on the veer-off distance. As described above, we then used Tukey's honest significant difference test post-hoc to determine, which patterns had led to this significant effect. We found

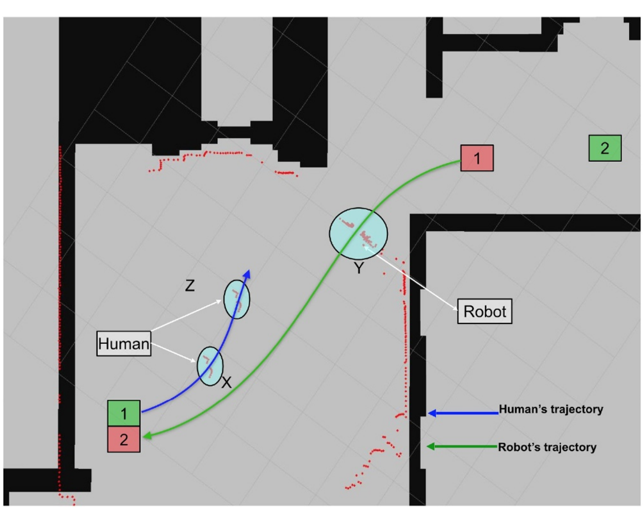


Fig. 12. Definition of veer-off distance as the distance between the point X at which the participant starts to deflect from their approaching trajectory and the location Y of the robot at that point in time.

that there is a significant difference between the projection patterns "Arrow" and "Nothing", "Blink" and "Nothing", and "Line" and "Nothing". The mean and standard deviations of the veer-off distances for each condition were: Line: 2.65 m ± 0.23 m; Arrow: 2.87 m ± 0.38 m; Blinking Arrow: 2.62 m ± 0.37 m; Nothing: 2.01 m ± 0.34 m, see Fig. 13.

Influence of trial number on veer-off distance: A further one-way ANOVA test with grouping by trial order indicates, $F(3, 84) = 1.72$, $p = 0.1697$, that the order of the trials had no significant effect on the veer-off distances. This again suggests that the participants did not experience a significant learning effect in subsequent trials in our experiments.

Projection vs. no-projection condition: To find out how any of the projections used in this study influenced the veer-off distance compared to the condition no-projection ("Nothing"), we conducted a *t*-test as above, i.e. comparing the average veer-off distance for patterns A, B and C with pattern D. Here, the null hypothesis was rejected with $p = 4.6134e - 09$, indicating that projecting intentions led humans to veer-off at significantly larger distances. The veer-off distances for the projection group were 2.72 m ± 0.28 m, compared to 2.01 m ± 0.34 m if no projection was used (pattern D).

Our results imply that the projection of intentions (as it was realized in our work) has a significant influence on how humans plan their trajectory around the robot. This is further supported by the results of the SRIs (see Section 6.1.3), where participants mentioned that *they perceived the projected patterns as a part of the robot and did not want to walk over it.*

6.1.3. Analysis of the stimulated recall interviews (SRIs)

We analyzed the Stimulated recall interviews of the 22 participants for which we could record gaze data over the full time of the experiment with a deductive approach. In the following, we first outline general findings (Section 6.1.3.1), spanning all projected patterns. After this, we elaborate on each pattern respectively. The following results emerged from the participants' reports on their evaluations about the robot during SRI. We describe our conclusions about the participants' understanding of the projected patterns, their interpretations of the robot's intention, and their decision making.

6.1.3.1. SRIs: General insights. The most commonly expressed strategy of the participants in their encounters with the robot was to choose the direction depending on how big the available clearance space was. Some participants chose to wait and let the robot go first. Others took a proactive approach to avoid the robot. In the SRI, the participants explained that they established a link between robot and projection in the first few seconds and that they observed the motion of the robot to fully understand the connection between projected pattern and the

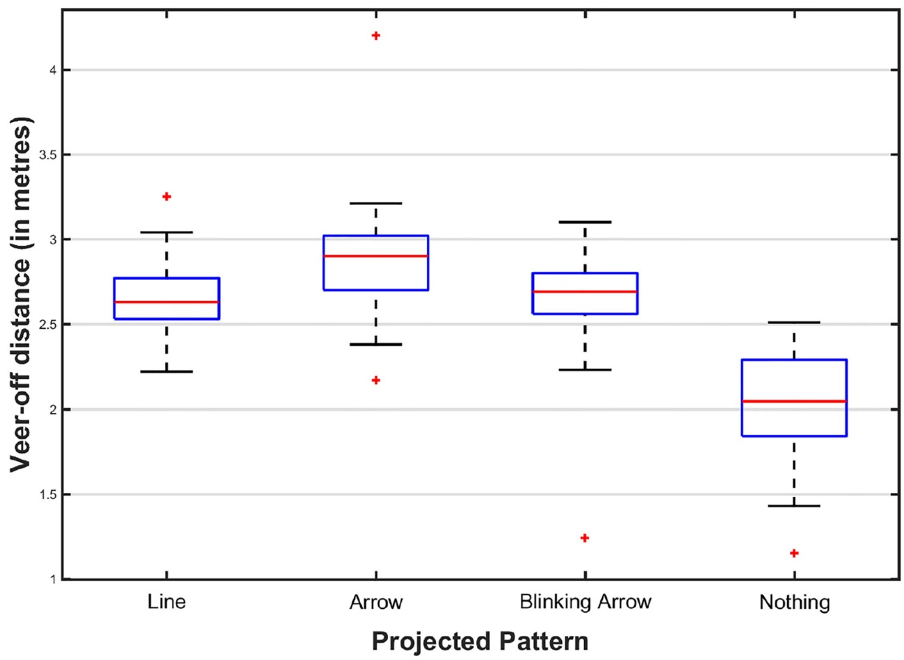


Fig. 13. Boxplot of veer-off distances (in meters) with respect to the projected patterns.

robot's motion. Most participants reported that they understood the pattern intuitively. Once a communication link was established, it appeared to be obvious that the robot would follow the motion intention projected. The projected intention increased the participants' confidence in the robot and allowed them to make navigation decisions quickly. The SRIs are summarized in more detail below.

Detailed SRI results: understanding and experience of the projected patterns: All participants reported that they intuitively understood the projected intentions. None of them reported that the projections were disturbing. The participants perceived the projections as part of the robot and said that encounters were easier than without a projection. 18 participants reported that the intention projection was necessary for such encounters with the robot, three reported that it was not necessary, and one participant reported that it was not necessary given the slow speed of the robot (0.6 m/s). At the same time, a participant said, that intention projection could be very useful for robots moving at higher speeds. All except from five participants tried to avoid stepping on the projected patterns. The five exceptions reported that they stepped on the projection on purpose to see what happens.

Three participants mentioned that from a distance they focused mostly on the projection in order to plan their path. Once they were close to the robot, however, they focused more on the robot itself to make sure they were staying away from it. Similar observations were found in previous studies [38]. Eighteen participants reported that the projected intention was helpful in making their decision about how to encounter the robot. Two participants reported that the projection was useful but did not feel the need for it as the robot was perceived to be obvious enough. Two participants did not see a need for intention projection at all. Eight participants expressed that the projection was especially useful during encounters in narrow spaces.

6.1.3.2. SRIs: Results with respect to the different projected patterns. Below we summarize the results of the SRIs related to projection patterns.

SRI results pertaining to the line pattern: Nine participants said that "Line" was the best pattern in terms of intention transfer and that they easily understood this pattern. They perceived the "Line" projection as part of the robot and emphasized that it does not claim as much space as the pattern "Arrow". Some of the participants reported that it was appropriate even to walk over the "Line" pattern. However, some participants also reported that the "Line" did not give them an appropriate sense of clearance information as it is thin compared to the size of the robot.

SRI results pertaining to the arrow pattern: Eleven participants reported that the "Arrow" pattern was immediately clear, obviously linked to the robot and that they did not have to further reflect on the role of the projected pattern. Some of them also reported that the "Arrow" gave less information than the "Line", but expressed they experienced this amount of information as just right for the given situations. Correspondingly, some participants reported that the pattern "Line" gave more information than required. Most of the participants reported that they preferred the "Arrow" over the "Blinking Arrow" pattern as it was perceived to give information in a more consistent manner. Some of the participants reported that it took less attention to focus on the "Arrow" pattern compared to the "Blinking Arrow" pattern, because of the effort to refocus on the reappearing arrow. Some of the participants also reported that the size of the projected arrow (which is designed to be almost as wide as the robot) gave them a good idea of how much space the robot was going to occupy. On the other hand, some of the participants reported that the "Arrow" pattern was strongly claiming space around the robot, which was perceived as unpleasant in narrow cross sections. In this respect, the "Line" pattern was preferred, as it was perceived to leave more space for the human.

SRI results pertaining to the blinking arrow pattern: The participants of our experiment mentioned in the SRI that every time the blinking arrow re-appeared, this absorbed their attention momentarily and in some cases the eye-tracking data show that the attention was switching between the robot and the projection synchronized with the frequency of the blinking arrow. Accordingly, some of the participants reported in the SRI that the blinking arrow required more attention in comparison to the continuously projected arrow. Some participants even reported that the blinking arrow was confusing and that they felt they lost information when the arrow vanished. Along these lines, most of the participants expressed that they experienced the blinking arrow as best for catching attention. In the long run, however, the robot appeared more reliable if the arrow was projected without interruptions.

SRI results when no pattern was projected: Two of the participants reported that they were not feeling confident without any projected pattern because it was unclear what the robot was going to do next. Especially in narrow passages, this led to uncertainty among the participants. One of them even reported being scared in narrow spaces when the robot was approaching. This corresponds to the trajectory analysis in Section 6.1.2, which showed that the participants came closer to the robot when no pattern was projected. Indeed, two participants mentioned that they felt the robot came too close and that it was following a strange path compared to the trials with a projection.

As a result of the SRIs, we tentatively conclude that projecting an arrow to communicate the robot's navigation intentions appears to be the best choice among the selected patterns (for the given experimental conditions). The information communicated by an arrow was intuitively clear to the participants and was experienced as providing the required information, thus, leading to a high level of perceived safety. We also found that many of the participants perceived the projections as a part of the robot, which encouraged them to choose safer trajectories with the point of closest approximation during the encounter further away than in the trials without a projection.

6.2. Implicit navigation intention recognition

In this section, we investigate how well the directional navigation intention of the human participants can be inferred (implicitly) from their tracked eye movements. During the encounters, we therefore extracted the number of gaze points on AOI-left and AOI-right (see Fig. 8) and computed the relative percentages $GazePt_{left}$ and $GazePt_{right}$. We considered all gaze points in the time span ranging approximately between 2 and 5 s during which the fiducial markers were visible and could be tracked. We use 264 decisions (22 participants and 12 encounters) in our analysis. The decisions of the participants to go left or right were identified manually from the recorded video and assigned to categorical numbers: $decision = 0$ for *left*, $decision = 1$ for *right*. Gaze support, denoting the percentage of gaze points on the AOI corresponding to the decision taken, was then computed as follows:

$$Gazesupport = GazePt_{left}.\ (1 - decision) + GazePt_{right}.\ decision \quad (1)$$

The distribution of gaze support is shown in Fig. 14 by two histograms, one with 20 bins (dark red/green bars) and one with 2 bins (light red/green bars). Overall, gaze support was in agreement with the navigation decision in 72.3% of the encounters, i.e. people moved in 191 out of the 264 encounters to the side they were looking at more often before passing the robot (they evaded the robot 106 times to the left and 85 times to the right). In 27.7% of the encounters gaze support was not in agreement with the navigation decision, i.e. people decided to move to the side they gazed at less frequently. Out of 73 such instances, people passed by 43 times to the left and 30 times to the right.

Next, we evaluated the influence of the intention projection on the observed gaze patterns. The robot used four different projection patterns: Line, Arrow, Blinking Arrow, and Nothing. The leftmost four bar pairs in Fig. 15, show the distribution of gaze support over all participants and all types of encounters, separately for each pattern. The rightmost three bar pairs in Fig. 15 show gaze support for each type of encounter: from left, frontal, and from right. The 2-bin histogram in Fig. 14 is reproduced for comparison in Fig. 15 (labeled "All Cases"). We observed most encounters with agreeing gaze support when a line was projected to communicate the navigation intent of the robot.

To investigate whether gaze support differed significantly, we conducted a two-sample Kolmogorov–Smirnov test (considering two types of projection at a time and for six combinations in total). We did not find a significant difference in gaze support at the significance level of 0.05.

Finally, we analyzed whether the type of encounter had a significant influence on the observed gaze patterns and counted cases of agreeing and non-agreeing gaze support for all participants, all projections but separately for the different types of encounters. The corresponding results are shown in the three rightmost bar pairs in Fig. 15. Again, we did not find a significant difference at $p = 0.05$, indicating that neither the projection nor the type of encounter had a distinct influence on the gaze support measure.

7. Conclusions and future work

This article addresses bi-directional intention communication between robots and humans with the goal to improve perceived and general safety of humans when they encounter a robot. We study communication and recognition of motion intentions inspired by the use case of autonomous transport vehicles in material handling or flexible manufacturing systems. To improve perceived safety, we developed a Spatial Augmented Reality (SAR) based intention communication system and mounted it on an AGV. To understand how SAR intention communication from robot to human affects the navigation behavior of humans, we then conducted experiments in which the AGV and the participants had to negotiate different encounters in a realistic scenario. We used eye-tracking glasses, a laser scanner to obtain human trajectory data and stimulated recall interviews (SRI) to get detailed insights into a total of 264 encounters.

By analyzing the recorded trajectories, we found that a mobile robot projecting its intentions on the shared floor space encourages humans to actively choose safer paths and reduces the shortest distance during an encounter. The analysis of the SRIs (which used the gaze-overlaid video as stimulus) revealed that the "Arrow" projection pattern was preferred among the patterns tested and that the projections were often perceived as part of the robot.

Our previous work [6,7] compared the human response to robot's using SAR intention projection to robots that did not use a projection. On a Likert scale, the robot's with intention projection got higher ranked in key attributes such as communication, reliability, predictability, transparency, and situation awareness. Complementary to [6,7], this article presents an improved experimental setup, substantially more extensive experimental data, additional analyses of eye-tracking data and stimulated recall interviews. This allowed us to obtain statistically significant results and to understand better why humans respond differently to different projection patterns.

Access to gaze information constitutes a valuable source of information that could allow autonomous vehicles to take attention and intentions of a human into account and thus improve general safety in human–robot encounters. We describe a control approach that takes this information into account and investigated the possibility of human-to-robot implicit intention transference through recognition of navigation intentions solely from eye gaze data. Our results show that, in the given scenario, a navigation intent predictor based on the simple rule, "if people look more often to one side of the robot, they intend to go to that side" would have predicted the correct navigation intention in 72.3% of the encounters. The result is encouraging and a springboard for further research. More experiments in different scenarios are needed to reach general conclusions (independent of our particular setting) about differences with respect to the projection pattern of the robot or the type of encounter. Finally, future research should address the question at which distance to a robot navigation intent shows most strongly in the gaze of humans.

Gaze is not the only modality from which navigation intent can be inferred. Head and body pose and a person's recent trajectory [5] also allow inference of navigation intent. Future research should aim to find confidence models for predictors based on different modalities with the goal to derive more reliable joint predictors. Recent developments suggest the use of wearable augmented reality (AR) equipment for increased efficiency and faster on-demand production [61]. Integrating eye-tracking as suggested in this work could help to use AR equipment also for establishing safe human–robot interactions, possibly with customized intent communication. Correspondingly, future work should investigate the usage of smart glasses with in-built augmented reality and eye-tracking such as the HoloLens 2.[3] Finally, navigation intent prediction needs to be integrated into human-aware motion planning.

[3] https://www.microsoft.com/en-us/hololens .

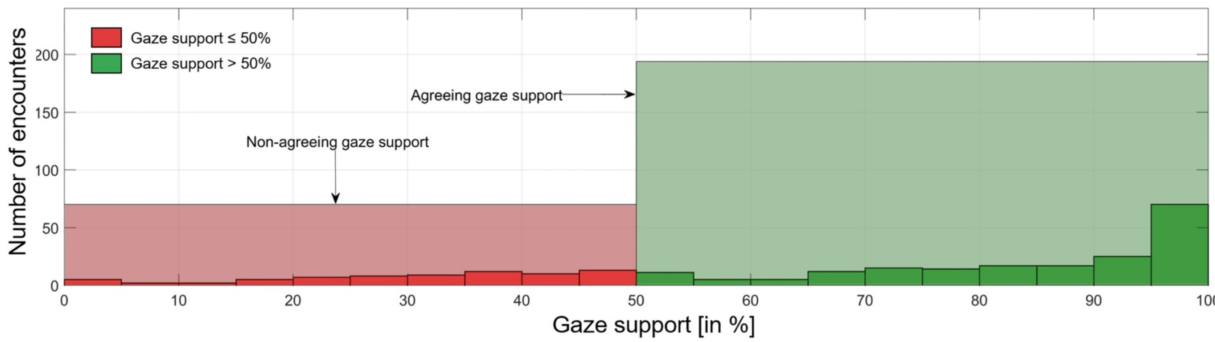


Fig. 14. Histograms showing the distribution of gaze support for all participants, all patterns, and all types of encounters. Red bars represent cases where people predominantly looked on one side and still moved to the other side. Green bars represent encounters where gaze was predominantly on the side chosen. Dark bars show a histogram with 20 bins. Light bars show another histogram of the same distribution with two bins. Accordingly, the height of the two light bars equals the added height of the ten dark bars of the same color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

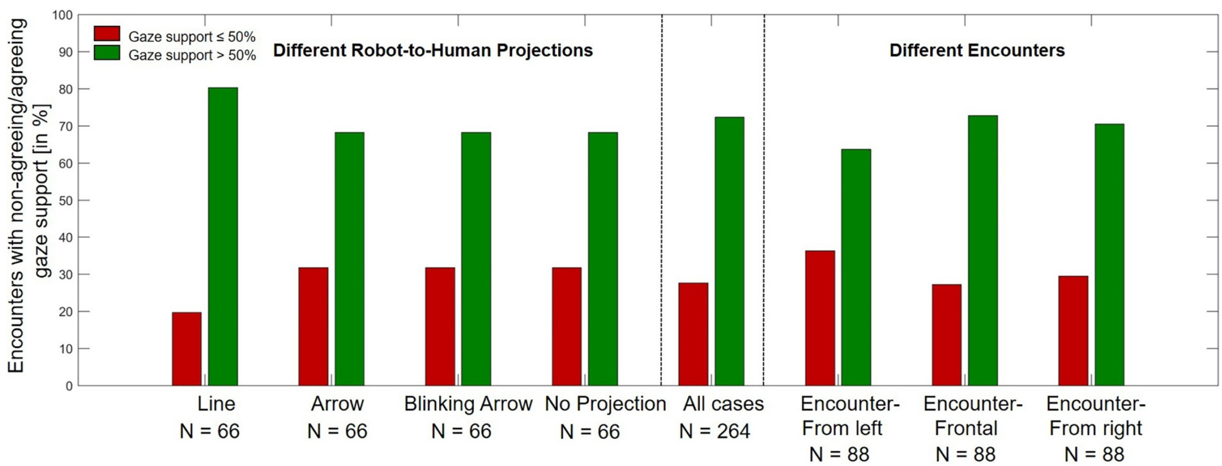


Fig. 15. Percentage of encounters with non-agreeing (red) and agreeing (green) gaze support. From left to right: all participants and all types of encounters, separated by robot-to-human projection pattern (Line, Arrow, Blinking Arrow, and Nothing). Fifth bar pair: all participants, all tasks, and all projections (corresponding to the 2-bin histogram in Fig. 14). Rightmost three bar pairs: all participants, all projections, separated by types of encounter. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Authors' contributions

Ravi Teja Chadalavada contributed to the design, development, and execution of the experiments, data analysis, and interpretation and wrote the manuscript. Henrik Andreasson contributed to the design, development, and execution of the experiments and was instrumental in writing the manuscript. Maike Schindler contributed by introducing the design of the study, in particular by introducing the concept of SRI and designing this part of the study; she contributed to the data analysis and interpretation; and to the writing process. Rainer Palm contributed to intention recognition between human and robot, especially on how to take recognized intention into account. Achim J. Lilienthal contributed to the design, development, and execution of the experiments and edited the manuscript.

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CRediT authorship contribution statement

Ravi Teja Chadalavada: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Henrik Andreasson:** Conceptualization, Data curation, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Maike Schindler:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Rainer Palm:** Conceptualization, Methodology, Investigation, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing. **Achim J. Lilienthal:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.rcim.2019.101830.

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