Locating Nearby Physical Objects in Augmented Reality

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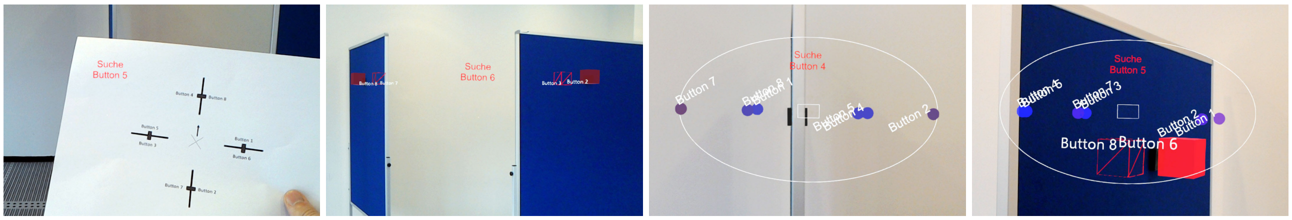

(a) Printed map. (b) In-view visualization. (c) Out-of-view visualization. (d) Combined.

Figure 1: Different visualization strategies to locate nearby physical objects with the Microsoft Hololens. ***Best seen in color.***

ABSTRACT

Locating objects in physical environments can be an exhausting and frustrating task, particularly when these objects are out of the user's view or occluded by other objects. With recent advances in Augmented Reality (AR), these environments can be augmented to visualize objects for which the user searches. However, it is currently unclear which visualization strategy can best support users in locating these objects. In this paper, we compare a printed map to three different AR visualization strategies: (1) in-view visualization, (2) out-of-view visualization, and (3) the combination of in-view and out-of-view visualizations. Our results show that in-view visualization reduces error rates for object selection accuracy, while additional out-of-view object visualization improves users' search time performance. However, combining in-view and out-of-view visualizations leads to visual clutter, which distracts users.

CCS CONCEPTS

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

KEYWORDS

head-mounted, augmented reality, out-of-view, in-view, occlusion

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1 INTRODUCTION

Searching for physical objects is a problem with which we are constantly confronted (e.g., as a child on an Easter egg hunt). Here, locating objects can become a difficult task, because objects might be occluded by other objects, out of view, or hard to distinguish from their environments. For example, a service technician who maintains a product (e.g., a robot arm) needs to understand the locations of relevant devices within a certain area of a manufacturing plant. These objects can be occluded by other objects in the environment (e.g., repositories), and the order with which these objects have to be dealt can change and may only be known by a technician. Further, it is not uncommon that the service technician has to deal with multiple objects that are located very close to each other (e.g., several peripheral devices) [30]. Another example is a network engineer that has to resolve hardware issues in a server room. In this case, the engineer has to locate the relevant hardware quickly to avoid long downtimes. Here, the environment, with which engineers are confronted is different every time and several sever racks are often distributed within the server room, rendering most objects occlude. However, the possible locations of relevant hardware is defined by the positions of the server racks, reducing the number of possible locations for relevant nearby objects.

With recent advances in Augmented Reality (AR) technology (e.g., rendering quality [40], refresh rate [23], or registration accuracy [27]), environments can be augmented to show additional information to the user. As it is experienced in a head-mounted device, people can use such technologies hands-free and while mobile. This has advantages in many spatial working environments where machines have to be operated by hand, or in situations in which the user is moving. Furthermore, the head-mounted device allows one to visualize the locations of surrounding objects from an egocentric perspective. Thereby, the cognitive load required to mentally integrate the displayed information into the user's perspective is low [4, 10, 26]. Additionally, in some scenarios, a head-mounted AR device can easily be combined with safety helmets that workers are required to wear (e.g., in manufacturing plants). Since digital content presented on an Augmented Reality device is already easily distinguishable from the real world [31], it is well-suited for presenting visual cues to the user.

In previous work, different techniques have been investigated for guiding to objects in view in AR (e.g., [6, 37]) or visualizing occluded objects (e.g., [11, 35]). However, due to the limited field of view of current AR devices, it remains unclear if visualizations for objects on screen are sufficient for locating real-world objects, especially if those objects are spatially distributed in the environment. Additionally, previous work either focuses on objects that are not occluded [2, 21] or on a single object at a time [6, 37]. On the contrary, visualizing the positions of out-of-view objects has already been well explored in previous work (c.f., subsection 2.2). However, related work shows that these techniques are not sufficient for guiding to spatially distributed objects because they do not assist in identifying these objects when they appear on the user's screen [12]. Here, we hypothesize that a combination of in-view and out-of-view visualization techniques works best for locating physical objects in the environment. However, to our knowledge, it has not been investigated in how far the different visualization strategies (in-view, out-of-view, and their combination) influence user performance for locating physical objects in AR.

In this paper, we investigate the influence of the different visualization strategies on locating physical objects in AR. To compare the different visualization strategies, we select one representative visualization technique for each strategy. To do so, we compare different in-view visualization techniques in a user study to identify the best-performing technique. The representative technique for the out-of-view visualization strategy is selected from previous work. Thereafter, in a second user study, we compare the four different visualization strategies: (1) printed map (baseline condition), (2) in-view visualization (best-performing technique from the first user study), (3) out-of-view visualization (best-performing technique from related work), and (4) the combination of in-view and out-of-view visualizations. We evaluate the different strategies using quantitative measurements such as search time performance and object selection accuracy. Our research contributions include:

(1) Comparison of four different in-view visualization techniques in head-mounted Augmented Reality.
(2) An evaluation and thereby comparison of four different visualization strategies (printed map vs. in-view vs. out-of-view vs. combination) for locating physical objects in AR.

2 RELATED WORK

We discuss the related work regarding: (1) visualization of objects in view and (2) visualization of objects out of view. Thereby, we want to identify the best-performing technique for each strategy.

2.1 Visualization of In-View Objects

Guide to Objects in View. Augmented Reality allows one to overlay digital content onto the real world, in order to alter perception of it [3]. In the last decades, researchers have focused on improving tracking, interaction, and display technologies [44] to create more immersive experiences. However, due to the low degree of fidelity which is influenced by rendering quality [40] or refresh rate [23], users can still distinguish between digital content and the real world [31]. While this inhibits full immersion, it is helpful for shifting the attention of user to physical objects in the environment. In the work 'Attention funnel' by Biocca et al. [6], the authors demonstrated that their general purpose AR interface technique interactively guides the attention of the user to any object, person, or place in space. This approach is not limited to physical objects in-view, but supports only one object at a time. Schwerdtfeger and Klinker used a similar technique to support order picking with Augmented Reality [37]. In this work, a red frame was displayed to the user to highlight a shelf in view. For visualization of out of view content, an arrow was used. However, previous work showed that arrows are not well suited for pointing to out-of-view content [13].

X-ray Visualization in Augmented Reality. A feature of Augmented Reality systems is that hidden and occluded objects can be readily visualized [11]. In the work by Tsuda et al., five different see-through-walls visualization techniques were compared in outdoor scenes [41]. Their results showed that overlaying the wire-frame models of occluded objects worked best. However, they manipulated the real environment by removing walls that occluded objects. Another use-case for an x-ray visualization technique is to show underground infrastructure information with hand-held AR devices [35] or on images [45]. Both approaches use a semi-transparent visualization for the ground to make it see-through. Furthermore, related work discusses how to support the comprehension of spatial relationships between virtual and real world objects [2, 21]. Their results show that giving information about occluded objects can be beneficial for understanding the positions of virtual objects relative to physical objects. While when interacting with occluded objects, view stability and point-of-view are most important [22].

2.2 Visualization of Out-of-View Objects

Extending the Field of View. The problem of objects receding from view is amplified when a head-mounted device (HMD) further limits the human field of view (FOV) [33]. Here different strategies have been proposed in previous work. One approach to extend the limited FOV of HMDS is to compress the information in the periphery by using a fisheye view [28] or two different lenses with different magnifications [43]. Another approach is to extend the FOV using a matrix of LEDs in the user's periphery [42]. However, all approaches require additional hardware and do not allow to encode textual information (e.g., labels to identify the object out of view).

Off-screen Visualization Techniques. Off-screen visualization techniques can be classified into three main approaches: Contextual views, Focus+context, and Overview+detail [10, 16]. Contextual views (e.g., arrows pointing to off-screen space [8]) and Focus+context (e.g., fisheye-views that convey a distorted view [34]) both overlay the screen borders with context information, while Overview+detail shows a miniature map of the surrounding area. A disadvantage of the miniature map is the cognitive load required to mentally integrate all views [10], while context information along the borders is more in line with the human frame of reference [20].

In previous research, Contextual views were shown to be best for the visualization of off-screen objects on small-screen devices [8]. One of the first Contextual views was Halo [5]. It uses circles drawn with their centers around the off-screen objects, cutting the border of the screen slightly. However, a problem of Halo is cluttering, which is the accumulation of many Halos in corners. In Arrow, the smaller shape of arrows is used to point towards off-screen objects. A first study on Arrows in virtual environments showed their potential as a navigation aid [9]. Later, several studies compared Halo with Arrow approaches [8, 19], revealing that Arrows with fixed sizes performed worse than Halo, while scaled arrows performed slightly better. Also, the amount of visible objects has a high impact on the performance. To avoid cluttering, researchers developed Wedge [16], which uses less space with isosceles triangles.

Out-of-View Visualization Techniques. In recent work, different techniques have been suggested to point to objects out of view. Some of them focus on visually shifting the user's attention to a single object out of view [24] or help the user to inspect the scene from a specific camera pose [38]. However, they do not support multiple objects out of view. Therefore, Gruenefeld et al. [13] adapted Arrow, Halo, and Wedge to head-mounted Augmented Reality to visualize several out-of-view objects at a time. Their results showed that all of these techniques are applicable for head-mounted devices, but their approach was limited to 90 degrees in front of the user. Therefore, they developed HaloAR and WedgeAR, which make use of 3D shapes to guide to out-of-view objects [12]. However, the 3D shapes add visual clutter to the screen and are not well suited for small field-of-view devices (e.g., Hololens) or the visualization of many objects at the same time. To visualize multiple out-of-view objects at the same time without addding too much clutter, a new visualization technique called EyeSee360 was proposed [14, 15]. EyeSee360 uses a radar-like visualization to display out-of-view objects and performs better than Halo, Wedge and Arrow [14]. Recently, Bork et al. compared EyeSee360 to five other techniques (3DArrows [36], AroundPlot [20], 3D Radar, sidebARs [39], and MirrorBall [25]) and found significantly lower completion times and better usability when using EyeSee360 [7]. Therefore, we choose EyeSee360 to represent the out-of-view visualization strategy in our second study.

2.3 Research Gap

Previous work proposed several visualization techniques to guide users to physical objects in AR. These techniques can be classified into three different strategies: (1) visualization of objects in view, (2) visualization of objects out of view, and (3) the combination of in-view and out-of-view visualizations. However, there are two remaining issues: (1) in-view visualization techniques mostly focus on one object at a time (e.g., [6, 37]), or lack support for occluded objects (e.g., [2, 21]); and (2) the different visualization strategies have not been compared to each other, leaving their individual benefits for locating physical objects in AR unexplored. For example, since out-of-view visualization techniques do not offer any support when objects appear in view [12], would a combination with an in-view visualization help users to identify those objects when they appear on screen?

3 GENERAL APPROACH

The process of locating physical objects can be divided into two steps: (1) Understanding the head-movement to bring the selected object in view, and (2) perceiving the location of that object in view [14]. In related work, we discussed different visualization strategies that mostly focus on either the first or second step. In contrast, we hypothesize that a visualization strategy assisting in both steps works best for locating physical objects. To evaluate our hypothesis, we first needed to select representative in-view and out-of-view visualization techniques. Here, we designed four different in-view visualization techniques that fulfill our requirements and then conducted a user study in which we compare them to identify the best working technique. As our out-of-view visualization technique we chose EyeSee360 [14] from related work because it has been compared to eight other techniques and resulted in fastest search time and best usability [7]. Afterwards, we compared four different visualization strategies: (1) printed map (baseline condition), (2) in-view visualization, (3) out-of-view visualization, and (4) the combination of in-view and out-of-view visualizations, in a second user study, to evaluate which visualization strategy works best for locating physical objects in Augmented Reality.

4 STUDY I: IN-VIEW VISUALIZATIONS

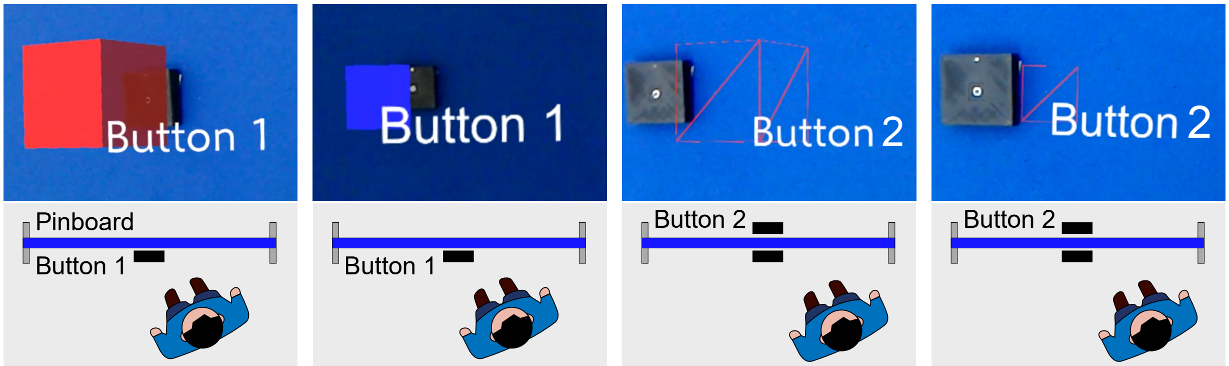
In our first study, we compared four different techniques for visualizing objects in view, to select a representative visualization technique for the second study (see Figure 2).

4.1 Cue Design

We analyzed the two scenarios from the introduction (service technicians and network engineers) using a hierarchical task analysis [1] and raised the following requirements:

- **(R1)** The visualization technique should support visualizing multiple objects at the same time.
- **(R2)** It should visualize objects in interaction range as well as objects that are more distant.
- **(R3)** The visualization should add as little visual clutter as possible to the screen.
- **(R4)** Optional: the technique can indicate when an object is occluded to better support locating it [2, 21].

To compare the different visualization strategies in the second study separately, it is important that the in-view visualization technique focuses on in-view objects only and presents no information for objects that are out of view. To our knowledge, no existing in-view visualization fulfills our requirements and focuses on in-view visualization only. Therefore, we designed four in-view visualization techniques inspired by previous work. To avoid visual clutter on small FOV HMDs, we kept the visualization as simple as possible (cf. **(R3)**). This also allows one to visualize multiple objects at the same time (cf. **(R1)**). To locate a physical object in the environment, previous work used either a cue presented at the object's position [37] or a cue presented at the user's screen position pointing in the direction of that object [14]. For the cue presented at the position of the physical object, it is important to use a shape of which the 3D attributes can be clearly perceived. Thereby, the cue can be more easily located in space. Here, we used a 3D representation of the object for which the user searches, which is located in front of the object to avoid overlapping (see Figure 2a). For the cue that points in the direction of the physical object, we do not need to



(a) 3D representation. **(b) 2D representation.** **(c) 3D repres. and occlusion.** **(d) 2D repres. and occlusion.**

Figure 2: In-view visualization techniques for buttons placed on pinboards. Top: user's view through Hololens captured with built-in RGB camera and merged with displayed AR content; bottom: illustration explaining relative positions (bird's eye view). ***Best seen in color.***

use a shape with 3D attributes because it only points in the direction of the object. Here, we used a 2D representation of the object, which always faces the user (see Figure 2b). Since the 2D variant encodes the direction but not the distance to the physical object, we used a color gradient from blue to red to encode this distance. We based this on the cold and warm metaphor used, for example, in heatmaps[1] [17]. Here, red stands for very close and blue for far away (cp. **R2**). We decided to use color because size is problematic when only one object is present (relative size), transparency would fade out the cue for objects that are far away or close depending on the chosen encoding, and color is already used to encode distances in EyeSee360 [14]. Therefore, it might support users when objects switch between in-view and out-of-view visualizations. Additionally, we created a version of the 2D and 3D representation that shows a wireframe of the visual cue when the object is occluded (cp. **(R4)**) in order to improve spatial perception [2] (see Figure 2c and Figure 2d). We used a wireframe model to show occlusion as suggested by related work [41]. For all in-view visualization techniques, we used the color red as default since it is easily perceived [29]. To avoid occluding the physical objects, all in-view visualizations are turned off when the user moves into the interaction range of the object. We implemented the different in-view visualization techniques using Unity3D[2], a 3D game development platform.

Further, we added labels to the in-view visualization technique (see Figure 2). Thereby, users are able to distinguish the physical objects they represent. Here, we decided to use text for labeling to be able to use names for the physical objects. This is supported by our examples mentioned in the introduction (e.g., the robot arms are identified and addressed by their identification text). To be able to read the labels, we dynamically change their alignment to always be oriented towards the center of the AR display. Thereby the label is never hidden off screen.

[1]www.en.wikipedia.org/wiki/Heat_map, last retrieved October 10, 2019
[2]www.unity3d.com, last retrieved October 10, 2019

4.2 Study Design

To explore different visualization techniques for objects in view, we conducted a within-subjects controlled laboratory study in Augmented Reality with the Microsoft HoloLens. Our study had one task: locate objects that are in view. Our independent variable was in-view visualization with four levels (2D vs. 2D+Occlusion vs. 3D vs. 3D+Occlusion). We used quantitative methods to evaluate user performance, taking search time, object selection accuracy, and subjective Likert-items as our dependent variables.

For this study, we asked: **(RQ1) Which in-view visualization (2D vs. 2D+Occlusion vs. 3D vs. 3D+Occlusion) works best to locate physical objects in view?**

- H_1 We expect the in-view visualization techniques with occlusion information to perform better than the techniques without.
- H_2 We expect 3D+Occlusion to work best with regard to search time and object selection accuracy.

4.3 Apparatus

In order to abstract from concrete scenarios such as industrial plants or server rooms and to be able to control external factors, such as sunlight or varying distances, we created a controllable lab condition. Here, pinboards represent physical entities, which might occlude the objects for which the user is searching. Physical buttons attached to the pinboards represent potentially relevant objects with which the user needs to interact. An advantage of using pinboards is that physical buttons can be placed very close to each other, simulating realistic conditions (e.g., buttons placed on the back and front of a monitor [22]).

The study setup for this study can be seen in Figure 3b. We decided to use five 3D printed buttons as our representation for physical objects. The buttons were placed on three pinboards and their locations were not changed during the study. However, we did change their labels in each trial to reduce learning effects throughout the experiment. We decided to place some of the buttons very close to each other (5cm) to make sure the task was difficult enough and motivated by real world situations (e.g., a button on the front

(a) Participant. **(b) Setup.**

Figure 3: Apparatus of first study. *Best seen in color.*

and back of a monitor). The three pinboards were placed in a row directly after one other as seen in Figure 3b. Thereby, we could ensure that all buttons were lining up and were visible in-view when a participant started a trial. The buttons were developed using a 3D printed case, a NodeMCU developer board[3] with WiFi integrated, a button, and an LED that lit up when the button was pressed. The 3D printed buttons are battery powered. For the head-mounted AR device, we decided to use the Microsoft Hololens[4] because it is the most state-of-the-art device. The 3D printed buttons were connected to the Hololens using WebSockets over Wifi. To determine the locations of the 3D printed buttons and whether a button was occluded or not, we used the spatial perception abilities of the Hololens. We used an empty room with darkened windows and an artificial light source to control the brightness throughout the experiment (around 500 lux) to make sure AR content on the Hololens could be perceived equally well.

4.4 Procedure

At the start of the study, participants received an introduction to the Hololens. After, we started the experiment. Participants were standing as shown in Figure 3b, facing the three pinboards. We tested each of the four visualization techniques in one block. All blocks were counterbalanced using a balanced Latin square design. Each block contained ten measured trials and two test trials in the beginning. In each trial, all five buttons were shown using the visualization technique of that block and a red search label on the Hololens indicated which button to search for. Then, participants had to walk to the button that they thought was the right one and press it. In all ten measured trials we ensured that every button was selected two times. After each block, participants were asked to fill out a Likert-items questionnaire. At the end of the experiment, participants had to fill out a demographics questionnaire. Each participant took approximately 30 minutes to finish the experiment.

4.5 Participants

We recruited 12 volunteer participants (5 female), aged between 25 and 54 years (M=35.75, SD=10.38). None suffered from color vision impairments, 8 had normal vision, and 4 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 they have limited experience (Md=2, IQR=1.5).

4.6 Results

Search Time. The median search times for the different in-view visualization techniques are: 2D=8.01s, 2D+Occlusion=8.84s, 3D=7.87s, and 3D+Occlusion=7.11s. They are compared in Figure 4.

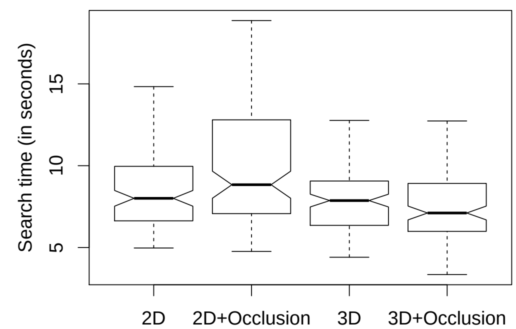


Figure 4: Boxplots of search times for different in-view object visualization techniques (top whisker to box: first quartile, box to bottom whisker: fourth quartile, box: second and third quartile separated by median).

A Shapiro-Wilk-Test showed that the search times are not normally distributed (p<0.001). Thereafter, we ran a Friedman test that revealed a significant effect of in-view visualization on search time (χ^2(3)=38.65, p<0.001, N=12). A post-hoc test using Wilcoxon Signed-rank with Bonferroni-Holm correction showed significant differences between all conditions (see Table 1). For the search time of the compared in-view visualization techniques, we can conclude 2D+Occlusion > 2D > 3D > 3D+Occlusion.

Table 1: Pairwise comparisons of in-view visualization techniques (r-values report the calculated effect sizes: >0.1 small effect, >0.3 medium effect, and >0.5 large effect).

Comparison	p-value	r-value
2D vs. 2D+Occlusion	0.019	0.15
2D vs. 3D	0.026	0.14
2D vs. 3D+Occlusion	< 0.001	0.25
2D+Occlusion vs. 3D	< 0.001	0.30
2D+Occlusion vs. 3D+Occlusion	< 0.001	0.38
3D vs. 3D+Occlusion	0.035	0.14

Object Selection Accuracy. The total number of correctly selected objects per in-view visualization technique are: 2D (115/120, 95.8%), 2D+Occlusion (100/120, 83.3%), 3D (116/120, 96.7%), and 3D+Occlusion (119/120, 99.2%). A Shapiro-Wilk-Test showed that the object selection accuracies are not normally distributed (p<0.001). After that, we ran a Friedman test that revealed a significant effect of in-view visualization technique on object selection accuracy (χ^2(3)=9.13, p=0.028, N=12). However, a post-hoc test using Wilcoxon Signed-rank with Bonferroni-Holm correction showed no significant differences between any of the conditions.

[3]www.en.wikipedia.org/wiki/NodeMCU, last retrieved October 10, 2019
[4]www.microsoft.com/hololens, last retrieved October 10, 2019

Likert-scale Questionnaire. After each condition, we asked the participants to answer two questions with 5-point Likert-scale items. The results are shown in Figure 5. Participants stated that they could quickly locate the in-view objects for all techniques: 2D=4 (IQR=1), 2D+Occlusion=4 (IQR=2.25), 3D=5 (IQR=1), and 3D+Occlusion=4 (IQR=0.25). Further, participants stated that they did not get distracted by the visualization techniques: 2D=2 (IQR=0.5), 2D+ Occlusion=2 (IQR=0.75), 3D=1 (IQR=1), and 3D+Occlusion=1 (IQR=0.25).

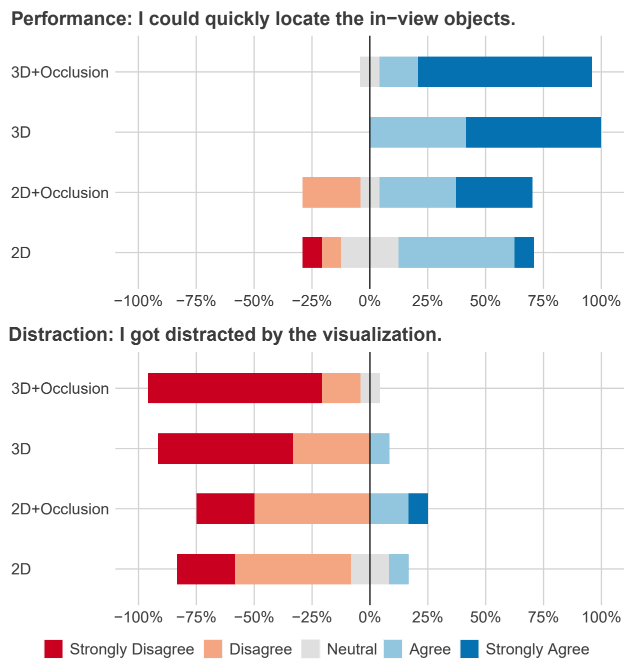


Figure 5: Results from 5-point Likert-item questionnaires. *Best seen in color.*

Additionally, we ask our participants which in-view visualization technique they prefer. Overall, eight preferred 3D+Occlusion, two preferred 2D, one preferred 3D, and one preferred 2D+Occlusion.

4.7 Discussion

Occlusion. Interestingly, occlusion information has a negative effect on our in-view visualization technique 2D. We think this is due to the fact that the color information was not well perceived by participants because of the wireframe visualization (see Figure 2d). Interestingly, for 3D+Occlusion we could not observe a similar effect (see Figure 2c). This is probably because the location information is not encoded with color, but with the 3D position. Therefore, we cannot accept our hypothesis H_1.

Performance. Our results show that 3D+Occlusion has a significantly lower search time than the three other in-view visualization techniques. Further, 3D+Occlusion also has the highest object selection accuracy (99.2%). However, this result is not significant and therefore, we cannot except our hypothesis H_2. From the Likert-items we saw that both 3D techniques are well rated by the participants with regard to performance and distraction. Further, most participants preferred 3D+Occlusion and the technique scored the significantly lowest search time. Therefore, we chose 3D+Occlusion for the second study to represent the in-view visualization strategy.

Physical Objects. When we placed the buttons very close to each other, we were worried that it might be too hard for users to locate them. However, the reported object selection accuracy from three of the in-view visualization techniques was higher than 95%. Therefore, we decided to keep this design choice for the second study.

5 STUDY II: VISUALIZATION STRATEGIES

After we identified a representative visualization technique for each visualization strategy, we can compare the different strategies to evaluate how to best locate physical objects in head-mounted AR. In our previous study, we found that 3D+Occlusion works best for in-view objects, and from our analysis of related work we saw that EyeSee360 works best for objects out of view. Therefore, we picked both to represent the in-view and out-of-view visualization strategy accordingly. Furthermore, we combined both techniques for our third AR strategy. As baseline condition we use a printed map that looks similar like to the setup in Figure 6b.

5.1 Study Design

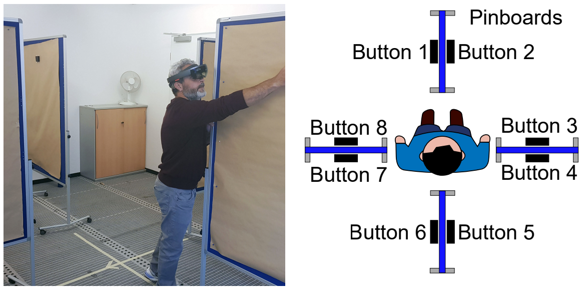
To explore different visualization strategies for locating physical objects in AR, we conducted a within subjects controlled laboratory study with the Microsoft Hololens. Our independent variable was visualization strategy with four levels (printed map vs. in-view vs. out-of-view vs. combined). All visualization strategies can be seen in Figure 1. We used quantitative methods to evaluate user performance, taking search time, object selection accuracy, NASA RAW-TLX [18], and subjective Likert-items as our dependent variables.

For this study, we asked: **(RQ2) Which of the four strategies works best to locate physical objects?**

- H_3 We expect the combination of in-view and out-of-view visualizations to result in lowest search time.
- H_4 We expect the worst object selection accuracy for the out-of-view visualization technique because of missing visual guidance for objects in view.

5.2 Apparatus

The setup for this study can be seen in Figure 6b. In this study, we decided to use four pinboards to be able to place a pinboard in every cardinal direction. Thus, there is one pinboard in front of the participant, one to the right, one to the left, and one behind. We placed two 3D printed buttons on each pinboard, and their locations were not changed during the study. However, we did change their labels in each trial to reduce learning effects. The 3D printed buttons were the same ones we used in the first study. Here, we used the Hololens as our AR device again. Our setup was done in an empty room with darkened windows and an artificial light source to control the brightness throughout the experiment (around 500 lux) to make sure AR content on the Hololens could be perceived equally well. We added the same labels for EyeSee360 as we did for our in-view visualization techniques (cf. subsection 4.1).



(a) Participant. **(b) Setup.**

Figure 6: Apparatus of second study. ***Best seen in color.***

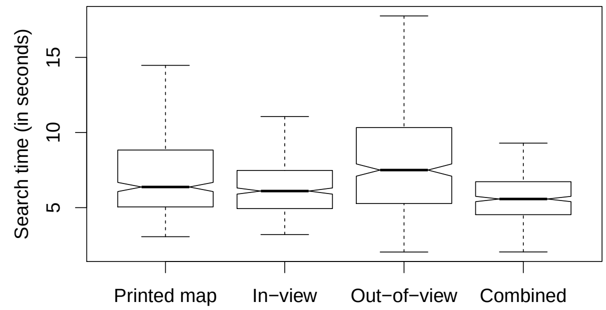


Figure 7: Boxplots of search times for different visualization strategies (see explanation of boxplots in Figure 4).

5.3 Procedure

At the start of the study, participants received an introduction to the Hololens. After, we started with our study. Participants were standing as shown in Figure 6b, facing the pinboard to the north. We tested each of the four visualization strategies in one block. All blocks were counterbalanced using a balanced Latin square design. Each block contained twelve measured trials and two test trials in the beginning. In each trial, participants had to press two buttons after each other, starting from a marked position in the center of all four pinboards. We randomized this task by randomly starting with each pinboard three times and then taking one of the other three pinboards in each of the three times for the second button press. Thereby, we could ensure that the distances participants had to walk were the same for all conditions. In each trial, all eight buttons were shown to the user with the visualization strategy of the current block. Again, a red search label indicated which button has to be located and pressed by the user (see Figure 1). After each block, participants were asked to fill out a Likert-items questionnaire and a NASA RAW-TLX. After all blocks, we asked participants to fill out a demographics questionnaire.

5.4 Participants

We recruited 16 volunteer participants (7 female), aged between 24 and 55 years (M=33.63, SD=8.72). None suffered from color vision impairments, 11 had normal vision, and 5 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 they have limited experience (Md=2, IQR=1).

5.5 Results

Search Time. The median search times for the visualization strategies are compared in Table 2 and Figure 7.

Table 2: Median search times for the visualization strategies.

Condition	First button	Second button	Overall
Printed map	6.49s	6.35s	6.37s
In-view	6.09s	6.13s	6.11s
Out-of-view	6.80s	8.00s	7.50s
Combined	5.48s	5.69s	5.58s

A Shapiro-Wilk-Test showed that the search times are not normally distributed ($p<0.001$). Therefore, we ran a Friedman test that revealed a significant effect of visualization strategy on search time ($\chi^2(3)=107.08$, $p<0.001$, N=16). A post-hoc test using Wilcoxon Signed-rank with Bonferroni-Holm correction showed significant differences between all conditions (see Table 3). For search time, we can conclude Out-of-View > Printed map > In-View > Combined.

Table 3: Pairwise comparisons of search times with significant results (r-values explained in Table 1).

Comparison	p-value	r-value
Printed map vs. in-view	0.003	0.11
Printed map vs. out-of-view	0.020	0.08
Printed map vs. combined	< 0.001	0.28
In-view vs. out-of-view	< 0.001	0.25
In-view vs. combined	< 0.001	0.21
Out-of-view vs. combined	< 0.001	0.41

Furthermore, we did a post-hoc test using Wilcoxon Signed-rank with Bonferroni-Holm correction to compare the search time for the first button with the search time for the second button within each condition. Here, we found significant effects for out-of-view ($p<0.001$, r=0.16) and combined (p=0.03, r=0.08). Here, both for out-of-view and combined, participants were significantly slower in finding the second button vs. the first button.

Object Selection Accuracy. The total numbers of correctly selected objects over all button presses are: printed map (344/384, 89.6%), out-of-view (357/384, 93.0%), in-view (381/384, 99.2%), and combined (383/384, 99.7%). A Shapiro-Wilk-Test showed that the object selection accuracies are not normally distributed ($p<0.001$). After that, we ran a Friedman test that revealed a significant effect of visualization strategy on object selection accuracy ($\chi^2(3)=29.93$, $p<0.001$, N=16). A post-hoc test using Wilcoxon Signed-rank with Bonferroni-Holm correction showed significant differences between some of the conditions (see Table 4). For object selection accuracy, we can conclude that in-view and combined, both have a significant higher object selection accuracy than printed map or out-of-view.

Table 4: Significant results from pairwise comparisons of object selection accuracy (r-values explained in Table 1).

Comparison	p-value	r-value
Printed map vs. in-view	<0.001	0.43
Printed map vs. combined	<0.001	0.43
Out-of-view vs. in-view	0.004	0.35
Out-of-view vs. combined	0.001	0.40

NASA RAW-TLX. For NASA Raw-TLX [18] scores, printed map scored 33.09 (SD=10.22), in-view scored 20.14 (SD=12.99), out-of-view scored 35.62 (SD=17.56) and, combined scored 23.12 (SD=10.00). In-view and combined both indicate a low workload, while printed map and out-of-view have higher workloads. A Shapiro-Wilk-Test showed that the NASA Raw-TLX values are not normally distributed (p=0.009). Therefore, we ran a Friedman test that revealed a significant effect of visualization strategy on workload ($\chi^2(3)=19.19$, p<0.001, N=16). A post-hoc test using Wilcoxon Signed-rank with Bonferroni-Holm correction showed significant differences between some of the conditions (see Table 5). For workload, we can conclude that printed map and out-of-view had both a significantly higher workload than in-view or combined.

Table 5: Significant results from pairwise comparisons of workloads (r-values explained in Table 1).

Comparison	p-value	r-value
Printed map vs. in-view	0.007	0.46
Printed map vs. combined	0.022	0.40
Out-of-view vs. in-view	0.003	0.49
Out-of-view vs. combined	< 0.001	0.59

Likert-scale Questionnaire. After each condition, we asked the participants to answer two questions with 5-point Likert-scale items. The results are shown in Figure 8. Participants stated that they could quickly locate the physical objects for the printed map (Md=4, IQR=1.25), in-view (Md=4, IQR=1), and combined visualization strategy (Md=4, IQR=1.25). While they were neutral about the out-of-view visualization strategy (Md=3, IQR=2). Further, participants stated that they did not get distracted by the in-view (Md=1, IQR=1) and the printed map visualization strategy (Md=2, IQR=2). While they were neutral about the out-of-view (Md=3, IQR=1) and combined visualization strategy (Md=3, IQR=2).

Additionally, we ask our participants which visualization strategy they prefer. Overall, 8 participants like the in-view visualization the most, 4 participants preferred the combined visualization, 3 participants liked the out-of-view visualization the most, and one participant liked the printed map visualization the most.

5.6 Discussion

Search Time Performance. We expected the combination of in-view and out-of-view visualizations to result in the lowest search time. At 5.58s, the combined visualization is significantly faster than the other conditions. Therefore, we can accept our hypothesis H_3. The worst performance we measured was for the out-of-view

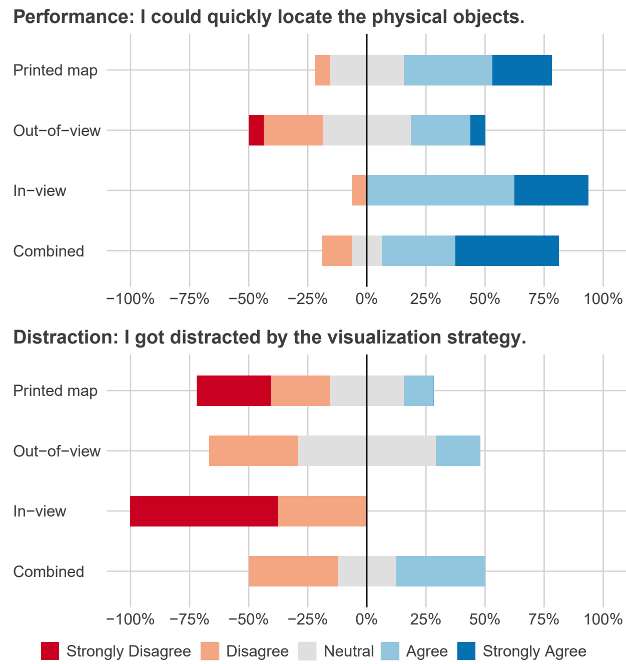


Figure 8: Results from 5-point Likert-item questionnaires. *Best seen in color.*

visualization technique. Here, participants could easily rotate towards the out-of-view object they were seeking, but as soon as it was in-view and the visual cue was no longer given, participants struggled with choosing which button to press. Findings in related work support this [12]. However, we think that participants would have performed better with the out-of-view visualization strategy if the buttons had been farther from each other. In our setup, some buttons were placed only five centimeters (pinboard thickness) away from each other (front and back of pinboard).

Object Selection Accuracy. Here, again the combination of in-view and out-of-view visualizations performed best. However, the visualization in view especially helped participants to select the right button. We expected the out-of-view visualization to perform worst, but participants actually made more errors with the printed map. Therefore, we cannot accept our hypothesis H_4. We think that the high error rates in both studies are again due to our challenging setup. This led to difficulties with the out-of-view visualization technique, such as when both buttons almost simultaneously appeared in view and therefore, were hard to distinguish from each other.

Printed Map. We observed participants rotating the map to match their orientation. This was especially true for the second button because for the first button the map was handed to the participants in the right rotation. In many cases, participants went back to the starting position for the second button and rotated towards north again. Others tried to do the rotation as a mental step, but then made errors.

Visual Clutter. Although the combination of in-view and out-of-view visualization techniques works best from our quantitative results, participants stated that they got distracted by the technique similar to the out-of-view visualization technique alone because of too much visual clutter (see Figure 8). This is supported by previous findings [32]. Here, we suggest an adaptive strategy to reduce visual clutter. We think that by collecting contextual information (e.g., eye-tracking data), we can determine whether the user is interested in locating a physical object in view or out of view. Thereby, only the required visualization stays active. Further, it may be possible to encode less information in the out-of-view visualization technique. EyeSee360 encodes the precise location of an out-of-view object, although the general direction in which a user needs to turn his head might be sufficient. For the in-view visualization strategy, however, users think that the technique is not distracting at all, highlighting the usefulness of the technique to visualize in-view objects (see Figure 8).

Limitations. In our study setup for both studies, participants remembered the positions of the 3D printed buttons because we placed them on static pinboards. We argue that in several scenarios this is the case (e.g., for the network engineer where the server racks are placed at fixed positions in the room). However, for scenarios in which all possible positions are known to the user beforehand and only a small number of positions exists, an in-view visualization strategy may have an unfair advantage over an out-of-view visualization strategy. We think this is reflected by our results that show fast search times and subjectively favor the in-view visualization strategy. Therefore, future studies are required to investigate changing positions and a larger number of physical objects. Here, we decided to only use eight objects in our second study because with more objects the small field of view of the Hololens would have been overloaded with information for the out-of-view and combined visualization strategy. A newer generation of AR headsets with a wider field of view and an improved out-of-view visualization technique may allow to test a larger number of objects in the future. Further, in our study, we focused on objects that are located nearby. However, in many scenarios (e.g., manufacturing plants) objects are more spatially distributed, requiring the user to walk longer distances. This may negatively impact users performance because the chance to "get lost" in the environment is higher. Future work should address this and test larger environments.

6 CONCLUSION

In this paper, we first compared different visualization techniques for objects in view. Our results show that a 3D representation including occlusion information works best when physical objects appear on the AR device screen. After that, we compared three different Augmented Reality visualization strategies against a printed map. Our results show that in-view visualization helps to improve object selection accuracy, while out-of-view visualization improves search time performance when used in combination with in-view visualization. However, when designing for small field-of-view AR devices, visual clutter has to especially be taken into account to avoid distracting users from their surroundings. Here, the field of view of the AR headset limits the number of objects that can be visualized at the same time. Interestingly, participants made the most errors with the printed map, indicating how useful AR is for locating physical objects. In the future, we want to investigate adaptive strategies that detect the required visualization strategy based on contextual information in order to reduce visual clutter. Further, we want to evaluate the performance of the different visualization techniques for a larger number of physical objects that are distributed in a wider area.

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