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Using Augmented Reality to Enhance Worker Situational Awareness In Human Robot Interaction

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Abstract— **This study investigates the potential of augmented reality (AR) to enhance users' ability to predict the position of a robotic tool when it enters their blind spot. Augmented reality is increasingly utilized in industrial settings to improve situational awareness and user interfaces. In this experiment, participants performed tasks involving the prediction of the tool's position using both conventional methods and AR displays. The Situational Awareness Global Assessment Test (SAGAT) was employed to evaluate the effectiveness of the AR display as a user interface and its impact on users' awareness. Results reveal improvements in several metrics when using AR, including a reduction in average perception error and an increase in subjective confidence levels. Additionally, the AR display led to a higher percentage of correct responses in predicting the direction the tool of the robot was moving when the worker had no direct line of sight to it. These findings suggest that AR displays have the potential to enhance situational awareness and improve the current state of user interfaces in industrial environments.**

I. Introduction and Related Works

In recent years, manufacturing needs have greatly changed, driven by the market's demands for quickly produced, low-cost, and easily customizable products [1]. Standard production lines and traditional robotic systems no longer satisfied these evolving demands, which required a more responsive and systematic approach [1], [2]. The need for flexibility in the production process resulted in an alternative to traditional factory floors [3], as manufacturing industries worked to create a synergistic working environment using the different skill sets of humans and robots. In this interdependent atmosphere, robots perform straightforward "non-value-added" manual work with reliability, precision, and strength, and the perception, intuition, and flexibility of a human are utilized to perform the "value-added" work demanded in the so-called fourth industrial revolution [4], [5]. This symbiotic solution became the new focus of industrial robotics and has inspired new concepts such as human-robot collaboration (HRC) and technologies such as collaborative robots [2], [6], [7]. HRC refers to the collaborative processes in which robots and humans work together to achieve common goals in a shared workspace, and the ISO 10218-2:2011 standard defines collaborative robots as robots designed for direct interaction with a human within a limited collaborative workspace [8]. These ideas of a human and a robot safely and efficiently sharing a workspace and task have become widely accepted in many industries as a promising way to achieve productivity increases [3], [7], [9]–[13]. This collaboration applies not only in manufacturing, but in other fields such as healthcare and warehousing [14], and comes with many new considerations.

A. Percieved Safety of Workers in HRC

While physical safety always remains a crucial consideration, ensuring the "perceived" safety of the human participants in HRC is equally as significant. Workers tend to view a cobot teammate as a unique social entity, with the power to affect their psychological states [15]. Consequently, participants' perceived safety depends on their enhanced vigilance and awareness of robot motion, in the attempt to avoid unpleasant emotions [16]. This hyper-vigilance greatly affects the efficiency of an HRC system which depends on a variety of complex factors, including the operator's trust, comfort, awareness, and perceived safety of the robot as well as their cognitive load [2], [17]. Many of these concerns are exacerbated by the lack of efficient human-robot communication. In a typical human-human interaction, the parties can use cues such as body language to anticipate each other's behavior and tend to interact in higher-level communication of intentions [18], [19]. Such implicit and explicit expression is essential for fluent human-robot collaboration [19], and the successful design of these communication methods is one of the main objectives of the field of HRC [10]. However, in dynamic environments, where humans and robots move around continuously, the robot is not in the field of vision of the human the majority of time. In addition, the bustling nature of many fields such as manufacturing and healthcare means that there are often high noise levels that interfere with this robot-human communication.

B. Situational Awareness

One possible metric to determine the perceived safety of the worker is to assess their situational awareness when working with robots. While trust, comfort, and cognitive load are important elements to consider, human-robot interaction studies analyzing collaboration have determined that the key component to task fluency is the awareness and anticipation

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of intention by human and robot agents [16]. The abilities to perceive (Level 1), comprehend (Level 2), and project (Level 3) elements in the environment are referred to as the different levels of situation awareness (SA) [20], and are paramount for effective decision-making in dynamic systems [21], [22]. The Situation Awareness Global Assessment Technique (SAGAT) is widely regarded as the best method for the measurement of SA [4], [22]

C. Situational Awareness Global Assessment Test

The technique, as outlined by Endsley [23], usually consists of three main components:

- Baseline Task: Individuals perform a task or scenario of interest related to their domain, such as monitoring a system or completing a procedure.
- Interruption: At a random critical point during the task, all informational elements of the system are removed from the field of vision, and the subject must stop all relevant activities. This interruption is typically sudden and unexpected, representing a real-life scenario that requires immediate attention.
- Questioning: Participants are then asked a series of targeted questions related to their perception of the current state of the task or elements of their situation at that time. Questions may focus on details about the environment, status updates, or the potential implications of the interruption, each assessing the different levels of situational awareness.

The purpose of SAGAT is to evaluate how individuals understand their surroundings and their situational awareness, despite interruptions or unexpected changes. It helps determine their ability to gather, process, and comprehend information relevant to the task at hand, and determines the quality of the informational system [20]. This method provides an objective assessment of operator SA, as it allows for detailed information to be evaluated against reality since the ground-truth facts can be compared to the responses at the time of interruption.

D. User Interfaces

The method of communication of relevant information between robots and their human coworkers is the "user interface". This is simply how the robot conveys important details and intentions necessary for collaboration and can include auditory, visual, or haptic responses [3]. Generally, visual and auditory interfaces prevail as these systems provide clear sensory inputs that humans utilize to quickly form an accurate perception of their environment [10]. Proper user interfaces should be both easy to interact with and enable comprehension of the current system behavior [6], and provide essential situational awareness to adapt and allow for informed decision-making during uncertain and dynamic situations [6], [24].

In robot development, the most common user interface for expressing visual and auditory cues involves a video feed from the robotic platform [18] through display screens [3]. Other visual-modality-based work, summarized in Sonawani and Amor [25], focuses on discrete visual signals, combinations of colors and intensities, projection mapping using onboard projectors, and object-aware projection techniques. However, while these methods may present more flexibility for users to view information in different forms [18], they are not the most efficient method of conveying information. These visual, yet static methods require the frequent diversion of the worker's attention and constant surveillance of their environment to make operational decisions. According to Scholtz [18] and Ruiz et al. [26], computer-based displays are unable to show all necessary information on a single display, have decreased situational awareness due to visual contact loss, and fail to account for environments where computer access is difficult, such as factory settings [5]. These consequences greatly increase the likelihood of collisions and decrease the efficiency of task performance [27]. This risk can be even greater for individuals who are hard of hearing (HOH), deaf, or working in HRC environments with a high noise floor, such as manufacturing factory settings. They lack the auditory cues necessary to assess their surroundings while their vision is diverted. Factory machinery produces approximately 92-96 decibels of noise [28], and heavy construction equipment sound levels range from 80 to 120 decibels [29]. For HOH, deaf, or industry workers, the prototypical user interfaces of static visual feeds and auditory advisories can be catastrophically dangerous and hinder productivity. Future direction should focus on providing a more comprehensive understanding of the scene in a way that is easy to use and intuitive for the operator to understand, without relying on these measures [7].

E. Augmented Reality

Virtual reality is the creation of an entirely virtual environment where the user can interact with computer-generated objects. It has been used in the field of collaborative robotics research primarily for the simulation of HRC environments for safe testing and training [5], [30]. In between physical reality and complete immersion lies a continuum of mixed reality, blending the physical and digital worlds [2]. This creates an enhanced perception of the user's environment which has been introduced to the HRC world as augmented reality (AR). AR's blend of physical and digital avoids the restrictions of traditional means and provides systemic information simultaneous to human activity. Technical advancement in AR devices has led to the availability of powerful and reasonably priced devices for market use, opening an accessible pathway for research [31]. As a result, applications of AR technologies have been of increasing interest in HRC in recent years as a means of organizing and providing information about a robot to its human collaborators [3], [25], [30].

Providing relevant information about the robot's operation has been thoroughly explored, for example, displaying the task being performed [32], [33], or the robot's current position and future motion [34], [35]. Augmented reality aids in effective decision-making since the clear and constant visualization of task and environmental data allows human workers to gain insights into the task and heightens their situational awareness [24], [25]. As emphasized by Matsas and Vosniakos [16], the immersive tool of augmented reality provides a platform to most easily facilitate situational awareness at all three levels but it has not been applied to HRC situations where the robot operates outside the human's vision and cannot convey auditory cues.

F. Microsoft Hololens 2

The HoloLens 2 is a unique mixed-reality headset developed by Microsoft, that creates an immersive perception of the user's physical environment through the overlay of holographic images onto transparent lenses. Its field of view, spatial mapping, gesture recognition, and eye-tracking capabilities allow for diverse applications in industries like manufacturing, healthcare, education, gaming, and engineering [36]. A crucial component of seamlessly integrating digital content into the physical world is Microsoft's Unity World Locking Tool. As outlined in Microsoft's documentation, the tool utilizes fixed spatial anchors in the real world to keep digital content and virtual objects in a fixed location relative to the physical environment. This allows for "world-locked experiences" where digital elements remain in the same spatial position over time, maintaining the spatial continuity necessary for collaborative experiences [37].

Fig. 1: Microsoft Holo Lens 2 outfitted with IR markers for motion capture.

G. Digital Twin Generation

Industry 4.0 requires critical components such as cyber-physical systems (CPS) and digital twins to adapt to emerging technologies [38]. CPS utilizes computerized replicas of physical objects, or 'digital twins', to integrate virtual and physical environment assets [39]. In Choi et al., the combination of deep learning and digital twin generation enables real-time measurement of safety distances and enhances task assistance and effective collaboration [40]. In other works that use AR glasses, the digital twin, providing a synchronized virtual representation of the real robot, plays a crucial role in enhancing safety and providing the participant with a preview of the robot's actions during HRC [41], [42].

H. Contributions

This research aims to investigate the usage of augmented reality in increasing situational awareness in human-robot collaboration when the human's vision of the robot is obscured and auditory cues are undetectable. This work investigates a heads-up display application using the Microsoft HoloLens 2 and a situation that simulates a manufacturing environment with a high noise floor. The study uses the SAGAT method to analyze and evaluate the impact of the application on situational awareness and the confidence of human participants. We focus on the analysis of applications without auditory cues, such as factory and hard-of-hearing workers, using motion capture and digital twin creation to present spatial information and evaluate the participant's perception of their surroundings with augmented reality. This is a preliminary study with 10 participants, intended to gather exploratory data to determine the viability of such an AR system for the improvement of HRC environments.

II. Methodology

The overarching goal of these experiments is to evaluate the impact of using augmented reality to provide positional information of the end-effector of a robot during a collaborative task and assess the change in the human participant's situational awareness.

To analyze participant situational awareness, this experiment uses a UR-10 collaborative robot, OptiTrack motion capture system, the Microsoft HoloLens 2, and the SAGAT method as outlined in the flowchart to determine the human's estimate of the relative location of the robot end-effector and compare it to the ground truth.

A. Experimental Setup and Design

The physical setup imitates an automated assembly line scenario, consisting of four stations labeled A-D, a conveyor belt, a Sawyer robot, a UR10 cobot, 13 motion capture cameras, and 3-piece parts, positioned as shown in Fig. 3A. The task of the human participant is to walk from station to station, gathering each piece from stations A-C and placing the assembled part in station D, as shown in Fig. 3B, where they must answer a short questionnaire on an android tablet. This occurs as the UR-10 robot moves the second piece from the conveyor belt where it was deposited by Sawyer to the second bin, creating an overlapping HR workspace as shown in Fig. 4. An adjustment to the experiment requires the human participant to rearrange the stacking order of two 3D-printed blocks located at each station, which are all oriented to direct the individual's attention and vision away from the UR10 robot.

The entire workspace is visible to the Motion Capture system and a Digital twin of the environment is modeled with Unity game engine and deployed on the HoloLens 2. To accurately reflect the physical location of the robot in the virtual plane, the HoloLens 2 system's Unity world-locking tool is used to assign virtual coordinates to the robot base through the virtual projection of a pre-established mold of the robot which is matched to reality using fiducials (QR codes) around the room, shown in Fig. 5.

The informational augmented reality display presents the angular position of the end-effector of the UR-10 robot

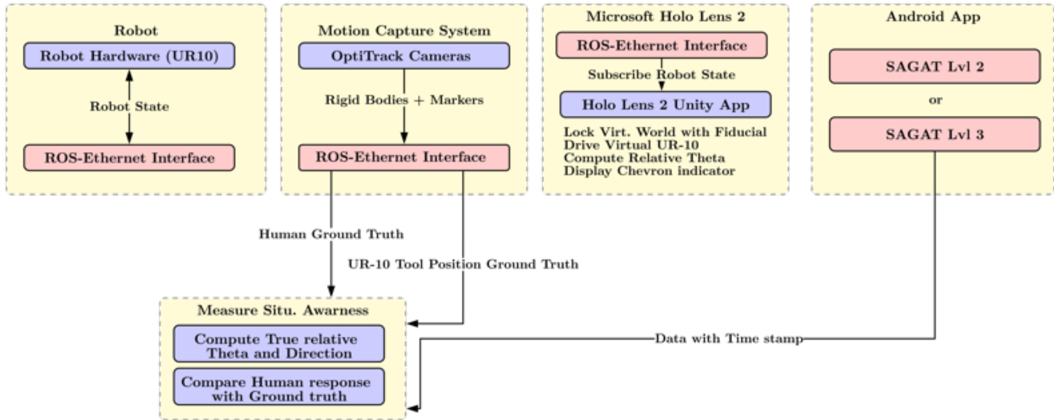


Fig. 2: Flow Chart of Positional Information and Processing.

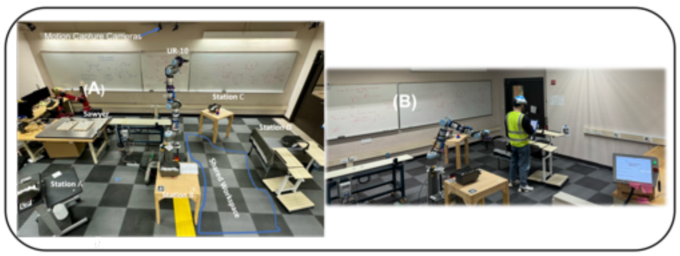


Fig. 3: Example of Participant Performing the Task

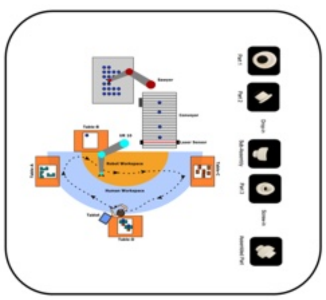


Fig. 4: Overview of the Shared Human-Robot Task [43]

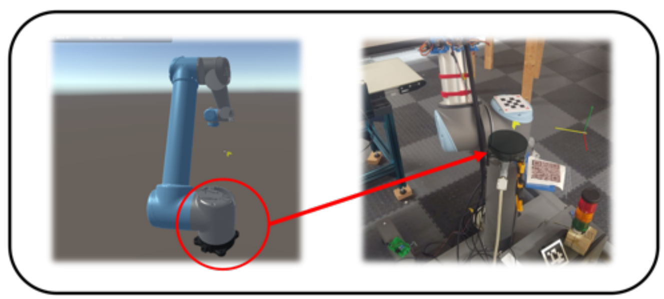


Fig. 5: Using Fiducials to align digital and real worlds.

relative to the head position of the wearer of the Hololens 2 device. This is done in the form of a chevron arrow which rotates in a fixed position in the center of the display, as shown in Fig. 6.

This requires reliable projection and determination of spatial data from the physical to the virtual space to allow calculations and visualization. An angle θ_r, representing the relative angle projected onto the flat plane of the ground (x-y plane) from the participant's head to the location of the robot end-effector must be determined. To do this, we used the transform obtained from the Human head pose as the local reference frame where the forward direction of the Human heading vector $\vec{H}$ where the x-axis represented by H_x and their left direction is the y-axis represented by H_y. This can be obtained both using the motion-capture system or through the unity game engine. We can then find the relative vector from the tool to the local frame of the Human head, this is represented by $\vec{T}$. This information is also available through both systems. The relative angle projected on the ground plan can then be obtained by using the $atan2(T_x, T_y)$ function. A visual representation of this is shown in Figure 7.

By tracking the head position of the user, and the position of the end-effector in the virtual world, we can compute the necessary rotation values which inform the rotation of the chevron to point towards the robot on the viewable plane. Built-in Unity functions combine the vectors of the forward of the head, left-side of the head, and direction from the head to the end-effector in 3D space to create a rotation matrix and obtain quaternions, which are representations of rotations in 3D space. Using these operations the physical information is converted into the real-time on-screen directional indicator.

Based on the Situation Awareness Global Assessment Technique (SAGAT), the participant must cease all activity

Fig. 6: Display visible to Human Worker through the HoloLens 2 application.

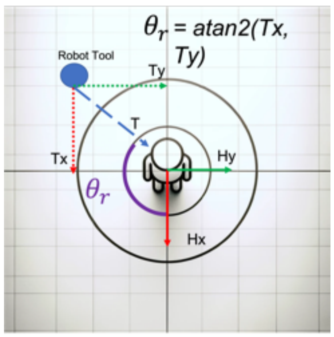


Fig. 7: Calculation of θ_r which is the projection of the relative angle between the Human and robot tool on the x-y plane.

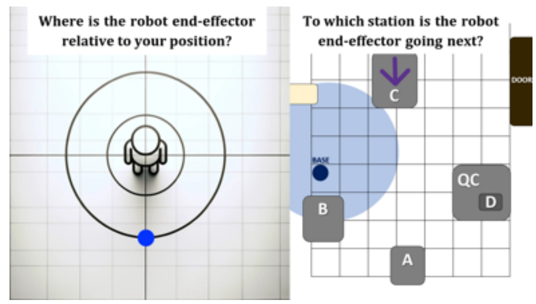


Fig. 8: Questions on Levels 2 and 3 of SA presented to the Participant.

related to the part assembly at random intervals and fill out a survey from a tablet carried in a pouch on their person [20]. This survey contains pre-determined questions about the position of the UR-10 robot, intending to assess the comprehension (Level 2), and projection (Level 3) levels of situational awareness, as shown in Fig. 8. Questions regarding Level 1 have not been included as any assessment of SA-2 and SA-3 requires adequate Level 1 perception [20]. The robot is temporarily halted at unspecified intervals independent of the human's pause to eliminate cognitive prediction of the end-effector affecting the results. The participant answered these questions by dragging the blue dot or the purple arrow, and submitting a confidence score of their responses. This data is time stamped and stored to be later compared with the ground truth obtained from the motion-capture system.

Along with their responses, participants indicate their confidence in their answers on a 'Likert' scale from 0-5, with 0 representing low confidence. Upon completion of the survey, the participant resumes their task, and the operator resumes the experimental conditions. Participant responses are meticulously recorded and compared with ground truth data, the collection and assessment of which are discussed later.

To simulate more accurate automated factory settings, each participant wears a pair of earbuds designed to provide 26 decibels of sound reduction to eliminate auditory perception of the robot. Therefore, to indicate the pause of the experiment, the visual display of the headset is changed to that of a red box, as shown in Fig. 8. It should be noted that there are different active-state displays for the two types of trials, with Augmented reality (AR) and No Augmented Reality (NAR). One provides the discussed real-time visualization of the UR-10 robot's end-effector position relative to the participant's head position as seen in Figure 6. On the other hand, the NAR experiment has no activity other than the freeze stimulus showing up when needed.

Fig. 9: Stimulus for a Freeze request by showing a red box.

The actual location of the end-effector must be obtained in a way that could be compared to their perceived response from the SAGAT questionnaire. To determine the true location of the robot relative to the participant's head position, we utilized the OptiTrack Flex 13 motion capture system. The system uses 13 cameras positioned around the workspace and is calibrated using the projection of a rigid body from the helmet. This allows the motion capture system to determine the position of the person, more specifically their head in the helmet, relative to the workspace. Since the base of the robot is fixed, using the base link position of the robot from motion capture, we can also determine the position of the tool of the robot in the universal reference frame.

The participant's responses are time-stamped when collected, which allows us to assess the accuracy of the participant's subjective estimate of the location of the robot's end-effector relative to their body. This requires the transformation of the 2D indicator location on the tablet screen to a ground-plane estimate of the projection of the path from the participant's head to the location of the end-effector. The pixel size of the indicator relative to the workspace representation on the app allows a realistic degree approximation of their response in the real world as shown in Figure 7.

Using similar projection processes and equations as the ground plane analysis used for the AR display, and the time stamp of each recorded response, we can find accurate relative data between the human and the robot at every moment in both the real and virtual worlds. This enables this system to be able to run without the motion capture system in a real-world application scenario.

B. Data Collection

The comprehensive experiment comprises six trials, three completed with the AR app enabled, and three without the additional informative display. Importantly, the sequence of these trials is randomized. Collected responses from the SAGAT queries are saved with the exact standardized time stamp when they were submitted, and this is used to draw ground-truth positional data at that point in time from the motion capture system. The approval for Human subject research was granted by Rochester Institute of Technology (approval number: 21081267).

C. Hypothesis and Metrics

1) The Augmented Reality display provides an advantage that allows workers to estimate the position of the tool more accurately. Associated Metric: 'Error in Perception'
2) While using Augmented Reality, when the robot is not directly visible to the workers, they can determine the direction in which the tool moves more correctly. Associated Metric: 'Percent Correct'
3) The workers feel more subjectively confident that they know the current position of the tool of the robot when utilizing Augmented Reality. Associated Metric: 'Subjective Reported Confidence'
4) The workers spend less time reporting the SAGAT Level 2 and 3 responses when given an Augmented Reality display. Associated Metric: 'Time taken to respond to SAGAT questions'

III. Results and Discussion

The experiment involved 10 participants, each assigned to one of two experimental conditions: Augmented Reality (AR) and No Augmented Reality (NAR). The participants' demographic characteristics. All were of normal hearing, 75 percent were men, 25 percent were women, 75 percent were graduate students, and 25 percent were undergraduates. All reported that they were familiar with technology, but did not have a lot of familiarity with robots as used in this task.

Figures 10-13 showcase worker performance in the two types of trials over the described metrics. The bar charts depict the average performance of the participants over the two types of trials and the error bars show the range of their performance. It can be seen that except for Participant 5, all participants were able to tell the position of the tool of the robot more accurately when provided with the Augmented Reality display. Similarly, all but one participant were better at determining the direction the tool of the robot was moving in when. All participants felt more confident in reporting the position or the direction of the robot with Augmented Reality. Most participants spent less time answering the questions when using Augmented Reality.

Figure 14 shows Contour Plots of Multivariate Gaussian Distributions for AR and NAR tasks for the best-performing participant, the worst-performing participant, and the data of all the participants combined. The x-axis represents worker-reported confidence values and the y-axis represents the error in the user-reported angular position of the robot tool.

Based on the visualization, it is clear that the maximum probability density occurs when higher confidence is reported. In addition, the worst, best, and all participants all show lower error difference values using Augmented Reality vs not using it.

Table 1 shows the statistical significance of each of these metrics.

The T-statistic indicates if there is a significant difference in metrics between the compared groups AR and NAR. Higher magnitudes of T signify larger differences between groups. However, the P-values lower than 0.005 indicate strong evidence against the null hypothesis, suggesting that the observed difference is not due to chance.

Based on the data in Table 1, we can say that there is a significant difference in ability of worker to correctly estimate the position and the direction of the robot tool when it is in their blind spot and they feel more subjectively confident when using Augmented Reality. However, there is not enough evidence to suggest that they are able to answer the questions about the position and direction of the tool quicker when they have Augmented Reality vs when they do not.

TABLE I: Statistical Significance of Metrics

Metric	**T-statistic**	**P-value**
Average Perception Error	-3.5871	0.002106
Percent Correct	2.4179	0.02643
Mean Confidence	4.0171	0.008085
Mean Response Time	-1.7847	0.09115

IV. Future Work and Conclusion

The findings and limitations of this preliminary study create many possible potential avenues for future research to broaden our understanding of user experience in HRC

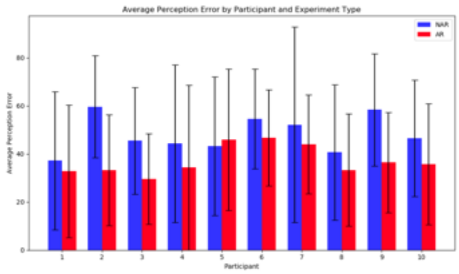


Fig. 10: Average Perception Error by Participant and Experiment Type.

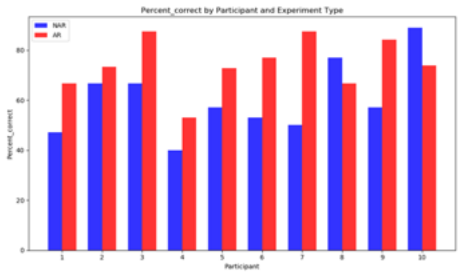


Fig. 11: Percent correct by Participant and Experiment Type.

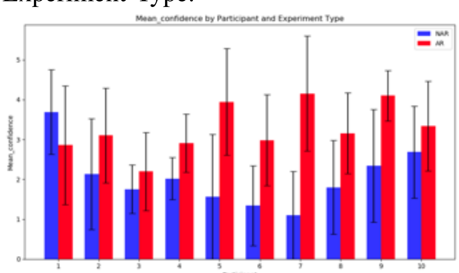


Fig. 12: Mean Confidence Level by Participant and Experiment Type.

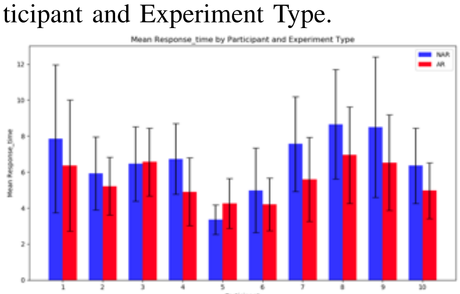
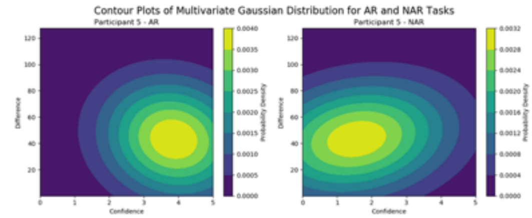
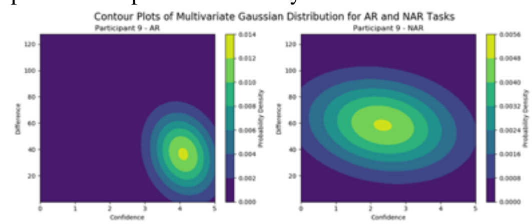


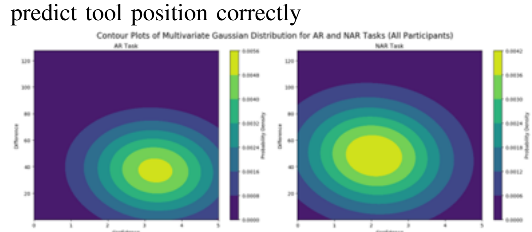
Fig. 13: Mean Response time by Participant and Experiment Type.



(a) Participant with the least performance: Ability to predict tool position correctly



(b) Participant with the best performance: Ability to predict tool position correctly



(c) All Participants: Ability to predict tool position correctly

Fig. 14: Contour Plots of Multivariate Gaussian Distribution for AR and NAR Tasks

dynamics and enhance the design and implementation of these scenarios in real-world applications. It can be seen from the data that Augmented Reality provides an advantage to workers by enabling more accurate estimation of the tool position of the robot without visual or auditory cues.

Although outside the scope of this paper, which focuses on augmenting situational awareness, we also collected subjective responses from each participant following the Russel Circumplex Model of Emotion [44] and NASA-TLX [45] to assess differences in valence and arousal, and cognitive workload caused due to the use of the augmented reality.

We are currently continuing experiments with a much larger and broader sample size, including individuals of a broader age range who are non-engineers, or hard-of-hearing. We intend to compare their perception models and human-robot interaction experiences. In addition, the replication of this system in a more accurate industrial setting may reveal practical challenges and opportunities for augmented reality in HRC. This system may require a risk assessment for AR-equipped collaborative automated settings [46]. Although promising, further and more extensive testing is needed to present AR displays with positional information as an acceptable improvement to HRC in industrial settings.

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