

Mind the ARm: Realtime Visualization of Robot Motion Intent in Head-mounted Augmented Reality

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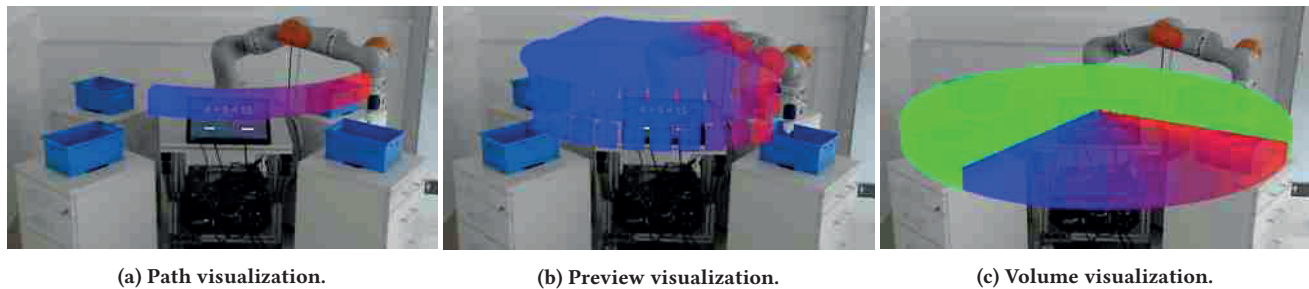


Figure 1: Different visualizations implemented on Microsoft HoloLens to display robot motion intent in Augmented Reality.

ABSTRACT

Established safety sensor technology shuts down industrial robots when a collision is detected, causing preventable loss of productivity. To minimize downtime, we implemented three Augmented Reality (AR) visualizations (*Path*, *Preview*, and *Volume*) which allow users to understand robot motion intent and give way to the robot. We compare the different visualizations in a user study in which a small cognitive task is performed in a shared workspace. We found that *Preview* and *Path* required significantly longer head rotations to perceive robot motion intent. *Volume*, however, required the shortest head rotation and was perceived as most safe, enabling closer proximity of the robot arm before one left the shared workspace without causing shutdowns.

CCS CONCEPTS

• **Human-centered computing** → **Mixed / augmented reality**; *User studies*; *Visualization techniques*.

KEYWORDS

collaborative robots, hazard warning, robot motion intent, visualization, augmented reality

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1 INTRODUCTION

Industrial robots have been locked behind cages for safety reasons for a long time. Facilitated by novel collaborative robots and safety sensors, the robot working area is slowly becoming more populated by people and therefore less predictable. The state of the art in safety systems for industrial robots is reactive [3]. Once a collision is detected, either through internal force sensors or external laser sensors, the system reverts to a safe state, usually by shutting down. This state has to be actively reset, which is commonly done by a designated safety officer in an industrial setting. While necessary and important for worker safety, accidental false positive events triggering the safety system result in a halt of production and therefore a loss of productivity.

One way to prevent this kind of downtime is to extend the safety concept towards proactive safety [8]. This includes communicating a potential collision ahead of time to a human to allow appropriate actions to be taken to deescalate the potential reactive safety event, e.g. by stepping away. In case of non-compliance, the system falls back to a reactive safety response.

The importance of understanding the behavior and the intent of industrial robots grows with the increasing use of Artificial Intelligence (AI) [10, 27]. Robots are able to make decisions based on complex conditions, which might not be immediately understood or foreseen by people. Explaining decisions and future actions by robotic AI systems has a unique geometric aspect, which can be exploited with 3D visualizations in Augmented Reality (AR) [6]. Clarifying robot motion intent was found as a building block of trust between people and robots [23].

The more humans and robots collaborate, the higher the need for adaptive behavior on both sides. Such behavior from the robot side

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can include planning for legible paths [7] and real-time obstacle avoidance [14]. On the other hand, modern industrial plants are designed with robots in mind [1]. This need exists in multiple settings, but is most pressing in collaborative manufacturing and logistics, as this is where most robots are used [18, 19]. It is therefore important to have a common spatial language that allows the person to understand intuitively what the industrial robot is doing and where it will move next. Not only does this language have to be intuitive in a way that does not require much training to understand, but it should also not cause much cognitive load so that the person can still perform their intended actions.

An illustrative use-case is the servicing of stacks within the workspace of an industrial robot performing assembly tasks. These stacks may have to be refilled or emptied. Such a task is somewhat irregular in nature, as the stacks may be serviced in various time intervals (i.e. a stack can be refilled any time before it runs empty). In this use-case, a person must be able to understand the robot motion intent in order to decide when to perform this task and judge if the area needed for the task remains clear of the robot long enough. This has to be possible while the robot is moving and with enough lead time to allow clearing of the way.

In this paper, we explore how to avoid robot shutdowns due to proximity. Thus, we investigate different ways of communicating robot motion intent to users. Following findings from previous work, we focus on head-mounted Augmented Reality (AR) devices to convey the motion intent to users [21, 28]. While different visualizations of robot motion intent have been explored already, it remains unclear which visualization works best for communicating the robot motion intent on a head-mounted AR device, primarily when the context induces additional workload to the user. Hence, we implemented different visualizations for communicating the robot motion intent and compare them in a user study that includes additional workload. We ask: **(RQ) Which visualization presented on a head-mounted Augmented Reality (AR) device communicates the motion intent of a robot in a way that empowers users to avoid robot shutdown due to proximity?**

We implemented three visualizations (see Figure 1) in head-mounted AR to show future motion intent for an industrial collaborative robot. The proposed visualizations show the robot motion only for a short time ahead while the robot is moving, but long enough for the human to perceive the oncoming robot and react. One visualization shows only the future path of the end-effector (see Figure 1a), while another shows a model of the complete robot configuration projected into the future (see Figure 1b). The third visualization shows which volume slice, projected onto a 2D circle, the robot will occupy in the future (see Figure 1c). We evaluate these visualizations in a user study in which one solves simple math equations while simultaneously avoiding the robot.

Our paper includes the following contributions:

- An implementation of three real-time visualizations (*Path*, *Preview*, and *Volume*), which show the robot motion intent in head-mounted Augmented Reality.
- An evaluation of these three visualization techniques in a laboratory user study, in which a small cognitive task is performed in a shared workspace.

2 RELATED WORK

2.1 Visualizing Safety Zones

Navigating spaces occupied with fenceless industrial robots requires human observers to be aware of the safety zones around these robots and their current states.

In previous work, Augmented Reality has shown great potential for conveying this type of information (e.g., for assembly [17]). To effectively communicate safety zones, San Martín and Kidal proposed six designs of visual and auditory feedback to indicate close proximity to a robot [22]. Their results show that participants prefer a design consisting of two severity steps in visual color overlay.

To cooperate with high-performance industrial robots, Vogel et al. [25] proposed a projection system that visualizes the safety zones on the floor. In addition to the projection, the shared human-robot working area is covered by a tactile floor that also informs users about the safety zones. One year later, they presented a projected AR system for dynamically generated safety zones in cooperative manufacturing processes between humans and robots [26]. These safety zones are projected onto the shared workspace and a camera system is used to monitor it.

Michalos et al. [17] presented a system to inspect assembly processes, also involving a robot. Their visualization in Augmented Reality includes 3D models and assembly instructions. In addition, the visualization shows online data, such as safety volumes of the robot controller.

2.2 Visualizing Future Intent

Watanabe et al. [29] examined the communication of robot intention in the context of navigation with wheelchairs. A light projection was used to communicate the motion intent to humans. The trajectories of mobile robots and wheelchairs were visualized. The results showed that humans prefer to interact with a robot when it visually reveals its intentions. Furthermore, it was found that human responses to the robot can already be effectively improved by adding simple contextual information [4]. An example is the display of the navigation intent of a robot.

Shrestha et al. [24] stated that the navigation intent of mobile robots became more clear through the use of external flashers. However, the systems described so far use conventional visualization methods such as screens or external light sources (turn signals). Interestingly, May et al. [16] found that communication of the motion intent using turn signals is still more effective compared to anthropomorphic features (such as a gaze to indicate the direction of navigational intent).

Other studies use head-mounted AR to communicate the intent of a robot. Chakraborti et al. [5] examined the task planning capability of a robot which visualizes its intended plan and contextual information. Using the Microsoft HoloLens, participants could interact with the robot's plan using gestures and see the robot arm's intent via added context information that was next to the objects that were part of the plan.

Rosen et al. [21] found that Mixed Reality is an improvement from the classic desktop interface when displaying paths of robot arms. Their AR visualization on the Microsoft HoloLens showed a trail of the robot path. The participants were then asked to evaluate

as quickly and accurately as possible whether or not the arm would collide with the blocks on this path. The arm itself did not move in the conditions with a 3D display of the path.

Walker et al. [28] developed explicit and implicit designs for the visual signaling of a (flying) robot's motion intent using AR. It was found that the complete visualization of the movement path, enriched with further context information, is best suited for the communication of the motion intent.

Ameri E. et al. [2] present a system for visualizing and checking manipulation plans in 3D (either in Augmented or Virtual Reality). Motion and gripper actions are visualized as lines and boxes, respectively.

3 DESIGN

Our design process started as an iterative process model with analysis of previous research to determine relevant previous results and to extract different visualization approaches for the robot motion intent. We focused on surveying research on Augmented and Mixed Reality technologies as the strong geometric nature of robot motion intent lends itself most readily for this modality.

For the purpose of visualizing highly dimensional paths of robot arms, head-mounted AR, specifically using the advanced Microsoft HoloLens [15] device, was shown to be most suited [21]. As an additional constraint from our use-case, only head-mounted AR allows hands-free operation. Therefore, we focus on head-mounted AR using the Microsoft HoloLens device exclusively. Although the Microsoft HoloLens itself has some challenges, such as a limited field of view of 30 by 17.5 degrees, it offers the best performance and the largest feature set compared to other head-mounted Augmented Reality solutions.

For all visualizations, we used a color gradient from blue to red to encode how close the robot arm is relative to the user. Here, red stands for very close and blue for far away. We based this on the warm and cold metaphor used, for example, in heatmaps¹ [11, 13]. Furthermore, the color red is commonly associated with danger [9, 20].

All three visualizations show the robot's future path over the subsequent five seconds. Ten waypoints on the path are interpolated over the five seconds. In the following, the three visualizations are described in more detail:

Path displays the path of the robot arm as a line, comparable to the Arrow design by Walker et al. [28]. The path shows the future positions of the robot's end-effector only (see Figure 1a). An advantage of this visualization is its simplicity, though by neglecting other parts of the robot, the visualization is not complete. This may increase load on the user as the rest of the robot motion must be understood from incomplete information. Additionally, the user may not see the path, even though significant parts of the robot on its path may collide with the user.

Preview shows the full robot configuration by rendering robot meshes at the interpolated waypoints, as in the visualization by Rosen et al. [21]. Unlike their visualization, our shows the robot along the instantaneous (future) motion path while the robot actually moves on the path (see Figure 1b). This visualization has the advantage of showing all degrees of freedom. However, one

could still miss a possible future collision by looking away from the visualization.

Volume is based on a cylinder around the robot, which is cut into slices along the radial axis from the centerline (see Figure 1c). The volume slices that the robot will occupy are visualized using the color gradient from blue to red, while empty (safe) slices are colored green. Thereby, the visualization incorporates previous findings that show it is beneficial to inform users where they are safe [22]. In total, the visualization consists of 72 slices that look like a pie chart centered on the first joint of the robot. The cylinder is chosen as it corresponds well to the circular workspace of the robot and we assume that it can be perceived well from different perspectives.

4 EXPERIMENT

We tested the visualizations described in the previous section in a laboratory user study.

4.1 Apparatus and Implementation



Figure 2: Apparatus of Experiment. Setup includes a 14" touch screen and a KUKA LBR iiwa 7 R800 with a Schmalz ECBPi Vacuum Gripper. *Best seen in color.*

The apparatus consists of a KUKA LBR iiwa 7 R800 with a Schmalz ECBPi (Cobot Pump) Vacuum Gripper situated in the middle of a table 84 cm in height. Around the robot arm, there are four boxes placed in the same distance of 70 cm to the robot arm. The boxes have a distance of approximately 80 cm to one another on the right and left sides, and the distance across between the two front and back boxes is approximately 130 cm. The arm moves from one box to another by turning only the bottom-most joint (Joint 1), pretending to grab items from one box and shifting them to another. The arm ran at a maximum angular velocity of approximately $0.05 \frac{rad}{s}$ leading to an end-effector speed of $4 \frac{cm}{s}$.

The participant has to solve math puzzles on a tablet to create a small cognitive load. The tablet is 35 cm from the base of the robot arm. It is located between the two boxes in front of the robot. At the start and end of each trial, the arm intersects the space in front of the tablet where the participant solves the math puzzles.

¹Heatmap. en.wikipedia.org/wiki/Heat_map, last retrieved July 14, 2020

The math puzzles consist of equations with simple additions of two single-digit numbers. The participant decides whether the presented equation is correct or incorrect by pressing the corresponding button on the tablet. The equation is true in 50% of cases. If a proposed solution is wrong (i.e. it is displayed wrong), two is either added or subtracted from the correct result, both with a probability of 50%.

The visualizations of the robot intent are displayed on the Microsoft Hololens. For the implementation, we used Unity (v.2018.4.5) and the Siemens ROS# library (v.1.5) for the communication with the ROS-Bridge Suite (v.0.11.3). Vuforia (v.8.3.8) marker detection is used for aligning the coordinate systems of the arm and the Microsoft Hololens. An Intel NUC computer with an Intel i7 CPU and 16GB RAM was used to run ROS and control the experiment. A second Intel NUC with an Intel i5 CPU and 4GB RAM was used as a supervisor interface to select the condition and trial block to run as well as to control the recording of experimental data.

Safety Aspects. For safety reasons, the maximal torque of each robot joint was set to be 25 Nm. In the case of higher torques, for example, generated during a collision, the robot would perform an emergency stop. Since the end-effector moved in a circular motion of about 0.8 m around the robot's center, this would lead to a collision force of 31.25 N. Assuming a collision area of about 4 cm², the pressure of a collision would be $7.81 \frac{N}{cm^2}$. However, according to the DIN-ISO/TS 15066, which specifies the safety requirements for human-robot interactions, a maximal force of 65 N and a maximal pressure of $110 \frac{N}{cm^2}$ would be allowed even in the most sensitive area, the face. Our values are thus far below the upper threshold, which is why we can consider our setup to be safe even if a collision should occur.

4.2 Participants

We recruited 18 volunteer participants² (5 female), aged between 18 and 49 years ($M=31.39$, $SD=6.51$) from the province Lower Saxony in Germany through public and online advertisements. Participants received no compensation for their time, which was communicated in the advertisement. None of the participants suffered from color vision impairments, 8 had normal vision, and 10 had corrected-to-normal vision. We asked the participants to rate their experience with Augmented Reality on a 5 point Likert-scale. The participants stated that they had basic to intermediate experience ($Md=2$, $IQR=2$). Participants were informed that they could end the experiment at any time without any negative consequences. Clearance for this research was obtained by the institute's ethics review.

4.3 Procedure

Before the experiment started, the participants were informed about the study and the experimental setup. We marked the working area of the robot with a line on the ground. Each experiment started with two test trials, in which a participant could enter the working area of the robot and get to know the respective visualization before the actual experiment.

²For mean effect sizes of ($f=0.20$), at least 285 observations are necessary, which requires testing at least 18 participants (for each comparison we have 16 trials per participant). We calculated this value with G*Power under Wilcoxon signed-rank test for matched pairs ($\alpha=0.05$ and $1-\beta=0.95$).

The actual experiment consisted of three blocks, each of which tested a visualization, and lasted about 10 minutes. After the last block, a short questionnaire was completed. In total, the experiment lasted about 40 minutes. Each block consisted of 8 trials in which the arm of the robot moved between the four blue boxes as seen in Figure 2. Four trials moved from the left two boxes towards the right ones and into a possible collision with the user, while four moved from the right. Each combination of box-to-box motion was used to elicit a potential collision by traveling through the position of the user (meaning front-left to front-right, front-left to back-right, etc). A set number of stops at boxes on the starting side were added per trial to force the participants to understand if the robot would continue its movement towards them or stop at the front boxes. A summary of the motions in each of the 8 trials is shown in Table 1.

While the participants were in the working area of the robot, they were to solve mathematical problems on a tablet and at the same time observe the visualization through the Microsoft Hololens. As soon as the participants felt that the robot arm was moving into their work area, they were to leave the area with one step backward. The order of the visualizations was chosen according to the Complete Counterbalanced Measure Design. Since three visualizations were tested in our experiment, the order was repeated after the 6th and 12th participants. After a participant had completed a condition, the subjective evaluation of the respective visualization and task was recorded with a Likert-item questionnaire. Each block followed the basic structure:

(1) Perform test trial with visualization $x \rightarrow$ (2) Perform trial block with visualization $x \rightarrow$ (3) Complete Likert-item questionnaire about visualization x

At the end of the last block, a short questionnaire regarding demographics, eyesight, experience with AR, and subjective measures was administered.

Table 1: Trial motions, with number of stops taken before starting the move into collision.

#	Direction	From Box	To Box	# Stops
1	$R \rightarrow L$	Back	Front	2
2	$R \rightarrow L$	Back	Back	5
3	$R \rightarrow L$	Front	Front	3
4	$R \rightarrow L$	Front	Back	4
5	$L \rightarrow R$	Back	Front	3
6	$L \rightarrow R$	Back	Back	4
7	$L \rightarrow R$	Front	Front	2
8	$L \rightarrow R$	Front	Back	5

4.4 Study Design

To evaluate the performance of different real-time visualizations of robot motion intent, we conducted a within-subjects controlled laboratory study in Augmented Reality with the Microsoft Hololens. Our independent variable was visualization with three levels (*Path* vs. *Preview* vs. *Volume*). We used quantitative methods to evaluate user performance, taking robot angle on leave, head pose in robot area, task performance, workload, and subjective measures as our dependent variables.

For this study, we asked: **(RQ) Which visualization presented on a head-mounted Augmented Reality (AR) device communicates the motion intent of a robot in a way that empowers users to avoid robot shutdown due to proximity?**

- H_1 We expect higher robot angles on leave for *Volume* than for *Path* and *Preview* because we expect participants to perceive the robot arm approaching earlier in the *Volume* condition.
- H_2 We expect the condition *Path* to result in stronger head rotations than *Preview* and *Volume* because of the limited field of view of the used AR device, which may require participants to rotate their heads more to perceive the *Path* visualization.

4.5 Results

Robot Angle on Leave. For all conditions, all participants managed to exit the robot working area before a collision could occur. We consider robot angle on leave to be the angle of the base joint of the robot at the point in time when the participant left the robot working area. We had to exclude one participant from the analysis of robot angle to leave, as the participant did not leave the robot working area backward across the specified line, but rather evaded the robot arm sideways. A Shapiro-Wilk-Test showed that our data is not normally distributed ($p < 0.001$), and thereafter we ran a Friedman test that revealed a significant effect of *Visualization* on robot angle on leave ($\chi^2(2)=6.37$, $p=0.041$, $N=17$). A posthoc test using Wilcoxon Signed-rank with Holm-Bonferroni correction showed a significant difference between *Volume* ($Md=37.12$, $IQR=13.79$) and *Preview* ($Md=40.53$, $IQR=18.93$) ($r=0.17$, $p=0.018$). *Volume* led to smaller robot angles on leave than *Preview*, meaning the participants let the robot arm come closer before leaving. There were no significant differences from *Path* ($Md=39.93$, $IQR=17.28$) (see Table 2). Figure 3 shows the robot angle on leave distribution per visualization.

Head Pose in Robot Area. To understand how participants used the different visualizations, we compared their head rotations (looking left or right) for each condition to another. We recorded all head poses (including position and rotation; interval 50Hz) with the Microsoft Hololens. In a first step, we extracted all head poses that had been recorded within the robot working area during a trial. Overall, we identified 552478 data points as relevant: *Path*=185115, *Preview*=184031, and *Volume*=183332. Afterward, we calculated the

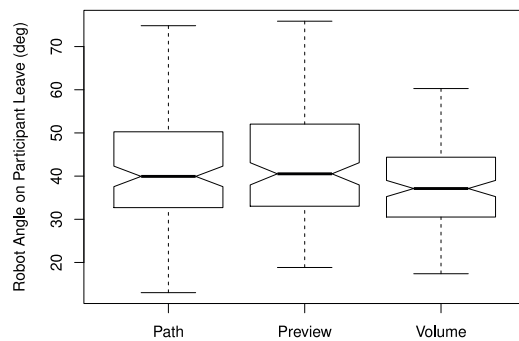


Figure 3: Robot angle (base joint) to participant on leaving the robot area.

Table 2: Pairwise comparisons of robot angle on leave for the different visualizations (r : > 0.1 small, > 0.3 medium, and > 0.5 large effect).

Comparison			W	Z	p	r
Path	vs.	Preview	4515	0.31	0.757	0.02
Path	vs.	Volume	5578	2.00	0.092	0.12
Preview	vs.	Volume	3394	2.75	0.018	0.17

mean head rotation (deviation from 0° for left or right head rotation) for each trial. The median head-rotations per condition in ascending order are: *Path*= 6.62° ($IQR=6.57^\circ$), *Preview*= 4.06° ($IQR=5.46^\circ$), and *Volume*= 2.28° ($IQR=3.17^\circ$). The head rotations are compared in Figure 4.

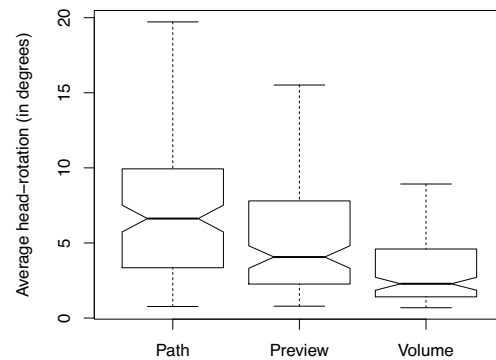


Figure 4: The median head rotations per condition.

A Shapiro-Wilk-Test showed that our data is not normally distributed ($p < 0.001$), and thereafter we ran a Friedman test that revealed a significant effect of visualization on head rotation ($\chi^2(2)=76.24$, $p<0.001$, $N=18$). A posthoc test using Wilcoxon Signed-rank with Bonferroni-Holm correction showed significant differences between all conditions (see Table 3). Here, we can conclude *Path* $>$ *Preview* $>$ *Volume* for the median head rotation during the trials.

Table 3: Pairwise comparisons of head-rotations for the different visualizations (r : > 0.1 small, > 0.3 medium, and > 0.5 large effect).

Comparison			W	Z	p	r
Path	vs.	Preview	7316	5.77	<0.001	0.35
Path	vs.	Volume	8265	7.84	<0.001	0.48
Preview	vs.	Volume	7134	5.38	<0.001	0.33

Task Performance. We consider the effect of visualization on the number of solved math puzzles per trial. The mean numbers (total numbers over all trials) of solved math puzzles per condition in ascending order are: *Preview*=14.99 (2158), *Path*=15.32 (2206), and *Volume*=16.44 (2368). The numbers of solved math puzzles for each condition are compared in Figure 5.

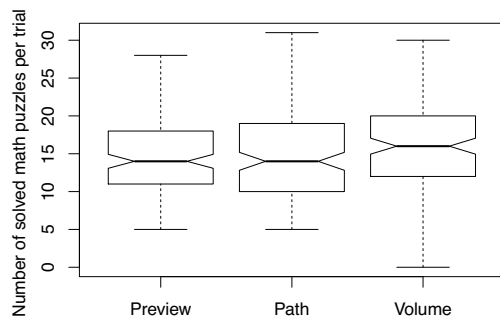


Figure 5: The median number of solved math puzzles.

A Shapiro-Wilk-Test showed that our data is not normally distributed ($p < 0.001$), and thereafter we ran a Friedman test that revealed no significant effect ($\chi^2(2)=4.81$, $p=0.090$, $N=18$).

Furthermore, we consider the effect of visualization on the percentage of correctly solved math puzzles per trial. The mean percentages of correctly solved math puzzles per trial in ascending order are: *Preview*=98.20%, *Path*=98.43%, and *Volume*=98.89%. A Shapiro-Wilk-Test showed that our data is not normally distributed ($p < 0.001$), and thereafter we ran a Friedman test that revealed no significant effect ($\chi^2(2)=2.36$, $p=0.307$, $N=18$).

Task Load. The results of the task load ratings as measured by the Raw NASA Task Load Index (Raw-TLX) [12] are shown in Table 4. We conducted a Friedman test for each scale of the Raw-TLX and found significant differences for two scales: physical demand ($\chi^2(2)=6.78$, $p=0.034$, $N=18$) and frustration ($\chi^2(2)=10.58$, $p=0.005$, $N=18$). A posthoc test using Wilcoxon Signed-rank with Bonferroni-Holm correction showed significant differences between some of the conditions. For physical demand, we found significant differences between *Path* and *Preview* ($W=53.5$, $Z=2.63$, $p=0.026$, $\phi=0.38$), and *Path* and *Volume* ($W=69$, $Z=2.03$, $p=0.039$, $\phi=0.29$), indicating a higher physical demand for *Path*. For frustration, we found a significant difference between *Path* and *Volume* ($W=228$, $Z=2.78$, $p=0.018$, $\phi=0.40$), indicating that users were less frustrated when using *Volume*.

Subjective Measures. After each condition, we asked participants to answer a question with a 5-point Likert-item (1=strongly disagree, 5=strongly agree). The results are shown in Figure 6. Participants stated that the *Path* visualization did not support them ($Md=1$, $IQR=2$), while they were neutral for *Preview* ($Md=3$, $IQR=2.25$) and *Volume* ($Md=3$, $IQR=2$).

Furthermore, at the end of the experiment, the participants were asked to vote for the visualizations that made them feel the most and least safe. Eleven participants stated that they felt the safest with *Volume*, while five voted for *Preview* and two voted for *Path*. Fourteen participants stated that they perceived *Path* as the least safe visualization, while four voted for *Preview* and nobody voted for *Volume*.

5 DISCUSSION

Avoiding Close Proximity. In all trials, participants left the robot working area before a collision with the robot arm could occur.

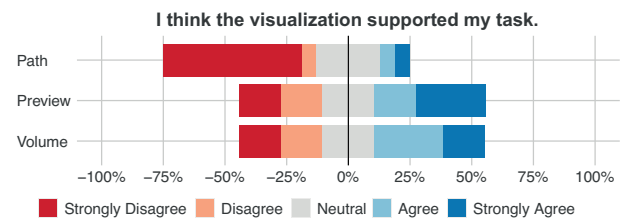


Figure 6: Results from Likert-item questionnaire.

Nevertheless, we observed differences among the conditions for the angle between participant and robot arm on leave. In our hypothesis H_1 , we expected *Volume* to result in higher angles than *Path* and *Preview* because we thought participants would perceive the robot arm motion sooner and therefore leave earlier. However, our results showed that the angle to the robot arm on leave was significantly lower for *Volume* than for *Preview*. It might be that the participants stayed longer in the shared workspace because they trusted the *Volume* visualization more. This is reflected in the subjective measures, where *Volume* was rated as the safest visualization. The smaller variance of angle on leave in *Volume* may be explained by a more reliable perception of the robot motion, whereas other conditions would be less reliable and cause some participants to leave much earlier or much later when the robot itself was perceived with peripheral vision.

Head Movement. Because of the limited field of view of current AR devices (including the used Microsoft HoloLens), we expected in our hypothesis H_2 that participants would need stronger head rotations to perceive the *Path* visualization than for *Preview* and *Volume*. In our results, we found a significant effect giving evidence for this and therefore, we accept our hypothesis H_2 . However, we also found that *Volume* results in significantly fewer head rotations compared to *Path* and *Preview*. This is interesting because it suggests that the *Volume* visualization can be perceived quite well even without much effort in terms of head rotation.

Task Performance. For the number of solved math puzzles and the percentage of correctly solved equations, we did not observe any significant differences among the three conditions. However, as the reported head rotations suggest, stronger head rotations are required for the *Path* visualization than for the *Volume* visualization. Therefore, participants have more time and potentially could solve a larger number of math puzzles. This is somewhat reflected in the results (*Path*=2158 and *Volume*=2368 solved math puzzles), however, the effect size may be too small to find any significant differences with the given sample size. Overall, all visualization led to more than 98% correctly solved math puzzles on average.

Task Load. We found that *Path* resulted in significantly higher physical demand and frustration compared to *Volume*. This supports our previous findings that *Volume* can be perceived quite well and does not require strong head rotations to be understood. Furthermore, it can explain the higher frustration for *Path* because participants are more likely to miss the information provided by

Table 4: Task load ratings (Raw-TLX) for all visualizations (values range from 1 (very low) to 10 (very high)).

Visualization	Mental Demand Median (IQR)	Physical Demand Median (IQR)	Temporal Demand Median (IQR)	Performance Median (IQR)	Effort Median (IQR)	Frustration Median (IQR)
Path	3.0 (3.00)	2.0 (4.00)	4.0 (3.25)	5.5 (4.00)	3.5 (3.25)	5.0 (5.00)
Volume	3.0 (2.25)	2.0 (1.25)	3.5 (3.00)	7.5 (3.25)	3.0 (2.00)	2.5 (3.00)
Preview	3.0 (2.00)	2.0 (1.00)	3.0 (3.00)	6.5 (4.00)	2.0 (3.25)	3.0 (3.25)

the visualization. Hence, we argue that *Volume* is best-suited for devices with a limited field-of-view, which includes all most currently available AR headsets, such as the HoloLens.

Subjective Measures. Participants were neutral about the volume and preview visualizations, while they disliked the path visualization. We think this is due to the limited field of view of the Microsoft HoloLens. Participants stood very close to the touch interface to solve the math puzzles. Thereby, the augmentation often required strong head rotations to prove useful. However, at the end of the study, we asked all participants for the safest visualization. Here, most participants (11/18, 61%) stated that they perceived *Volume* as the safest visualization. We think this is due to the fact that *Volume* managed to utilize the small screen in the best way, while *Path* was perceived as least safe because stronger head rotation is required to see the augmentation.

Limitations. A technical limitation of our study is in current AR devices. The limited field of view of these devices cannot use the potential of human peripheral vision to arouse visual attention naturally. On top of that, every augmentation needs to be placed in the center of the field of view to be perceived well, resulting in visual clutter that may negatively influence the performance of any tasks carried out. However, by using an AR device with a limited field of view, we were able to measure the performance of what is currently possible. Our study was limited to some extent by our simplified setup (four boxes) and the same slow speed for all robot motions during the study. However, since this user study is one of the earlier studies on AR interfaces that involves participants within the workspace of a robot arm in motion, we did not want to risk participants getting injured or frightened. Additionally, our research focuses on users that enter the robot working area knowingly. While this makes sense in some scenarios (e.g., refilling stacks for the robot to work with), it remains unclear how far our results can be replicated in situations in which the users accidentally enter the robot operating area.

Future work. In the future, we consider doing further experiments in Virtual Reality (VR). VR has certain advantages that allow one to, for example, test visualizations that require a larger field of view. Furthermore, in VR we could increase the speed of the robot arm while at the same time avoiding any danger for participants from a real robot arm in motion.

6 CONCLUSION

When humans and industrial robots share a workspace, humans need information about the robot's intent so that interruptions due to collisions are avoided. We implemented three different visualizations in AR, which are intuitive and easy to process while

performing tasks in a shared human-robot workspace. We found that the *Path* and *Preview* visualizations caused the participants to rotate their heads away from the task towards the robot. *Volume* required significantly less head movement, indicating easier perception of the robot motion intent. The participants also reported that they felt this visualization was most reliable. Our results also show that a head-mounted AR device with the appropriate visualization can help to improve the mediation of intents between robots and humans, so humans can avoid collisions.

REFERENCES

- [1] E. Ackerman. 2019. Amazon Uses 800 Robots to Run This Warehouse. <https://spectrum.ieee.org/automaton/robotics/industrial-robots/amazon-introduces-two-new-warehouse-robots> Accessed: 2019-10-01.
- [2] A. Ameri E., B. Akan, and B. Çürüklü. 2010. Augmented Reality Meets Industry: Interactive Robot Programming. In *Proceedings of SIGRAD 2010*. Linköping University Electronic Press; Linköpings universitet, 55–58.
- [3] R. Behrens, J. Saenz, C. Vogel, and N. Elkmann. 2015. Upcoming Technologies and Fundamentals for Safeguarding All Forms of Human-Robot Collaboration. In *8th International Conference Safety of Industrial Automated Systems, SIAS 2015*.
- [4] R. T. Chadalavada, H. Andreasson, R. Krug, and A. J. Lilienthal. 2015. That's on my mind! robot to human intention communication through on-board projection on shared floor space. In *2015 European Conference on Mobile Robots (ECMR)*. 1–6. <https://doi.org/10.1109/ECMR.2015.7403771>
- [5] T. Chakraborti, S. Sreedharan, A. Kulkarni, and S. Kambhampati. 2018. Projection-Aware Task Planning and Execution for Human-in-the-Loop Operation of Robots in a Mixed-Reality Workspace. (Oct 2018), 4476–4482. <https://doi.org/10.1109/IROS.2018.8593830>
- [6] F. De Pace, F. Manuri, and A. Sanna. 2018. Augmented Reality in Industry 4.0. *American Journal of Computer Science and Information Technology* 06, 1:17 (01 2018). <https://doi.org/10.21767/2349-3917.100017>
- [7] A. D. Dragan, K. C.T. Lee, and S. S. Srinivasa. 2013. Legibility and Predictability of Robot Motion. In *Proceedings of the 8th ACM/IEEE International Conference on Human-robot Interaction (Tokyo, Japan) (HRI '13)*. IEEE Press, Piscataway, NJ, USA, 301–308. <http://dl.acm.org/citation.cfm?id=2447556.2447672>
- [8] RE Earnest. 1997. Characteristics of proactive & reactive safety systems. *Professional Safety* 42, 11 (1997), 27.
- [9] A. Elliot, M. Maier, A. Moller, R. Friedman, and J. Meinhardt. 2007. Color and psychological functioning: The effect of red on performance attainment. *Journal of experimental psychology. General* 136 (03 2007), 154–68. <https://doi.org/10.1037/0096-3445.136.1.154>
- [10] M. Fox, D. Long, and D. Magazzeni. 2017. Explainable Planning. arXiv:1709.10256 [cs.AI]
- [11] C.L. Hardin. 2000. Red and yellow, green and blue, warm and cool: explaining colour appearance. *Journal of Consciousness Studies* 7, 8-9 (2000), 113–122. <http://www.ingentaconnect.com/content/imp/jcs/2000/00000007/F0020008/1046>
- [12] Sandra G. Hart. 2006. Nasa-Task Load Index (NASA-TLX); 20 Years Later. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 50, 9 (2006), 904–908. <https://doi.org/10.1177/154193120605000909> arXiv:https://doi.org/10.1177/154193120605000909
- [13] H-N. Ho, G. Van Doorn, T. Kawabe, J. Watanabe, and C. Spence. 2014. Colour-Temperature Correspondences: When Reactions to Thermal Stimuli Are Influenced by Colour. *PloS one* 9 (03 2014), e91854. <https://doi.org/10.1371/journal.pone.0091854>
- [14] O. Khatib. 1990. *Real-Time Obstacle Avoidance for Manipulators and Mobile Robots*. Springer New York, New York, NY, 396–404. https://doi.org/10.1007/978-1-4613-8997-2_29
- [15] B. C. Kress and W. J. Cummings. 2017. 11-1: *Invited Paper* : Towards the Ultimate Mixed Reality Experience: HoloLens Display Architecture Choices. *SID Symposium Digest of Technical Papers* 48, 1 (May 2017), 127–131. <https://doi.org/10.1002/sdtp.11586>

- [16] A. D. May, C. Dondrup, and M. Hanheide. 2015. Show me your moves! Conveying navigation intention of a mobile robot to humans. In *2015 European Conference on Mobile Robots (ECMR)*. 1–6. <https://doi.org/10.1109/ECMR.2015.7324049>
- [17] G. Michalos, P. Karagiannis, S. Makris, Ö. Tokçalar, and G. Chryssolouris. 2016. Augmented Reality (AR) Applications for Supporting Human-robot Interactive Cooperation. *Procedia CIRP* 41 (2016), 370 – 375. <https://doi.org/10.1016/j.procir.2015.12.005> Research and Innovation in Manufacturing: Key Enabling Technologies for the Factories of the Future - Proceedings of the 48th CIRP Conference on Manufacturing Systems.
- [18] International Federation of Robotics Statistical Department. 2019. World Robotics 2019: Industrial Robots.
- [19] International Federation of Robotics Statistical Department. 2019. World Robotics 2019: Service Robots.
- [20] K. Pravossoudovitch, F. Cury, S. G. Young, and A. J. Elliot. 2014. Is red the colour of danger? Testing an implicit red–danger association. *Ergonomics* 57, 4 (2014), 503–510. <https://doi.org/10.1080/00140139.2014.889220> arXiv:<https://doi.org/10.1080/00140139.2014.889220> PMID: 24588355.
- [21] E. Rosen, D. Whitney, E. Phillips, G. Chien, J. Tompkin, G. Konidaris, and S. Tellex. 2019. Communicating and controlling robot arm motion intent through mixed-reality head-mounted displays. *The International Journal of Robotics Research* 0, 0 (2019), 0278364919842925. <https://doi.org/10.1177/0278364919842925>
- [22] A. San Martín and J. Kildal. 2019. Audio-visual AR to Improve Awareness of Hazard Zones Around Robots. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) (*CHI EA '19*). ACM, New York, NY, USA, Article LBW2213, 6 pages. <https://doi.org/10.1145/3290607.3312996>
- [23] K. E. Schaefer, E. R. Straub, J. Y.C. Chen, J. Putney, and A.W. Evans. 2017. Communicating intent to develop shared situation awareness and engender trust in human-agent teams. *Cognitive Systems Research* 46 (2017), 26 – 39. <https://doi.org/10.1016/j.cogsys.2017.02.002> Situation Awareness in Human-Machine Interactive Systems.
- [24] M. C. Shrestha, A. Kobayashi, T. Onishi, H. Yanagawa, Y. Yokoyama, E. Uno, A. Schmitz, M. Kamezaki, and S. Sugano. 2016. Exploring the use of light and display indicators for communicating directional intent. In *2016 IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*. 1651–1656. <https://doi.org/10.1109/AIM.2016.7577007>
- [25] C. Vogel, M. Fritzsche, and N. Elkmann. 2016. Safe human-robot cooperation with high-payload robots in industrial applications. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 529–530. <https://doi.org/10.1109/HRI.2016.7451840>
- [26] C. Vogel, C. Walter, and N. Elkmann. 2017. Safeguarding and Supporting Future Human-robot Cooperative Manufacturing Processes by a Projection- and Camera-based Technology. *Procedia Manufacturing* 11 (2017), 39 – 46. <https://doi.org/10.1016/j.promfg.2017.07.127> 27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017, 27–30 June 2017, Modena, Italy.
- [27] S. Wachter, B. Mittelstadt, and L. Floridi. 2017. Transparent, explainable, and accountable AI for robotics. *Science Robotics* 2, 6 (2017). <https://doi.org/10.1126/scirobotics.aan6080> arXiv:<https://robotics.sciencemag.org/content/2/6/ean6080.full.pdf>
- [28] M. Walker, H. Hedayati, J. Lee, and D. Szafrir. 2018. Communicating Robot Motion Intent with Augmented Reality. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (Chicago, IL, USA) (*HRI '18*). ACM, New York, NY, USA, 316–324. <https://doi.org/10.1145/3171221.3171253>
- [29] A. Watanabe, T. Ikeda, Y. Morales, K. Shinozawa, T. Miyashita, and N. Hagita. 2015. Communicating robotic navigational intentions. (Sep. 2015), 5763–5769. <https://doi.org/10.1109/IROS.2015.7354195>