

Proxemic-aware Augmented Reality For Human-Robot Interaction

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Abstract—This study introduces a novel proxemic-aware augmented reality (AR) system to mitigate information overload in AR-enabled human-robot interaction (HRI). The system leverages human-robot proxemics to automatically adjust what and how much visual content needs to be presented. Therefore, the operator can perceive the relevant data through AR interfaces without being overwhelmed by excessive information exposure. We propose a task-specific model for evaluating human-robot proxemic (HRP), where the system can identify HRP levels based on raw features, such as distance and orientation. Based on HRP levels, we design a set of visual elements for presenting robots' information at various levels of detail. To demonstrate the functionality of the system, we present a series of proof-of-concept applications showing that our system can assist the operator in a wide range of HRI tasks. The user study proves that the proxemic-aware AR system can reduce mental loading, increase visual clarity, and improve interaction efficiency in HRI.

I. INTRODUCTION

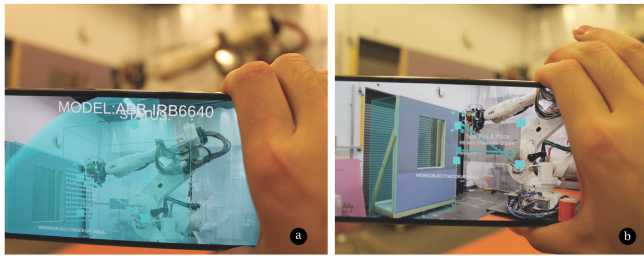


Fig. 1. Proxemic-aware augmented reality (AR) may mitigate information overloading in AR-based human-robot interaction (HRI) (a) an AR interface displays all robot information at the same level of detail (b) virtual information is filtered based on human-robot proxemics, only the most relevant information is presented in the AR view.

Augmented reality (AR) systems can serve as a human-robot interface, providing visual feedback to the operator by overlaying digital content onto the physical environment. However, the information-intensive environment can easily result in information overload that can negatively impact the user [1] and cause safety issues in human-robot interaction (HRI). For instance, the annotations or labels in AR interfaces may occlude physical objects within the area point of interest. Too much information superimposed in AR views can cause ambiguity and make it difficult to filter out relevant information from trivial information [2]. To mitigate the information overload in augmented reality, contextual factors are harnessed for optimizing user interfaces that can adapt to the user's cognitive load [3], ongoing tasks, and device

characteristics [4]. Contextualized in the domain of AR for HRI, this paper set a first step to build a context-aware AR system that leverages human-robot proxemics (HRP) as an implicit cue for automatically adjusting the information presented in the user's field of view (Figure 1).

In this paper, we will first discuss how we define human-robot proxemics. Proxemics was initially introduced by Edward T. Hall in the 1960s, defined as “the interrelated observations and theories of humans’ use of space as a specialized elaboration of culture” [5]. It has been widely used in human-machine interaction for the design of interfaces, devices, and systems that involve physical interaction with users. For example, fine-grained measurement of inter-entity relationships such as distance, orientation, identity, movement, and location can be exploited to design contextual-aware interfaces that mediate the simultaneous interaction of multiple people [6]. By understanding how humans use space and distance to communicate with each other, we can design robots with socially acceptable behaviors in scenarios such as navigation [7] and object handling [8]. Many studies have been done to quantitatively define human-robot proxemics [9], [10]. Expanded from previous works, we introduced a novel approach to building a task-specific HRP model. The model is based on empirical data collected from robot operators on-site. Different from previous proxemic models built upon discrete zones, we used a continuous function together with fuzzy inference to estimate human-robot proxemics. The non-crisp model better aligns with human's experience of proxemics, as we interpret spatial relationships in a gradual and progressive manner.

We then designed an adaptive visual system for presenting the robot information at different granularities or levels of detail (LoD) [3]. Each LoD reveals the information most relevant to the operator's current HRP levels. For example, when the operator shows minimal engagement with the robot, the AR interface will present overview information of the robot model and task in a brief textual format. When the operator moves toward the robot, the HRP level increases accordingly, indicating a higher possibility of interaction; more detailed information, such as trajectory and waypoints, will be revealed in the AR interface. For each HRP level, we designed a collection of widgets, such as panels and points, to help users understand and interact with the virtual information at the LoD tailored to the current context.

Finally, we will illustrate how the system can assist the operator in specific HRI scenarios such as surface inspection

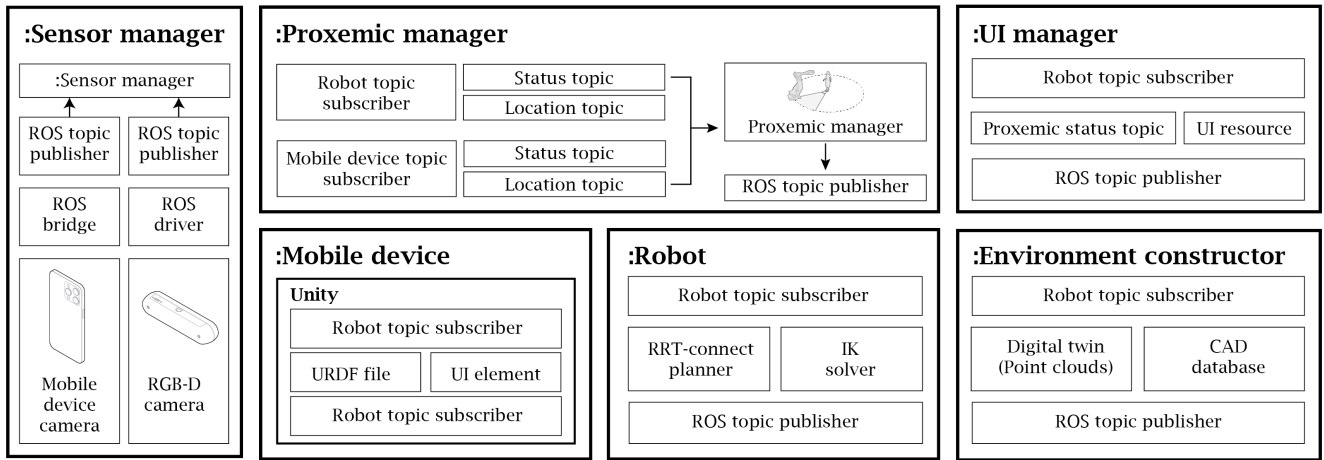


Fig. 2. System deployment diagram of the proxemic-aware AR for HRI

and pickup & place. We implemented our AR interface on a mobile phone to control and supervise a six-axis industrial mounted on a linear actuator. We compared our system with the baseline - an AR interface for HRI without proxemic awareness. We evaluated the task performance and collected responses from the participants through a post-experiment questionnaire. The results show that our system significantly outperformed the baseline in terms of reducing mental loading in the surface inspection and pick & place task (all $p < 0.01$). We believe our proxemic-aware AR system can serve as a novel human-robot interface that provides operators with relevant robot information when and where they need it.

II. RELATED WORK

A. Augmented Reality For Human-Robot Interaction

The integration of robotics in complex scenarios such as construction, healthcare, and space exploration still requires human intervention at varied levels. However, bidirectional communication between humans and robots can be limited by the lack of information that robots can present [11]. Augmented reality (AR) interfaces can potentially address the constraint by overlaying supplemental virtual information onto robotic work cell. Suzuki, Ryo, et al. summarizes the categories of information presented in AR, which can be classified into robot information, environment information, pre-operative information, and supplemental information for expressive interaction [12]. Robot information describes the internal status of robots, such as poses, joint configurations, and robot position. Environmental information includes the robot's perception of the surroundings obtained from the equipped sensors. Pre-operative information is related to the robot's planned motion for the operator to perceive the future actions of the robot. Supplemental information can increase the robot's expressiveness by showing interactive content such as animation or dynamic data visualization [13]. To visualize virtual information, visual elements such as panels, labels, interactive points, lines, and simulated robots

are commonly used for presenting AR content at different levels of detail. Williams et al. outline how AR may enhance HRI in collaborative tasks, including navigation, object manipulation, prototyping, training, supervision, and social interaction [14]. AR systems have been adopted in application domains such as robotic-assisted surgery (RAS), maintenance, design, and education [15]. For example, AR interfaces can assist a surgeon in RAS by overlaying surgery plans, highlighting operational areas, and visualizing instrument status [16]. Within the context of manufacturing, AR for HRI can be used for teleoperated maintenance [17], assembly [18], and intuitive robot programming [19]. In social robotics, AR interfaces can augment robot expression to enhance human-robot trust [20]. In this work, we contextualize our AR for HRI systems in the manufacturing and construction domain and investigate how our proxemic-aware AR system may mitigate information overloading issues in AR for HRI.

B. Proxemic-aware interaction

Proxemics describes how people use spatial relationships to mediate their relationships [5]. People in interactions change distances and orientations to accommodate different social contexts. In ubiquitous computing, proxemic variables such as distance, orientation, identity, movement, and location [21] are used to identify the spatial relationship between humans and surrounding devices. The interpersonal spatial relationship can be leveraged as an implicit cue for human-computer interaction, such as context-aware display [22] and cross-device interaction [23]. For instance, by leveraging proxemic information, an interactive display surface can implicitly react to the surrounding people and their personal devices. When a person enters the room, the media player shows peripheral awareness content. As the person moves closer to the display, more detailed information is revealed [21].

Within the domain of robotics, proxemics, as a socio-scientific theory, have been used as guidance for the design

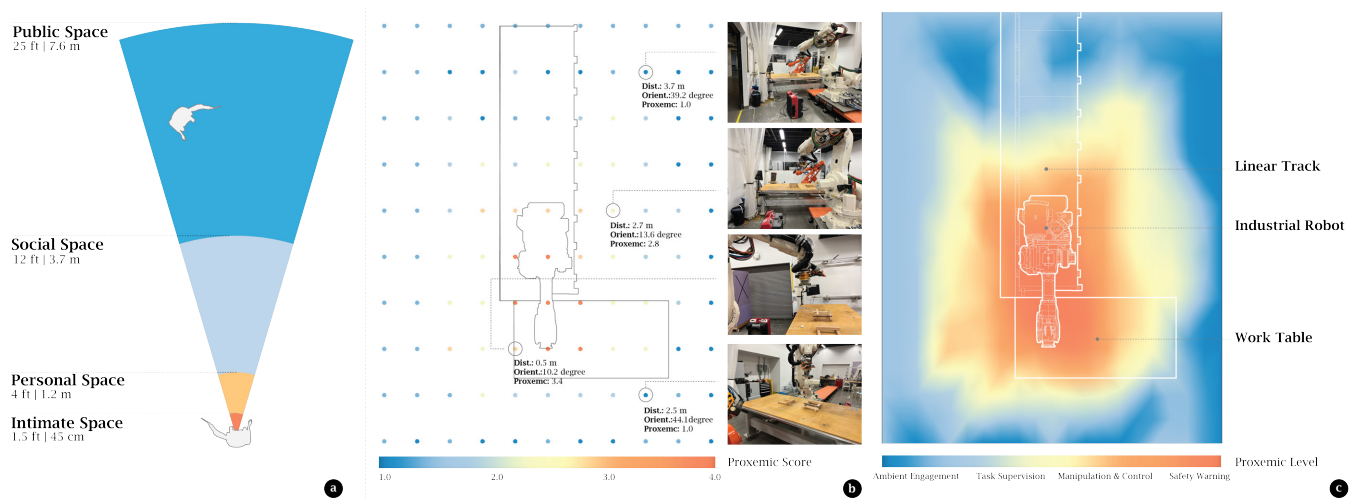


Fig. 3. The comparison between human-human proxemics and human-robot proxemics (a) human-human proxemics with discrete zoning (b) human-robot proxemic evaluation at sampled location (c) human-robot proxemic as a continuous function interpolated from the sampled location

of socially-aware human-robot interaction. For instance, in autonomous navigation, proxemics are integrated with traditional navigational algorithms to develop socially acceptable navigation strategies for robots operated in crowded environments [24] [25] [26]. Compared to human-human proxemics, humans kept interpersonal distances from robots (0.45 m to 1.20 m) on the first encounter [27] [28]. A number of HRI studies have been conducted to investigate the factors that can influence human-robot proxemics (HRP), such as robot appearance [29], robot height [30], robot behavior [31], and personal preferences [32]. To define HRP, multiple studies have been done to build a rule-based system based on empirical experiments [33], [34]. To extend the application range of HRP frameworks, adaptation mechanisms such as policy gradient reinforcement learning [35] and fuzzy inference systems [36] are integrated for more personalized HRI.

Previous studies provide elegant and simple definitions of human-robot proxemics. However, for different tasks, factors such as work environments, operation area, and robot appearance can change fixed spatial human-robot relationships. In this work, we assume that the HRP is task-specific rather than deterministic. We contribute an adaptive strategy to construct the HRP model based on empirical data. The model uses a continuous scale to measure human-robot proxemics, which can potentially avoid crisp transitions caused by discrete proxemic zoning.

III. METHOD

Our proxemic-aware AR for HRI system contains two parts, hardware and software (Figure 2). The software system is composed of four components, the proxemic manager, the view manager, the sensor manager, and the environment constructor. The sensor manager component publishes the location and pose of the robot and mobile devices obtained from sensor readings. The proxemic manager component subscribes to the sensor manager topic and outputs the

estimated human-robot proxemic level. The UI manager components then adapt to the HRP level by automatically changing the UI content and the level of detail based on a linear integer programming approach. The environment constructor component stores the CAD files of the robot and the reconstruction of the physical environment as a shared spatial coordinate system for both the robot and the mobile device. The communication between each component (node) is built upon the ROS framework.

For the hardware setup, we use ABB IRB 6640 for experiments. We used the MoveIt framework and RRT-connect provided by the OMPL (The Open Motion Planning Library) for planning a collision-free path to reach a target position. The AR interface is implemented based on the ARKit framework on a mobile phone. The ROS-Unity is adopted for data streaming between the mobile phone and a remote laptop communicating with the robot via TCP/IP.

A. Human-Robot Proxemics Estimation

Edward T. Hall defines proxemics as how people maintain the personal space around them. Space within 0.45 m is called intimate space. Space between intimate and personal distance is called personal space (ranging from 0.45 to 1.20 m). The space between social and personal distance is called the social space (ranging from 1.20 to 3.70 m). The space within public distance is called the public space (ranging from 3.70 m to 7.60 m) [5]. Similarly to human-human proxemics, in human-robot interaction, spatial cues such as distance and orientation can affect how the operator perceives the robot. Like human-human proxemics, human-robot proxemics can be highly context-dependent and non-deterministic. Factors such as the robot's work range and appearance can have a significant impact on how the operator interacts with the robot. For example, users tend to stay a greater distance with a humanoid robot with mutual gaze with it [37]. A robot of a smaller size can be more approachable than a large one [38]. To build task-specific

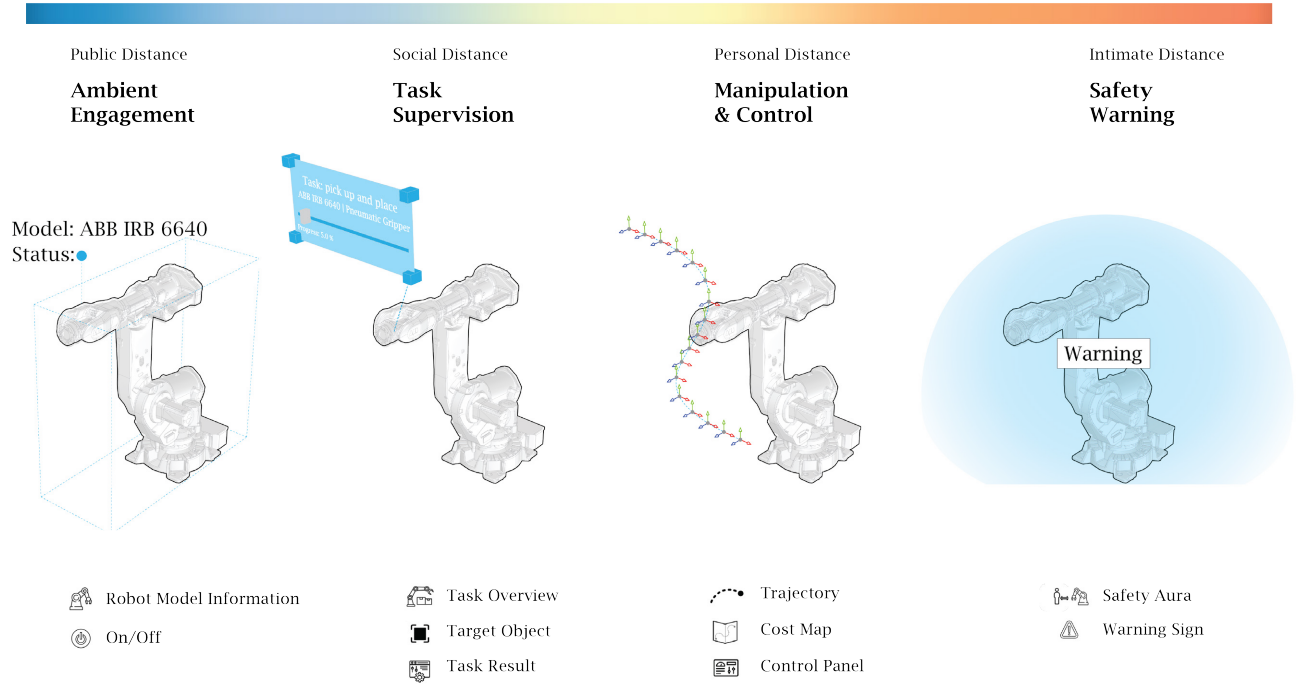


Fig. 4. Information visualization for various levels of human-robot proxemic - at the ambient engagement level, the AR system provides the overview information of the robot. At the task supervision level, more details of the ongoing task and robot will be revealed. At the third level, manipulation and control, the operator can view and edit the robot's trajectory. When the operator enters the danger zone, a safety aura and a warning sign will be displayed to alert the operator.

and user-centric HRP estimation systems, we collect the user's a priori information on HRP in a specific context. A user with a mobile device is asked to define the HRP level at a set of predefined locations around the robot. At each point, the user can assign a level of 1-4 (with 1 being the farthest and 4 being the nearest) to describe the perceived HRP (Figure 3). Meanwhile, we record the raw features at each location, including the user's location, user orientation, human-robot relative distance, and relative orientation. The relative distance and orientation are based on a fiducial marker attached to a known location in the workspace. Both the robot and the mobile device use the fiducial marker as a shared landmark to build a coordinate system relative to real-world space. We used the visual-inertial odometry of ARKit to track the real-time pose and location of the mobile device. The robot's location can be obtained through the status message published from the ROS-ABB driver node installed on the robot controller. Each sample point contains the raw features and user-defined proxemics in a set. Based on the collected sample data, we can create a continuous function to map the raw features to the HRP level. Since the collected points can be sparse, we chose to use an inverse distance weighting (IDW) approach.

Given a set of sample points x_i with known proxemic value p_i and $\{x_i, p_i \mid \text{for } x_i \in \mathbb{R}^n, p_i \in \mathbb{R}\}_{i=1}^N$, the IDW

interpolation function $p(x) : \mathbb{R}^n \rightarrow \mathbb{R}$ is defined as:

$$p(x) = \begin{cases} \frac{\sum_{i=1}^N w_i(x) p_i}{\sum_{i=1}^N w_i(x)} & \text{if } d(x, x_i) \neq 0 \text{ for all } i, \\ p_i & \text{if } d(x, x_i) = 0 \text{ for some } i, \end{cases}$$

where

$$w_i = d(x, x_i)^{-\beta}$$

x denotes an interpolated arbitrary point, x_i is a point with known proxemic value, d is a given distance from known x_i to the unknown point x , N is the total number of known points, β is a positive real number determining the degree to which the nearer point(s) are preferred over more distant points.

To ensure the safety of the operator, it is important for the user to keep a distance from the actual work area of the robot. We set all the points within the reachable area of the robot as level 4. The rest point will be evaluated and rounded to the actual proxemic level.

The output of the HRP model is converted into a fuzzy set through fuzzification. For each HRP level (from level 1 L_1 to level 4 L_4) we use the Gaussian membership function described as:

$$\mu(m, \sigma^2) = \begin{cases} \mu(m_{L_1}, \sigma^2) & \text{if } L_1 \\ \mu(m_{L_2}, \sigma^2) & \text{if } L_2 \\ \mu(m_{L_3}, \sigma^2) & \text{if } L_3 \\ \mu(m_{L_4}, \sigma^2) & \text{if } L_4 \end{cases}$$

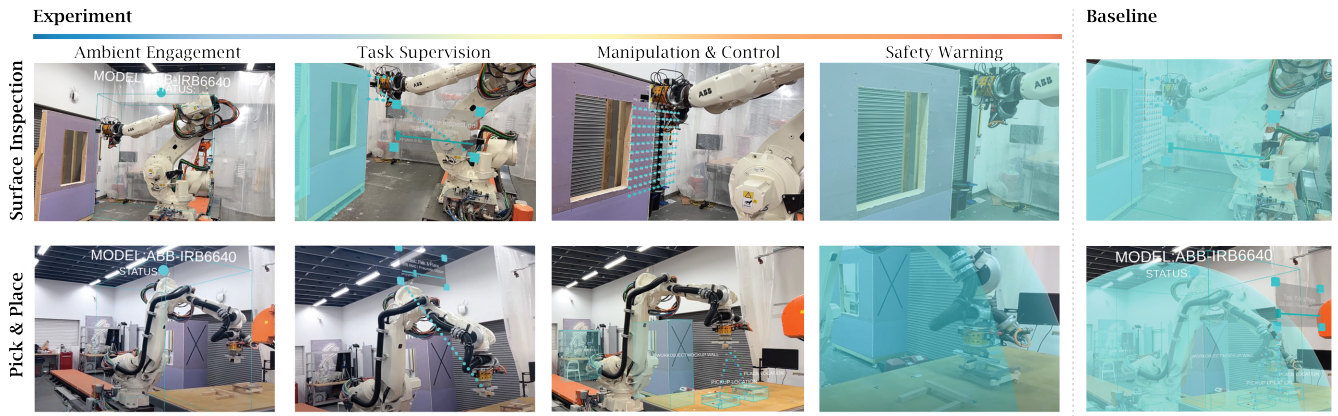


Fig. 5. Experiment and baseline setup for surface inspection and pick & place scenario, the baseline setup displays all virtual information at the same level of details, the experiment setup selectively displays the relevant virtual information tailored to the current human-robot proxemic level

The value of belongings determines the transparency of the visual elements at that level. When the user moves from one HRP level to another, the visual content of the previous level will disappear gradually when the visual content of the next level shows up, which can provide a seamless transition between HRP levels. To mitigate the interference between translucent visual elements, we created depth masks for visual elements with a larger value of belongings. The masks representing the shape of the visual elements were then used to occlude visual objects that may intersect within the user's view.

B. Adaptive view management

We conducted a co-design pilot workshop with four stakeholders, including three robot operators and one designer, to design an adaptive visualization system for robots. Before the start of the workshop, we drafted a document describing the information to be visualized in the process of robot manipulation, such as waypoints, safety zones, task descriptions, etc. The robot operators were then asked to rate the LoD of each piece of information, and the designer provided a set of low-fidelity sketches and wireframes for information visualization. Through rounds of collaborative design sessions, the opinions of the designer and the robot operators converge into a structured visual template, including a set of visual elements and their LoD. Designers then finalize the visual template by converting the sketches into digital assets for AR systems. There are four levels of HRP zones, each associated with a set of visual elements with a defined LoD. (Figure 4).

At level 1 — ambient engagement, the system presents an overview of the task and the robot's current state information using labels and annotations. At this level, the detected human-robot proxemics indicates that the operator demonstrates an intention to engage with the robot. The AR system can quickly provide awareness of the robot, such as its model type and operation status, to facilitate the potential human-robot interaction by helping the operator briefly preview the task and the robot to interact with.

At level 2 — task supervision, the AR interface provides task-related information to assist the operator in better supervising the robot's task performance. As the operator moves closer to a robot, based on the human-robot proxemics definition, the operator shows increased engagement with the robot. The AR interface will reveal more details about the task through an information panel. For example, the task name and brief introduction will be presented, and a bar with a slider will be displayed to show the task progress.

At level 3 — robot manipulation and control: the AR interface provides information to enable direct manipulation and control of the robot. For example, the work area will be highlighted to show the robot's intent. The pre-operative paths will be displayed for real-time control, and the operator can edit, add or delete the waypoints to program the robot on the fly.

At level 4 — safety warning: the AR interface presents information to ensure safe robot interaction and avoid collisions. As the operator enters the reachable region of the robot, a safety aura will be displayed to indicate the dangerous zones; the operator can thus avoid unexpected collisions while manipulating the robot.

IV. RESULT

A. Case Studies

The goal of case studies is to identify the impact of two independent variables - the adaptive view management system and the customized human-robot proxemics (HRP) model on AR-based robot manipulation. We designed two use cases — surface inspection and pick & place to investigate (1) the impact of the adaptive view management system on information overloading (2) the difference between the customized HRP model and the deterministic HRP model on task performance (Figure 5).

1) *Surface Inspection*: In the surface inspection scenario, the participant is asked to operate a 6-axis industrial robot to cover a designated area on a mock-up wall. In the baseline setup, virtual information, such as the inspection region, robot internal status, and guidance waypoints, is displayed at

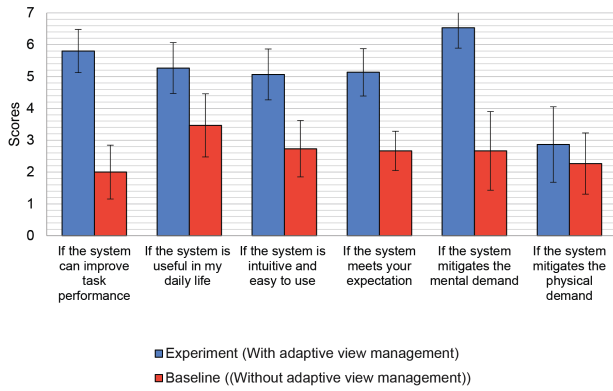


Fig. 6. Post-experiment questionnaire scores of the adaptive view management system. Error bars indicate the standard deviation.

the same level of detail at the start of the task. In the experiment setup, we integrated the adaptive view management system. Based on the human-robot proxemics between the operator and the industrial robot, the virtual information is displayed at four levels. At the first level, the operator enters the ambient engagement zone, the AR interface displays the bounding box of the robot, and the model and operating status of the robot will be displayed above the box. As the operator moves closer to the robot and enters the task supervision zone, an information panel will show up with textual information about the task name, the instrument, and the sensors being used, and a sliding bar showing the completion rate of the inspection task. The target inspection region on the mock-up wall will be highlighted. At the third level - robot manipulation and control, the AR interface will display the guidance trajectory and waypoints of the robot. The operator can leverage the guidance to control the robot and inspect the target region. As the operator enters the safe robot interaction zone, the AR interface will display the safety aura with a warning sign to inform the operator about the potential collision.

2) *Pick and Place*: In the pick and place scenario, the operator needs to control a 6-axis industrial robot with a suction gripper to pick up a target wood block and place it at a specified location. In the experiment setup, we leverage human-robot proxemics for adaptive information visualization. Similar to the surface inspection case, when the operator is in the safe robot interaction zone, the AR interface will display the reachable area of the robot to indicate potential collisions. As the operator moves further, the trajectory of the pick and place action will be overlaid with the physical environment. As the operator enters the task supervision zone, the AR interface will show detailed information about the ongoing task through an information panel. Finally, in the ambient engagement zone, the AR system will only display the operating status of the robot. Unlike the experiment setup, in the baseline setup, all of the aforementioned digital contents are displayed at the same level of detail.

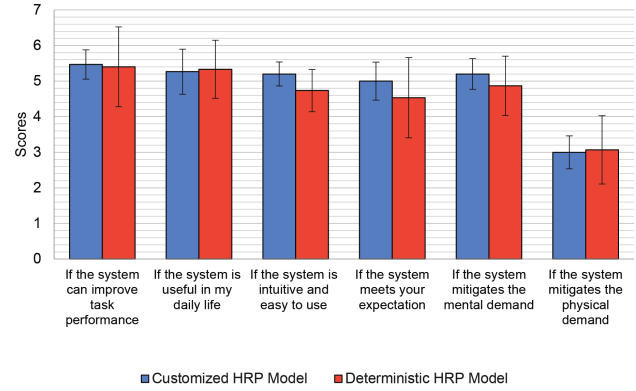


Fig. 7. Post-experiment questionnaire scores of the customized HRP model and the deterministic HRP model. Error bars indicate the standard deviation.

3) *Evaluation*: To evaluate the efficacy of the proxemic-aware AR system, we used a post-experiment questionnaire to collect user's feedback on the system. In addition to the questionnaire, we logged the task performance data of each use case. In the first task — surface inspection, the participants were asked to manually control a robot to cover a defined inspection area. The range of the area is visualized through a mobile device with an AR interface. The mobile device is attached to the teach pendant used for programming a 6-axis industrial robot. The participants can program the robot's orientation and location using a joystick on the teach pendant. To evaluate the impact of the adaptive view management system, we conducted a repeated measures design. In the baseline setup, the guidance information is displayed at the same level of detail. In the experiment setup, the guidance information is visualized in different levels of detail according to the human-robot proxemics.

To compare the differences between the deterministic HRP model and our customized HRP model, we experimented with two models in human-robot proxemics measurement. The deterministic model defines four crisp HRP zones based on human-robot distance unaffected by tasks. Our customized HRP model is based on empirical data collected from robot operators (Figure 3). The model uses a continuous function with a fuzzification inference to estimate the HRP level, and the definition of HRP zones is seamless and non-crisp. To minimize the order effect, the participants were split into two groups. The first group starts with the deterministic model, and the second group starts with the customized model. The task performance is measured by (1) task completeness: task completeness is defined by the coverage — the ratio between the actual inspected area and the target area (2) manipulation efficiency: this metric describes how many interactions the operator needs to make for an effective motion, which can be measured by the ratio between the number of interactions and the coverage rate.

There are 15 college students (7 females and 8 males, After a pilot study, we determined effect size $|\rho|$ as 0.50, error probability α as 0.20, and power as 0.80. Then we used a priori analysis in G * Power software to estimate

the total sample size N , $N = 15$.) participated in the user study. All of the participants have prior experience with AR interfaces or similar interfaces, but none of them was trained for robot manipulation. We provided a training session on robot manipulation before we started the user study. The order of the experiment setup and the baseline setup was switched between tests to counterbalance the order effect that could impact the study result. In each test, we removed the trials when participants claimed an error occurred (between 0 and 5 trials per test).

We found that in the surface inspection task, our proxemic-aware AR system outperforms the baseline setup in task completeness by 27.2% and motion efficiency by 31.3%. For the pick & place task, our system shows significant improvement in task completion time. The average time decreases from 51.27 sec ($SD = 11.27$ sec) to 22.18 sec ($SD = 7.11$ sec) with the integration of our proxemic-aware AR system (all $p < 0.01$). However, we did not find a significant effect of our system on the control accuracy. Based on the participants' feedback, the main reason could be (1) it can be difficult to perceive the location of virtual content in the real world, especially when there are occlusions between physical and virtual objects. (2) the participants mostly have limited experience in robot manipulation. It can be difficult for them to control the robot accurately with a joystick, which can be independent of differences in the AR setup.

We did not find a significant difference in task performance between the customized HRP model and the deterministic HRP model. The reason could be that the operator tends to remain static within the HRP zone suitable for robot manipulation until they complete the task. The differences in the definition of HRP zones did not significantly impact task performance.

We used a paired t-test to assess if the result demonstrated a statistically significant difference. The experiment setup yielded statistically significant improvements in the adaptive view management system test according to the post-experiment questionnaire (Figure 6). Participants rated the experiment setup ($M = 6.53$, $SD = 0.64$) higher in mitigating mental demand than the baseline setup ($M = 2.67$, $SD = 1.23$), $p < 0.01$. On the question "If the system can improve task performance?", participants rated the experiment setup ($M = 5.80$, $SD = 0.67$) higher than the baseline setup ($M = 2.00$, $SD = 0.84$), $p < 0.01$. On the question "If the system meets your expectation?", the participants rated higher on the experiment setup ($M = 5.13$, $SD = 0.74$) than the baseline setup ($M = 2.67$, $SD = 0.61$), $p < 0.01$. No significant differences were found between the experiment and baseline setup with regard to the physical demand.

We found that our customized HRP model outperformed the deterministic HRP model with respect to intuitiveness (Figure 7). Participants rated the customized HRP model ($M = 5.20$, $SD = 0.67$) higher in "intuitive and easy to use" than the deterministic HRP model ($M = 4.73$, $SD = 0.59$), $p = 0.014$. The context-sensitive customized HRP model may contribute to the intuitiveness of the system.

For instance, in the pick & place task, the dimension of the active working area is $0.50m \times 0.80m \times 0.50m$. At a distance of $3.50m$, the operators already felt less engaged with the ongoing task and expected to overview high-level information, such as the robot's status. However, based on the deterministic HRP model, a $3.50m$ human-robot distance indicates a higher engagement level (social distance). The AR system presents a detailed introduction of the task with information panels. The panels may distract the robot operator when he or she needs to overview the status of the surrounding robots. The customized HRP model factors in the properties of the ongoing task, which can impact the robot operator's perception of human-robot proxemics. With regard to the question "if the system meets your expectation?", the customized HRP model ($M = 5.00$, $SD = 1.07$) reasonably outperformed the deterministic HRP model ($M = 4.53$, $SD = 1.13$), $p = 0.125$. According to the feedback from the participants, the customized HRP model is a continuous function, and the transition between HRP zones is seamless. The smooth transition is more aligned with the participant's perception of human-robot spatial relationships. However, the participants mentioned that juxtaposing multiple translucent virtual elements could reduce legibility. Alternative to transparency, we can use the location of the visual elements as an indicator of LoD. For instance, as a robot operator enters a new HRP zone, the associated visual elements will be anchored to the main view, and the less relevant elements will be relocated to the peripheral area.

V. CONCLUSION

In this paper, we present a proxemic-aware AR system for human-robot interaction. The system leverages the spatial relationship between the operator and the robot to dynamically adjust the LoD of virtual information in AR interfaces. We collected empirical data from the operator to build a contextual and personalized HRP model. The model transforms the conventional model of human-human proxemics which is composed of four discrete zones with fixed thresholds into a continuous function. In combination with a fuzzy inference framework, the proxemic estimation process can be more robust to imprecision and uncertainty in sensor reading and more intuitive to human perception of proxemics. We designed a set of AR elements to visualize the robot's internal information and task information at different LoDs. To demonstrate the feasibility of the system, we present how the proxemic-aware AR system could be applied in HRI tasks such as surface inspection and pick & place. According to the user study, the integration of human-robot proxemics in AR interface view management can significantly alleviate the robot operator's cognitive load, increase the visualization clarity and enhance the HRI efficiency. We believe that proxemic-aware AR for HRI can aid robot operators by rendering necessary virtual information that can not be directly perceived while mitigating distraction caused by information overloading. This study can be the fundamental step toward computational view management in AR for HRI.

REFERENCES

- [1] Z. J. Lipowski, "Sensory and information inputs overload: behavioral effects," *Comprehensive Psychiatry*, 1975.
- [2] J. Keil, M. Zoellner, T. Engelke, F. Wientapper, and M. Schmitt, "Controlling and filtering information density with spatial interaction techniques via handheld augmented reality," in *Virtual Augmented and Mixed Reality: Designing and Developing Augmented and Virtual Environments: 5th International Conference, VAMR 2013, Held as Part of HCI International 2013, Las Vegas, NV, USA, July 21-26, 2013, Proceedings, Part I 5*, 2013, pp. 49–57.
- [3] D. Lindlbauer, A. M. Feit, and O. Hilliges, "Context-aware online adaptation of mixed reality interfaces," in *Proceedings of the 32nd annual ACM symposium on user interface software and technology*, 2019, pp. 147–160.
- [4] J. Zhu, Soh-Khim Ong, and A. Y. Nee, "A context-aware augmented reality assisted maintenance system," *International Journal of Computer Integrated Manufacturing*, vol. 28, no. 2, pp. 213–225, 2015.
- [5] E. T. Hall and E. T. Hall, "The hidden dimension," vol. 609. Anchor, 1966, p. 1.
- [6] T. Ballendat, N. Marquardt, and S. Greenberg, "Proxemic interaction: designing for a proximity and orientation-aware environment," in *ACM International Conference on Interactive Tabletops and Surfaces*, 2010, pp. 121–130.
- [7] R. Mead and M. J. Matarić, "Autonomous human-robot proxemics: socially aware navigation based on interaction potential," *Autonomous Robots*, vol. 41, no. 5, pp. 1189–1201, 2017.
- [8] K. L. Koay, D. S. Syrdal, M. Ashgari-Oskoei, M. L. Walters, and K. Dautenhahn, "Social roles and baseline proxemic preferences for a domestic service robot," *International Journal of Social Robotics*, vol. 6, pp. 469–488, 2014.
- [9] R. Mead and M. J. Matarić, "A probabilistic framework for autonomous proxemic control in situated and mobile human-robot interaction," in *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*, 2012, pp. 193–194.
- [10] R. Mead and M. J. Matarić, "Autonomous human-robot proxemics: socially aware navigation based on interaction potential," *Autonomous Robots*, vol. 41, no. 5, pp. 1189–1201, 2017.
- [11] M. Walker, H. Hedayati, J. Lee, and D. Szafrir, "Communicating robot motion intent with augmented reality," in *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, 2018, pp. 316–324.
- [12] R. Suzuki, A. Karim, T. Xia, H. Hedayati, and N. Marquardt, "Augmented reality and robotics: A survey and taxonomy for ar-enhanced human-robot interaction and robotic interfaces," in *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 2022, pp. 1–33.
- [13] R. Suzuki, C. Zheng, Y. Kakehi, T. Yeh, Ellen Yi-Luen Do, M. D. Gross, and D. Leithinger, "Shapebots: Shape-changing swarm robots," in *Proceedings of the 32nd annual ACM symposium on user interface software and technology*, 2019, pp. 493–505.
- [14] T. Williams, D. Szafrir, T. Chakraborti, and H. B. Amor, "Virtual, augmented, and mixed reality for human-robot interaction," in *Companion of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, 2018, pp. 403–404.
- [15] Z. Makhataeva and H. A. Varol, "Augmented reality for robotics: A review," *Robotics*, vol. 9, no. 2, p. 21, 2020.
- [16] L. Qian, J. Y. Wu, S. P. DiMaio, N. Navab, and P. Kazanzides, "A review of augmented reality in robotic-assisted surgery," *IEEE Transactions on Medical Robotics and Bionics*, vol. 2, no. 1, pp. 1–16, 2019.
- [17] A. W. W. Yew, S. K. Ong, and A. Y. C. Nee, "Immersive augmented reality environment for the teleoperation of maintenance robots," *Procedia Cirp*, vol. 61, pp. 305–310, 2017.
- [18] D. Mourtzis, V. Zogopoulos, and F. Xanthi, "Augmented reality application to support the assembly of highly customized products and to adapt to production re-scheduling," *The International Journal of Advanced Manufacturing Technology*, vol. 105, pp. 3899–3910, 2019.
- [19] Soh-Khim Ong, A. W. W. Yew, N. K. Thanigaivel, and A. Y. Nee, "Augmented reality-assisted robot programming system for industrial applications," *Robotics and Computer-Integrated Manufacturing*, vol. 61, p. 101820, 2020.
- [20] Y. Gao, E. Sibirtseva, G. Castellano, and D. Kragic, "Fast adaptation with meta-reinforcement learning for trust modelling in human-robot interaction," in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2019, pp. 305–312.
- [21] T. Ballendat, N. Marquardt, and S. Greenberg, "Proxemic interaction: designing for a proximity and orientation-aware environment," in *ACM International Conference on Interactive Tabletops and Surfaces*, 2010, pp. 121–130.
- [22] D. Ledo, S. Greenberg, N. Marquardt, and S. Boring, "Proxemic-aware controls: Designing remote controls for ubiquitous computing ecologies," in *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services*, 2015, pp. 187–198.
- [23] J. E. Grønbaek, M. S. Knudsen, K. O'Hara, P. G. Krogh, J. Vermeulen, and M. G. Petersen, "Proxemics beyond proximity: Designing for flexible social interaction through cross-device interaction," in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 2020, pp. 1–14.
- [24] M. Daza, D. Barrios-Aranibar, J. Diaz-Amado, Y. Cardinale, and J. Vilasboas, "An approach of social navigation based on proxemics for crowded environments of humans and robots," *Micromachines*, vol. 12, no. 2, p. 193, 2021.
- [25] P. Patompak, S. Jeong, I. Nilkhamhang, and N. Y. Chong, "Learning proxemics for personalized human-robot social interaction," *International Journal of Social Robotics*, vol. 12, pp. 267–280, 2020.
- [26] J. Rios-Martinez, A. Spalanzani, and C. Laugier, "From proxemics theory to socially-aware navigation: A survey," *International Journal of Social Robotics*, vol. 7, pp. 137–153, 2015.
- [27] H. Hüttenrauch, K. S. Eklundh, A. Green, and E. A. Topp, "Investigating spatial relationships in human-robot interaction," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2006, pp. 5052–5059.
- [28] M. L. Walters, K. Dautenhahn, K. L. Koay, C. Kaouri, R. te Boekhorst, C. Nehaniv, I. Werry, and D. Lee, "Close encounters: Spatial distances between people and a robot of mechanistic appearance," in *5th IEEE-RAS International Conference on Humanoid Robots*, 2005, pp. 450–455.
- [29] J. T. Butler and A. Agah, "Psychological effects of behavior patterns of a mobile personal robot," *Autonomous Robots*, vol. 10, pp. 185–202, 2001.
- [30] D. S. Syrdal, K. L. Koay, M. L. Walters, and K. Dautenhahn, "A personalized robot companion? The role of individual differences on spatial preferences in HRI scenarios," in *RO-MAN 2007-The 16th IEEE International Symposium on Robot and Human Interactive Communication*, 2007, pp. 1143–1148.
- [31] J. Mumm and B. Mutlu, "Human-robot proxemics: physical and psychological distancing in human-robot interaction," in *Proceedings of the 6th international conference on Human-robot interaction*, 2011, pp. 331–338.
- [32] M. L. Walters, D. S. Syrdal, K. Dautenhahn, R. T. Boekhorst, and K. L. Koay, "Avoiding the uncanny valley: robot appearance, personality and consistency of behavior in an attention-seeking home scenario for a robot companion," *Autonomous Robots*, vol. 24, pp. 159–178, 2008.
- [33] H. Hüttenrauch, K. S. Eklundh, A. Green, and E. A. Topp, "Investigating spatial relationships in human-robot interaction," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2006, pp. 5052–5059.
- [34] M. L. Walters, K. Dautenhahn, R. T. Boekhorst, K. L. Koay, D. S. Syrdal, and C. L. Nehaniv, "An empirical framework for human-robot proxemics," *Procs of new frontiers in human-robot interaction*, 2009.
- [35] N. Mitsunaga, C. Smith, T. Kanda, H. Ishiguro, and N. Hagita, "Robot behavior adaptation for human-robot interaction based on policy gradient reinforcement learning," *Journal of the Robotics Society of Japan*, vol. 24, no. 7, pp. 820–829, 2006.
- [36] P. Patompak, S. Jeong, I. Nilkhamhang, and N. Y. Chong, "Learning proxemics for personalized human-robot social interaction," *International Journal of Social Robotics*, vol. 12, pp. 267–280, 2020.
- [37] J. Mumm and B. Mutlu, "Human-robot proxemics: physical and psychological distancing in human-robot interaction," in *Proceedings of the 6th international conference on Human-robot interaction*, 2011, pp. 331–338.
- [38] L. Takayama and C. Pantofaru, "Influences on proxemic behaviors in human-robot interaction," in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2009, pp. 5495–5502.