

Intention Indication for Human Aware Robot Navigation

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Abstract: Robots are gradually making their ways from factory floors to our everyday living environments. Mobile robots are becoming more ubiquitous in many domains: logistics, entertainment, security, healthcare, etc. For robots to enter the everyday human environment they need to understand us and make themselves understood. In other words, they need to make their intentions clear to people. This is especially important regarding intentions of movement: when robots are starting, stopping, turning left, right, etc. In this study we explore three different ways for a wheeled mobile robot to communicate its intentions on which way it will go at a hallway intersection: one analogous to automotive signaling, another based on movement gesture and as a third option a novel light signal. We recorded videos of the robot approaching an intersection with the given methods and asked subjects via a survey to predict the robot's actions. The car analogy and turn gesture performed adequately, while the novel light signal less so. In the following we describe the setup and outcomes of this study, as well as give suggestions on how mobile robots should signal in indoor spaces based on our findings.

1 INTRODUCTION

Mobile robots are having widespread success in constrained, industrial environments, executing various logistic tasks and both freeing human resources as well as providing additional flexibility compared to solutions based on conveyors. However, in other domains such as healthcare, robots are still rarely found, although they are considered to be one of the means to mitigate the demographic challenge (Riek, 2017) and a large variety of technical challenges can be solved with existing technology already (Bodenhausen et al., 2019). In healthcare, unlike the industrial domain, robots are expected to encounter humans that are both unfamiliar with the robot and vulnerable. However, besides operating safely, which can be achieved by utilizing adequate safety mechanism, it is also required to operate robustly – for mobile robots this implies in particular to adapt the navigation strategies with respect to humans that share the environment.

In this paper we will in particular investigate how intention can be conveyed and aid humans in anticipating the actions of the robot without prior instruction. Understanding the intention of the robot allows for adjusting the own behaviour accordingly and thereby to minimize interference with the robot. It should be clarified that robots of course do not have intentions like humans, but as they are perceived as agents, we should focus on displaying signals that will be perceived as intentions by people. This understanding is important for the acceptance of robots in our everyday environments.

2 BACKGROUND

Mobile robots are entering into less constrained environments such as public institutions and even private homes. This shift is caused by technological progress enabling robots to be reactive and responsive to humans in their environment (Svenstrup et al., 2009) and to adjust the planned path online accordingly.

In the following, we will investigate prior work relevant for the communication of intention since the understanding of the robots' intention by humans can

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help avoiding conflicting situations which can impose challenges to traditional navigation solutions and lead to poor acceptance of robots (Hameed et al., 2016; Beer et al., 2011). There are several approaches to provide clues about the intention of robots including the use of embodiment, physical attributes, or expressive light (Juel et al., 2018). In the following, we will summarize how humans anticipate the intention of others (section 2.1) and use this to relate to relevant research focusing on how robots communicate their intentions (section 2.2).

2.1 Human Anticipation of Intention

Human-human interaction is often successful because we can respond and react to the intention and action of other humans. For this, we make use of the contextual information within the nearby environment where actions are performed. If a teacup is on a kitchen table with a tea-bag in it and a person reaches for a pot with boiling water, we predict that he is probably going to pour the boiling water into the cup. This type of contextual information surrounding an action allows us to limit the possible outcomes of human intentions (Kilner, 2011).

When the context in the environment cannot be used or is not present, we use other techniques to predict intentions. Experiments by (Castiello, 2003) suggest that the intentions of a human can be inferred by monitoring gaze. If both contextual information and gaze are absent it has been shown that from body motion we can predict intentions of humans (Sciutti et al., 2015) and that human actions translate into different kinematic patterns. (Ansuini et al., 2008) show that depending on the end goal, we grasp the same object differently which means we can use body motion to anticipate intention.

The different techniques humans use to anticipate intention and action are naturally also used when we want to understand the intention of robots. This means that we first and foremost will try to use contextual information to anticipate the intention or state of the robot. If contextual information is absent it is the robot's task to provide us with clues about its intentions. In the following section, we will describe how this has been done via anticipatory motion, augmented reality, animation techniques, expressive light, animated light, and biological inspired lights.

2.2 Communication of Robot's Intentions

(Gielniak and Thomaz, 2011) show that anticipatory motion can be used to communicate motion intent

earlier than motion without anticipation. They find that when robots are displaying their anticipatory motion, humans have more time to respond in interactive tasks. (Ferreira Duarte et al., 2018) show that when a robot arm overemphasizes a motion, the intentions of the robotic arms motion becomes predictable. In contrast, they also show that when adding gaze and reducing the motion of the robotic arm to normal the overall readability of the intention increases. This suggests that a combination of signaling modalities is stronger than an overemphasized signal alone which could increase the acceptability of the robot.

A number of HRI studies have employed animation techniques to improve robots' intention legibility. These techniques are borrowed from animated movies (cartoons). Some of these methods are: anticipation (reaching back before throwing a ball), squash and stretch (a falling character will squash at landing), secondary action (a character puts on a jacket while leaving a house), etc. For a detailed overview of the field, see (Schulz et al., 2019).

Augmented reality can also be used to display a mobile robot's intentions of movement. (Coovert et al., 2014) looked at a robot projecting an arrow in front of itself signaling its intended direction of movement. Experiment participants correctly interpreted these projections and rated such a robot more favorably. (Chadalavada et al., 2015) designed an augmented reality signaling system where the robot projected a line representing its exact intended path. People interacting with this robot thought that it was much more communicative, predictable and transparent compared to the same robot but without intention projection.

(Pörtner et al., 2018) hypothesized that colored light is a suitable feedback mechanism for mobile robots. They test which of six chosen colors represent three categories: Active, help needed from human, and error. They find that a green signal should be used to report active robot behavior, yellow/orange signal for reporting that the robot needs help and red signaling if an error occurs. Their results show that humans interpret light on robots in very specific ways and that it can be used to express the internal state of robots.

Utilizing colored light to signal a robot's state and action is supported by (Baraka and Veloso, 2018) that use light arrays to create both periodic and aperiodic expressive light signals on a mobile robot. Their results suggest that the presence of lights on a mobile robot can significantly increase people's understanding of the robot's intentions. They completed a user study where they demonstrate that when using expressive light to show that the robot needs help more

humans would help it and understand that the robot needed help. This shows that expressive light has an impact on the behavior of humans around the robot. Interestingly, their results also suggest that by using expressive light the trust between humans and robots increases.

(Pörtner et al., 2018) and (Baraka and Veloso, 2018) suggest that expressive light and animated light can be used to signal in what operating state the robot is in while also compelling humans to partake in interactions with a robot.

(Szafir et al., 2015) investigate how expressive light can be used to communicate directional flight intention in drones. They apply design constraints to a drone’s flight behaviors, using gaze, lighthouse beacon, blinkers, and airplane flight as inspiration and thereby design a set of signaling mechanisms to signal directionality. In a user study, they asked participants to predict the drone’s behavior. They find that using expressive light to signal directional movements significantly improves the understanding of the drone’s directional flight, where they found the gaze behavior to be especially useful in communicating the intention of the drone. (Hart et al., 2019) has made a user study with a mobile robot that drives towards participants of the study and the robot signals a lane switch. On the mobile robot, they mount a virtual head that can turn and have a gaze. They compare the performance of the gaze from the virtual agent head against an LED turn signal. They show that the gaze signal more often prevents the human and robot from choosing conflicting trajectories. This suggests that gaze has some advantage in being more explicit than expressive light but with the essential problem of only being visual when facing the robot which in turns are very limited for its overall usability in public spaces because in many scenarios humans would be interested in knowing the intention of the robot from both of its sides and from behind which could be possible with e.g. expressive lights. Another problem is the level of anthropomorphism required for being able to convey gaze. A very high level of anthropomorphism might not be suitable for mobile robots performing logistic tasks at e.g. hospitals. In general, the literature by (Ferreira Duarte et al., 2018), (Hart et al., 2019), (Szafir et al., 2015) suggests that using signaling mechanisms that follow known and human-aware conventions and biological signals (gaze) increased the understanding of both drone’s and robot’s intentions.

Inspired by the design methodology by (Szafir et al., 2015) we investigate in this paper the use of signaling schemes from the automobile domain. The benefit of employing such signals for mobile robots is, as suggested by (Pörtner et al., 2018) and (Baraka and



Figure 1: Robot test platform used for the experiments (left); top view of the robot with standard car light pattern (right).

Veloso, 2018), that animated lights occur (blinking, etc.) and they follow well-known conventions. We also incorporate anticipatory motion by using the embodiment of the robot to signal directional movement (turn cue) and we combined the usage of expressive light and anticipatory motion.

3 METHODOLOGY

This section covers all details of the research approach that was taken in this paper. First we will describe the mobile robot platform with the signaling unit (Section 3.1) and the implementation of the signals (Section 3.2). Finally we will detail the experimental design including the recording of the videos, online survey and data collection in Section 3.3.

3.1 Experimental Platform - The Robot

In order to perform the experiments, we built a test platform, using a MiR100 autonomous mobile robot as the base due to its stability, payload capacity and off the shelf implementation. We made electrical modifications to control the LEDs around the robot.

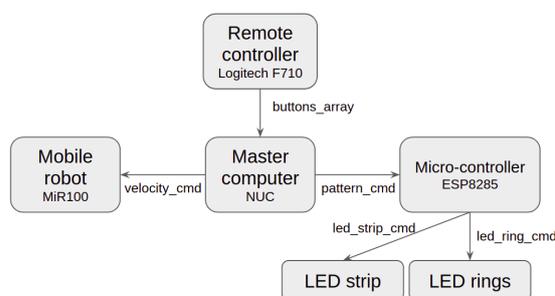


Figure 2: Robot system architecture.

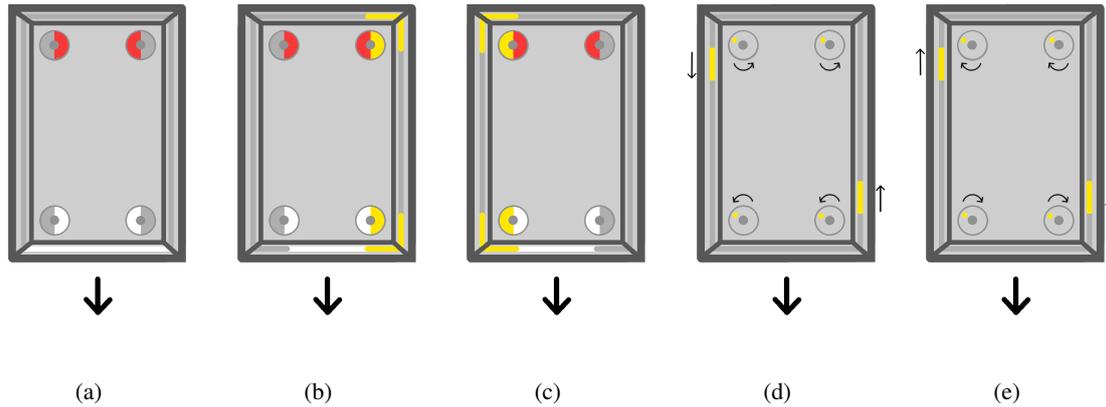


Figure 3: Signaling behaviors. Each image shows a robot top view where the lines in the perimeter represent the bottom LEDs, and the circles inside the rectangle represent the top LED ring arrays. The arrow in the top indicates the front side of the robot. (a) Standard car lights (b) Left blinking signal (c) Right blinking signal (d) Left rotating signal (yellow LEDs move in the arrow direction) (e) Right rotating signal (yellow LEDs move in the arrow direction).

On top of the mobile platform, a chest of drawers was placed to emulate a logistic use case and design of the Health-CAT robot. Atop the drawers we installed four LED ring arrays. Both, the bottom and top sets of LEDs, could be addressed individually by a controller, giving the possibility of defining the custom patterns needed for the experiments (see Figure 1).

The system architecture is outlined in Figure 2. We used an Intel NUC as the master computer. It had ROS (Robot Operating System) framework installed, and it provided an interface between the mobile platform and the microcontroller. In order to trigger the robot behaviors needed for the experiment, we used a Logitech Wireless Gamepad F710. This remote controller was constantly sending an array filled with 0 and 1 (buttons_array), representing which buttons from the gamepad were pressed. The array was then read by the master computer, which, based on the buttons pressed, ran the corresponding robot behavior. A robot behavior consisted of both, sending velocity commands (velocity_cmd) to the robot platform to move and pattern commands (pattern_cmd) with the light pattern ID to the microcontroller in charge of the light control. The communication between these two devices followed the MQTT messaging protocol, with the master computer being the MQTT server.

The light control was implemented on a ESP8285 microcontroller, which provides not only a digital I/O interface, but also a wireless communication with other devices. Following the master computer requirements, the microcontroller was programmed as a MQTT client. For the light control, we programmed the patterns, first, in a way they emulated car lights: white for the headlights, red for the tail lights and yellow for the signal lights (Figure 3a). Along with the car signals (Figure 3b), an extra pat-

tern was programmed, showing a LED rotation motion in each of the rings and the base strip in the direction of the turn (Figure 3d). Further explanation about the robot signals can be found in Section 3.2. Based on the reading from the pattern_cmd, it was selected which pattern to run, which was later decomposed into light commands that were sent to both, the LED strip (led_strip_cmd) and the LED rings (led_ring_cmd). The commands transmission followed a NZR communication protocol managed by open source libraries specific for each LED type (Fast LED for the strip and Adafruit NeoPixel for the rings). The structure of those commands consisted of the LED position and the color to light on.

3.2 Experimental Conditions - Robot Signals

It is important for a mobile robot intended for hospital use like ours, to communicate its intentions clearly. In the following sections, three potential solutions are outlined: blinking lights, rotating lights, and a turning gesture.¹

3.2.1 Blinking Lights

This solution for signaling was designed as an analogy with standard signaling on cars for making turns. In this, the outer halves of the top lights were blinking with yellow light at a frequency of about 1Hz. The blink frequency was designed to comply with automotive industry standards. The inner halves of the top front lights were kept constant white, while the

¹See a video of the implemented conditions here <https://youtu.be/J6jtDH6ZSuw>

inner parts of the top back lights were constantly red (Figures 3b, 3c and 4b). These patterns were emulating the front and back lights on cars. Using this setup also adds information about which end is the front of the robot (white inner lights) and which the back (red inner lights), again in analogy with cars. The bottom LED strip was also blinking at the corner position with the same color LEDs.

3.2.2 Rotating Lights

We implemented a rotation of the top and bottom lights as a novel signaling method. In this condition only two LEDs of each top light ring were on at one time. The lit LEDs kept changing to create an effect of rotating lights. All four lights were moving in the same direction. This direction was correspondent with the future turn of the robot: the lights were turning clockwise when the robot wanted turn right and anti-clockwise when it intended to turn left. The bottom lights were displaying a "running" pattern around the base of the robot, corresponding to the future turn direction of the robot Figures 3d, 3e and 4c.

3.2.3 Turn Gesture

A final signaling option was implemented in the form of movement: when the robot reached the intersection, it made a turning gesture of about 30 degrees towards the side it wanted to turn to (Figure 4a). We considered this the strongest signal indicating the intention of the robot: there was no reason why a turn gesture to one side would be interpreted as an intention to move in the other direction. In the experiment itself we used this signal in two ways: 1) by itself without additional indicators and 2) in combination with the above mentioned two other signaling methods.

3.2.4 Combination of Conditions

The main independent variable of our study was the signaling method with conditions: blinking light, rotating light and turn gesture. The last of the conditions could be administered either by itself or in combination with the first two methods. We also wanted to show movements of the robot using a standard car light pattern without any turn signals (none), to establish a baseline behavior. A secondary necessary independent variable we considered was turn direction with levels: left and right. All these combinations of conditions are represented in Table 1.

For the combination of no-turn and no-light the left and right conditions are the same, i.e. the robot just approaches the intersection without any turning

Table 1: Combination of conditions.

	without turn gesture			with turn gesture		
	blink	rotate	none	blink	rotate	none
left	•	•	•	•	•	•
right	•	•	•	•	•	•

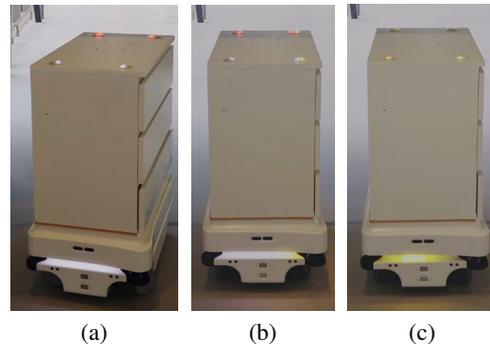


Figure 4: Signaling behaviors on real robot. (a) Right turn gesture with standard car lights (b) Blinking signal to left (c) Rotating signal.

lights or gestures. Therefore these two cases are conjoined into one condition. This give us a total of 11 combinations of conditions.

3.3 Experimental Design

We ran a human subject study to investigate which signaling approach would be the most appropriate for our robot. In order to ensure repeatability and efficient gathering of human data, we opted for recording videos of the robot's signaling movements and showing them to human participants via online surveys. As it was essential for all subjects to see exactly the same robot behaviors, video recordings were the best option.

3.3.1 Video Recordings

One video was recorded for each of the 11 combinations of conditions mentioned above. The videos were shot with a Motorola moto G7 Plus mobile phone's primary camera in 4K resolution with 30 frames per second. The recording was done from an initial distance to the robot of 3,5 m. At the end of the video the robot approached the intersection and was at a distance of 2,3 m to the camera, see Figure 5. The mobile phone was mounted on a fixed tripod at a height of 1,7 m, thus simulating the point of view of a person. The location of the video recording was exactly the same in all clips. We made a careful selection of a location that represents a symmetrical intersection of hallways at the university. The robot always started from the same position of 1,25 m from the intersec-

tion. It always ended its movement just at the borderline of the intersection box. It was always in the center of the corridor allowing the same amount of space on both of its sides. The width of the hallway at the entrance to the intersection was 2,22 m. The width of the robot is 0,58 m. This allowed a space of 0,82 m on both sides of the robot for passing around it. In the conditions where the robot also performed a turning gesture, this space somewhat decreased, because of its rectangular geometry. The videos ended at the point when the robot stops at the intersection and has performed the turn gesture and light actions. We intentionally cut it off before the robot performed the actual turn at the intersection, because we wanted to ask our participants to tell us what their prediction would be on what will happen next, thus giving us insight on the effectiveness of our signaling methods in conveying information about the robot's future actions.

3.3.2 Online Survey

An online survey was created to test the designed experimental conditions with human subjects. As a survey platform, we selected the site soscisurvey.de because of its high customizability. Among other things, most importantly it allows many options for randomizing the order of presentation of the videos. The survey started with a quick explanation of the experiment without giving away its scientific purpose. After the initial slide, we presented the 11 videos, each on a separate page, in pseudo-random order. It was designed to be counter-balanced, but not all fields of the procedure were covered because there were 120 combinations of order and 30 subjects. The videos were

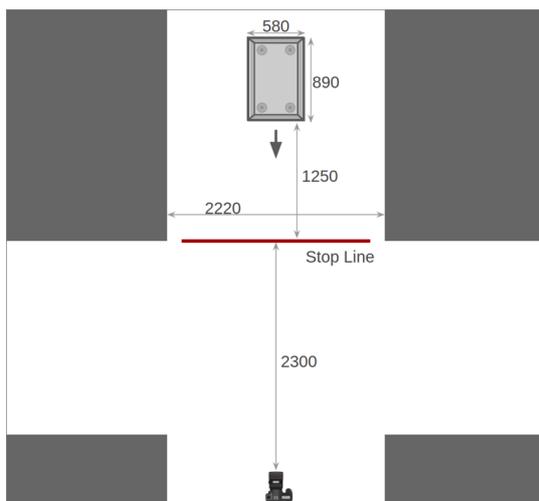


Figure 5: Video recordings setup layout. Dimensions are in mm.

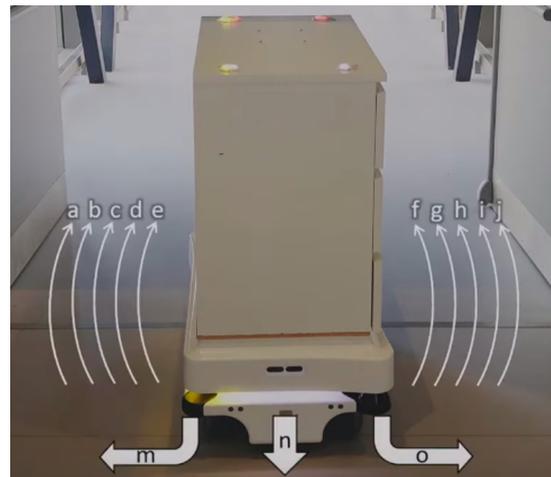


Figure 6: The last frame of the video, representing the route options in the multiple choice questions.

divided in two groups:

1. With turn gesture,
2. Without turn gesture.

The randomized first group was always shown before the randomized second group. The videos containing the turn gesture were selected to be shown later, because when they were in combination with either of the light signals, they could influence the subjects' subsequent decision on light signals appearing without the turn gesture. This could happen as we expected the turn gesture to be the strongest indicator for the turning intention of the robot. The questions we asked the participants right after showing each video are shown in Table 2.

Table 2: Questions about the videos.

QA1	Which way would you go around the robot to get to the end of the hallway ahead?
QA2	Which way will the robot turn after the end of the video?

For the first question we offered multiple choice radio buttons with the labels: a,b,c,d,e,f,g,h,i,j. These labels represented ten possible routes of movement for people to take and corresponded to arrow representations of these paths at the end of the video, which were added in a video editing application, see Figure 6. The second question's answers were three radio buttons with the labels m, n and o. These were also represented by arrows at the last frame of the video. The videos only played once (of which the subjects were informed at the initial page) and stopped at the last frame with the arrow representations.

After the survey pages with the videos the subjects

had two more pages with questions to fill out: one about the experiment and another about demographic information. The experimental page started with two questions for validating if subjects paid attention to the videos.

Table 3: Validation questions about the experiment.

QB1	What was the color of the robot?
QB2	What was the general shape of the robot?

The first of these questions had an open text field, so people could enter the name of the color they perceived. The second question was a multiple choice one with the following options: cylindrical, box-shaped, ball-shaped, snake-shaped, humanoid, other. The correct choice was 'box-shaped'. The following 9 questions were in the form of statements with 7-point Likert-scaled answers ranging from 'strongly disagree' to 'strongly agree', see Table 4.

With these statements we expected to learn more about people's preference for the conditions we were suggesting. This page ended with a comments section. We asked subjects in a large textual field to let us know about their thoughts, observations, and suggestions concerning the experiment. The last input page asked for demographic information, see Table 5.

3.3.3 Data Collection

We opted for collecting data using Mechanical Turk. Thirty-one participants were recruited with MTurk Master qualification and at least 90 percent job quality approval rating. They were all located in the United States. We opted for this country as our questionnaire was in English and the USA is the largest English speaking country (as their native language), thus we could get quick high quality responses. One of the subjects showed irregular behavior according to our survey collection system: she spent very little time on each slide (around 11,7 seconds per slide, while the average was 25,7 seconds), i.e. she didn't pay attention to the videos, thus we eliminated her from the results. Out of the leftover 30, 10 were female and 20 male. The average age was 41,9. Two people were left-handed and 28 right-handed. They all had driver's licenses except one. Twelve subjects never interacted with robots before, 16 a few times, while two experienced robots a number of times.

4 RESULTS

Results can be categorized into a number of groups. First we'll discuss subjective responses, then partici-

pants' movements as reactions to the robot and finally people's understanding of robot's intentions.

4.1 Subjective Results

This section will discuss the Likert-scaled agreements of participants with the statements found in Table 4. The first analysis focuses on opinions about the three basic signaling methods: blink, rotate and turn. These refer to statements QC1, QC2 and QC3. There is some disagreement in the literature on how Likert-scaled values should be analyzed. The more conservative approaches suggest non-parametric statistical methods as the Friedman test and the Wilcoxon signed-rank test, which we will use here.

Figure 7 shows the averages of responses to statements QC1, QC2 and QC3 about the clearness of signals when using rotating lights, blinking lights and turn gesture. We applied a Friedman test to assess the difference between these. The results show a statistically significant difference between the signaling methods, $\chi^2(2) = 44.1, p < 0.001$. Post-hoc analysis using Wilcoxon signed-rank test was conducted with a Bonferroni correction. This has shown significant differences between all pairs of conditions: rotate compared to blink ($Z = -3.781, p < 0.001$), blink compared to turn ($Z = -3.13, p = 0.002$) and rotate compared to turn ($Z = -4.475, p < 0.001$). This means that participants found the rotating lights the least informative, and the blinking more informative than rotation but less than the turning gesture. Therefore, the turning gesture was the strongest signal, followed by blinking, followed by rotating lights.

We intended to explore participants' preference of the LED rings on the top versus the LED strips near the bottom of the robot, statements QC6 and QC7 in Table 4. Figure 8 shows the averages and standard deviations for this comparison. Adapting a Wilcoxon signed-rank test we did not find statistically

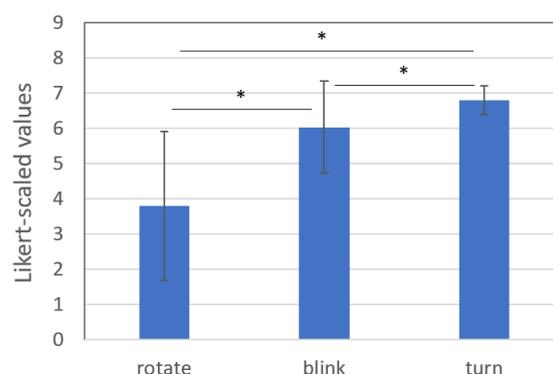


Figure 7: Averages of opinions on clearness of signaling with rotating lights, blinking lights and turning. +/- 1SD.

Table 4: Likert-scaled questions about the experiment.

QC1	The blinking lights on the robot in some of the videos made it very clear which way it would want to go.
QC2	The rotating lights on the robot in some of the videos made it very clear which way it would want to go.
QC3	The turning of the robot at the end of some videos made it very clear which way it would want to go.
QC4	The combination of blinking lights and turning made it very clear which way the robot would go
QC5	The combination of rotating lights and turning made it very clear which way the robot would go.
QC6	The lights on the top of the robot were very useful in understanding where it would go.
QC7	The lights near the bottom of the robot were very useful in understanding where it would go.
QC8	I did not notice any difference between the videos.
QC9	The different signals were insufficient for one to understand which way the robot would go.

Table 5: Demographic information questions.

QD1	What is your gender?
QD2	What is your age?
QD3	Are you left-handed or right-handed?
QD4	How many times have you interacted with robots before?
QD5	Do you have a driver’s license?
QD6	In your country of residence, which side of the road do cars drive on?
QD7	Have you participated in this experiment before?

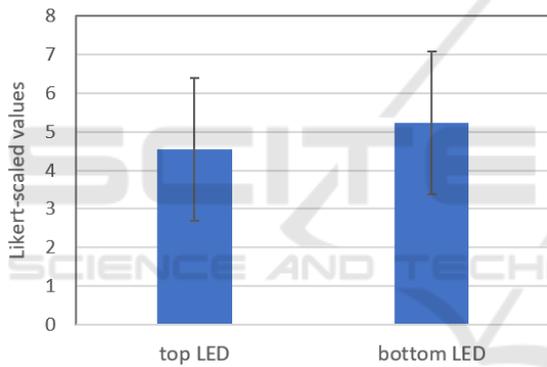


Figure 8: Averages of opinions on usefulness of top LED lights vs. bottom LED lights. +/- 1SD.

significant difference between the two conditions ($Z = -1.668, p = 0.095$). Even though this results is not significant, we report it because our expectation was that the top LEDs would be preferred, which was not the case at all.

4.2 Participant Movement Intentions

This section will present the results derived from participants’ answer to question QA1 in Table 2: *Which way would you go around the robot to get to the end of the hallway ahead?* This question was asked once for each of the 11 videos, showing the 11 conditions. The answers were in the form of multiple choices (a,b,...,j). These letters refer to paths proposed in the last frame of the videos, see Figure 6. Paths a,b,c,d,e led around the robot from the left side, while paths f,g,h,i,j went around from the right. Figure 9 con-

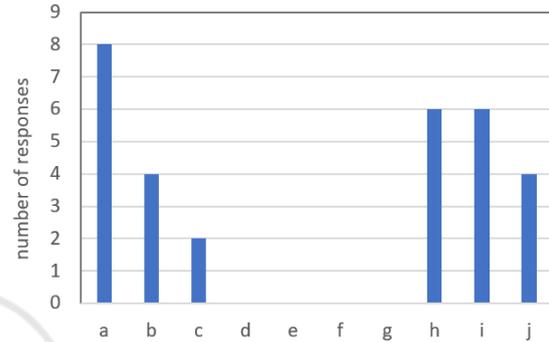


Figure 9: Histogram of participants’ bimodal choices on which way to go around the robot that doesn’t show any signals.

tains the histogram of answers to this question while showing the video of the robot with no signals. This was the baseline condition administered to investigate people’s default preference of sides.

Participants were fairly evenly divided between left and right sides. On the left they tended to stay further away from the robot while on the right, they approached somewhat closer. There were still more people (16) circumventing from the right, as opposed to left (14). This makes intuitive sense, if the robot

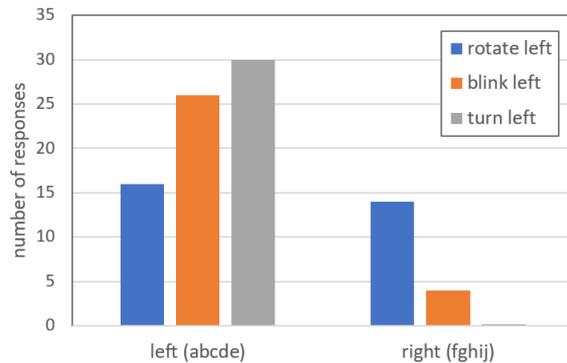


Figure 10: Histogram on participants’ binomial choices on which side to take to go around the robot while displaying rotation, blinking lights and turning gesture to the left. All direction labels (left, right) are from the subject’s point of view.

is perceived as a vehicle and right-hand-side driving road rules apply. It was noticed that these histograms have an irregular bimodal distribution. Therefore we opted to reduce the complexity by clustering all left side paths (a,b,c,d,e) together and all right side paths (f,g,h,i,j) together, thus simplifying the bimodal to a binomial (left, right) distribution. This allowed us to apply simpler statistical methods, while keeping the most important part of the data. With this new approach, we compared which way people want to circumvent the robot when it is signaling to the left and right. Figure 10 shows the binomial distributions of side selection when the robot wants to turn to its own left side. It can be noticed that for blinking and turning, people follow the expected route, to their left, because they are correctly perceiving the robot's intention to turn to its own left and want to avoid collision. However, for the rotating light, we don't see the same 'keep left' distribution. Rather, it is split between going left and right. This might be because the rotating light was not perceived as an intention to turn to that side. To check for differences between these three binomial distributions we ran a 3x2 Chi-squared test and found significant difference between the three conditions $\chi^2(2,N=30)=21.67, p<0.001$. Post-hoc analysis of adjusted residuals with Bonferroni correction revealed ($p<0.001$) that it was the rotating light condition that was significantly different compared to the other conditions.

We also investigated the analogous situation, but when the robot is signaling for a right turn, Figure 11. Here we do not see a deviation from the expected choice even for the rotating light. Most people chose to go to the right side from their point of view, to avoid the robot which was signaling a turn towards its own right. Indeed, a Chi-squared test also did not report a significant difference between conditions for this case, $\chi^2(2,N=30)=5.21, p<0.074$.

4.3 Understanding of Robot's Intention

In this section we report on question QA2 from Table 2: *Which way will the robot turn after the end of the video?* This question had three possible answers: paths m,n and o (see Figure 6). It was asked to see if the subject can make correct robot movement predictions based on the signaling methods. Similarly as in the previous section we see that blinking and turning are adequately interpreted, but the rotating light signal is not. Half of the participants thought that the robot will continue going straight even though it was rotating to signal a right turn. We conducted a Chi-squared analysis on this dataset too and found significant differences between levels $\chi^2(4,N=30)=27.6, p<0.001$,

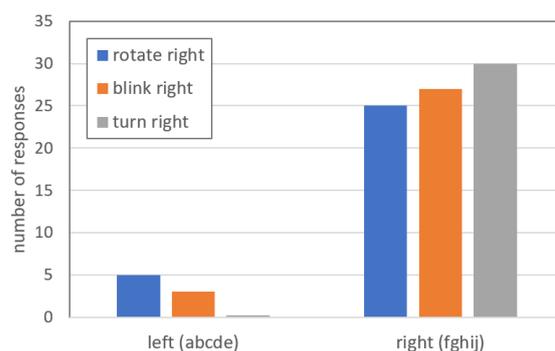


Figure 11: Histogram on participants' binomial choices on which side to take to go around the robot while displaying rotation, blinking lights and turning gesture to the right. All direction labels (left, right) are from the subject's point of view.

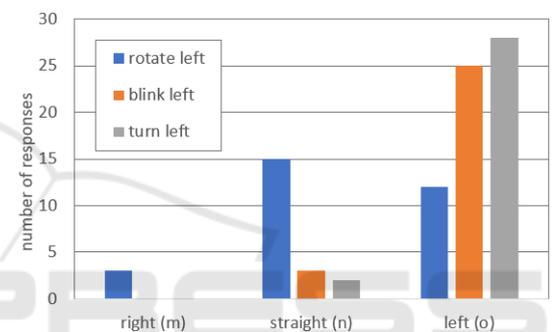


Figure 12: Histogram on participants' opinions on which way the robot will go for different signaling methods. Right, straight, left is from the robot's point of view. Rotate left, blink left and turn left are from the subject's point of view.

indicating that the rotation signal is improperly interpreted.

Regarding the signals in combination with turn, they were very correctly interpreted by almost all participants. Figure 13 shows three conditions "rotate&turn", "blink&turn" and "turn". It can be noticed that the turning signal already provides all information for making a right decision. The addition of the two light signals doesn't change the outcome. As expected, a Chi-squared test did not show and significant difference between these conditions $\chi^2(2,N=30)=0.36, p=1$. The results in this section tell us that all subsequent robot movements were correctly predicted by the subjects, except the rotating light.

5 DISCUSSION

Section 4.1 demonstrated that people found the rotating lights the least informative, the blinking lights

more and the turn gesture the most informative. These differences were also statistically very significant. We did expect that the turn gesture will be the most prominent indicator for the intention of the robot, but we did not expect the rotating lights to be evaluated so poorly. It was thought, that a rotational signal would clearly communicate the robot's intention to turn. However this was not reflected in the data. It might be the case that people associate rotating lights with heavy machinery or oversized vehicles on the road, which utilize similar signals, but only for attracting people's attention and not for signaling direction. Even the running lights on the bottom LED strips did not help in clarifying the intention. The blinking light performed quite well, as expected. As we were aiming for analogy with regular vehicles in terms of lights, we expected that people will easily make the connection between the robot and a car on the road. Even the turning gesture can be associated with vehicular traffic: in many situations at intersections cars will turn towards their intended final goal, especially for right turns in right-hand-side traffic countries. We emphasize that the turn gesture was not the turn itself. After the gesture, the robot made a full stop before performing the actual turning action. The actual turn was not part of our videos, as we wanted subjects to predict this.

Next, we looked at the preference of top or bottom lights. We expected that the top lights would be preferred as there were more of them and they were more in the line of sight of passers by. The ring LEDs were also more expressive, thanks to their numbers and customizability. However, this expectation was not supported by the results. Figure 8 shows participants' opinions on this matter: the average opinion was even better for the bottom lights, than top, even though this difference was not statistically significant. One of the possible explanations for this kind of outcome might

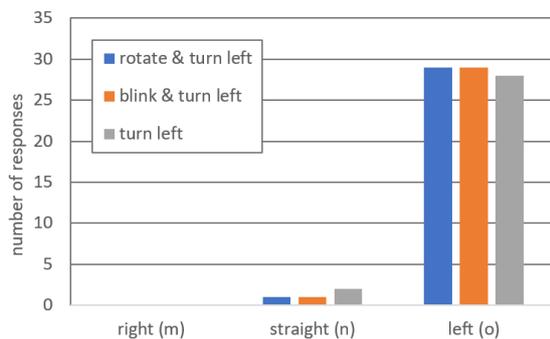


Figure 13: Histogram on participants' opinions on which way the robot will go for combined signals. Right, straight, left is from the robot's point of view. Rotate&turn left, blink&turn left and turn left are from the subject's point of view.

be the similar position of the bottom lights to lights on regular cars. Although, we designed the top lights to emulate car signals in one condition, maybe their location on the top was not appropriate for making a closer connection with automotive lights.

Regarding the analysis of participants' intention to go around the robot from the right or left, we looked at their answers to question QA1, see Table 2, Figure 10 and Figure 11. There is an inconsistency between the left and right turns. The leftward rotating condition produced an even outcome between taking either the right or left routes. This tells us that the rotating lights were not a good indicator of turning intention. On the other hand, for the rightward turn, rotation behaved as expected. This might be caused by the fact that more people tend to choose passing on the right (see Figure 9) in analogy with passing an oncoming car from the right. Figure 12 might give some insight on this: it shows people's prediction of the robot's turning intention under the basic conditions. It can be noticed that the leftward rotation signal is interpreted as an intention to go straight mostly and going left secondly. Thus, people who think that the robot will continue straight can go around the robot from their own right side, even though in the designer's intention this would lead them to collision with the robot. Finally, Figure 13 showed us that the turn gesture overpowers any additional light signal that might occur contemporaneously.

Regarding the number of experiment participants (30), we acknowledge that their number could have been higher for even more convincing results, but on the other hand most of our results showed very high levels of significance ($p=0.001$), thus adding more subject most likely wouldn't have changed these outcomes.

6 CONCLUSION AND FUTURE WORK

Signaling movement intention is essential for mobile robots in public environments like hospitals, universities, airports, etc. Finding an effective signal for indicating direction at a hallway intersection is crucial for the acceptance of such robots. In this paper, we discussed three such signals and their combinations. One was a turning gesture which was expected and proven to be the strongest indicator. Next there were the blinking signals in analogy with automotive signaling, which performed quite well too. Finally there was the newly designed rotational signal which proved to be the least efficient for the purpose, as some participants misinterpreted it as a general attention signal.

All in all, as expected we found that using car signals on vehicle-shaped mobile robots is a good idea and a design recommendation for the robotics community. What we did not expect was that the less visible bottom lights were at least as important for signaling as the top LED rings, which we expected to be more informative. We also noticed a tendency of people passing by an oncoming robot from the right side, as in vehicular traffic. We might have expected this to be more significant, which it was not, because many participants chose to go on the left side of the robot too. As future work it might be interesting to compare this effect with populations where the driving is on the left-hand-side of streets. We will also consider redesigning our robots lights and enforcing the ones near the bottom of the robot, according to our findings. Finally, based on the conclusions from this controlled study on the most efficient ways to signal turning intent, we plan to drive the robot on the university hallways and collect data in this uncontrolled environment and analyze how people flow around it depending on turn signaling.

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