All or Adaptive: The Effects of Adaptive Target Selection and the Number of Cued Targets on Visual Search

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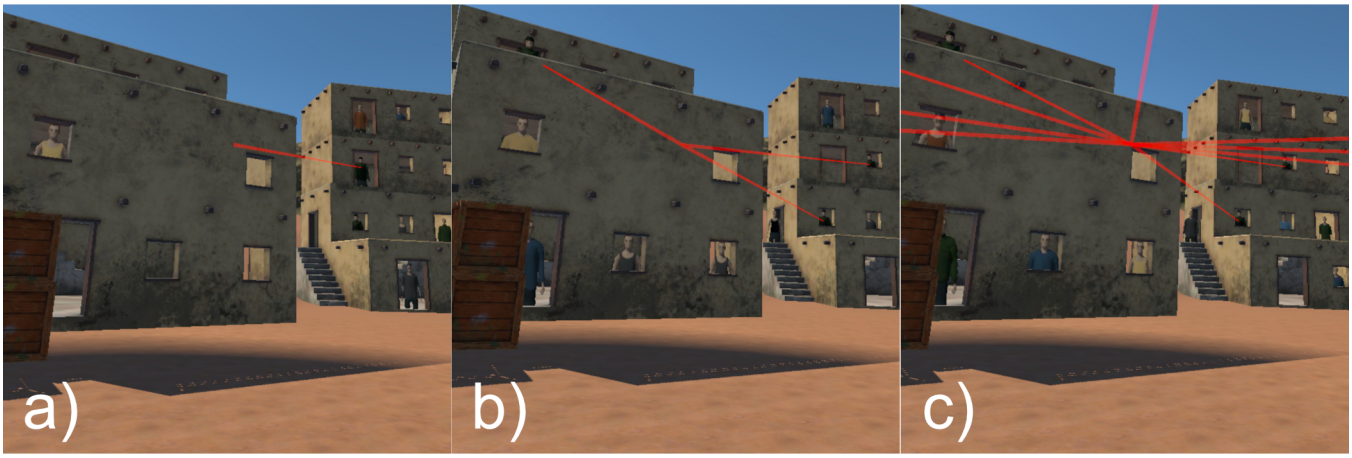


Figure 1: Three views from the user's perspective of our comparative experiment. From left to right: a) a single Gaze Line cue used for both the ordered and adaptive target selection conditions, b) three Gaze Line cues used for both the ordered and adaptive target selection conditions, and c) our All condition where every present target was cued simultaneously.

Abstract

Visual cueing in virtual reality (VR) and augmented reality (AR) head-mounted displays (HMDs) has been widely studied, yet adaptive target selection and the effects of cueing subsets of targets remain underexplored. This paper presents a within-subject study comparing five cueing conditions, ordered one (O1), ordered three (O3), adaptive one (A1), adaptive three (A3), and cue all (ALL), to address two research questions: does adaptive target selection improve visual search outcomes, and does cueing a subset of targets improve visual search outcomes? Using the Gaze Line cue in a VR environment with 23 participants, we evaluated search time, accuracy, mental effort, and head movement. Results show that adaptive target selection and cueing more targets simultaneously both reduce search time and head movement compared to single ordered cueing, but do not produce compounding benefits when combined. Cueing all targets proved a viable alternative to adaptive approaches when order is unimportant, while cueing a subset of three targets is recommended when selection order matters. Accuracy and mental effort were unaffected by target selection strategy, suggesting cue design plays a larger role in these outcomes. These findings offer practical guidance for designing adaptive visual cueing systems and highlight promising directions for future work.

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CCS Concepts

• **Human-centered computing** → **Mixed / augmented reality**; *Information visualization*; **Virtual reality**; User interface design.

Keywords

Augmented Reality, Virtual Reality, Visual Cueing, Visual Search, Information Processing, Attention, Adaptive

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1 Introduction

A variety of cue designs have been established over the years for virtual reality (VR) and augmented reality (AR) head mounted displays (HMD), with most producing similar, if not improved, task outcomes than baseline conditions [23, 56]. These cues are especially beneficial when completing complex tasks, such as visual searches with multiple targets, distractors, and full 360 degree environments [22]. Many visual search studies have focused on cue designs, with many presenting new or re-designed cues to address particular use cases or scenarios, such as out-of-view targets [5, 10, 14], field of view (FOV) transitions [52], or multi-modal cueing [35, 51]. However, there are several other factors, besides cue design, related to VR and AR cueing that have gone under explored; namely adaptive implementations, target selection, and the number of simultaneous cues.

Several prior works have utilized adaptive techniques for visual cueing [18, 22, 31, 41, 48], however each explores different methods of enhancing visual cueing, by applying adaptivity to different aspects of the cueing process. In this work, we specifically aim to apply adaptive techniques to the target selection process. There is also the question of how many targets should be cued simultaneously; most prior studies have either cued a single target [4–6, 10, 15, 17, 22, 24, 25, 33, 43, 47, 54, 56, 60], or cued all possible targets simultaneously [7, 8, 14, 26, 40, 47, 62], however, few studies have explored cueing a subset of targets over these approaches. The few that have are typically *precueing* studies [1, 29, 30] not *cueing*.

This study aims to address two key questions: 1) *Does adaptive target selection improve visual search outcomes?* and 2) *Does cueing a subset of targets improve visual search outcomes?*. In our exploration of these questions we revealed several key insights: *cueing more and using adaptive target selection provide similar benefits*, *cueing everything is a valid alternative approach to adaptive target selection*, *when order is important providing a subset of cues is recommended*, *accuracy and mental effort may be more impacted by cue design than target section techniques.* In addition to these insights we provide the following contributions:

- Integrates an adaptive algorithm for target selection into a visual search task.
- Evaluates our adaptive technique against common non-adaptive techniques (single-sequential selection and cueing all) for target selection.
- Evaluates the effect of cueing a subset of cues against common cueing strategies (single or all).
- Provides insights into adaptive selection implementation with respect to the number of cued targets.
- Demonstrates the potential benefits to using adaptive cueing strategies as well as the benefits of cueing more than one target simultaneously.

2 Related Work

2.1 Visual Search

Visual search tasks require the user to find objects within their environment. This may be for assembly [47, 51], threat assessment [24, 25, 33], environment awareness [16, 36, 45], or some other reason. In some cases, distractors may be present that siphon attention away from the true targets, creating a more complex search task. Other factors, such as environment complexity [57], user's cognitive state [46, 49], and target saliency [56, 58] can all further complicate these tasks. To overcome these factors and help users better attend to and identify targets, visual cues have been integrated into such search tasks.

2.1.1 Cueing for Visual Search. Over the years, a variety of cue designs have been developed and implemented into VR and AR HMD assisted visual search tasks. Many of which have been proven to be at least as effective as un-cued searches, if not more effective [23, 56]. However, not all cues are created equal [22, 24, 25]. A variety of factors including modality, purpose, markedness, trigger, embedded information, etc. can affect cue efficacy [12, 20, 21]. In some cases cues may be created for particular tasks or problems, such as indicating out-of-view targets [5, 10, 14, 15, 40, 60], indicating when a target has transitioned into a users FOV [51], where a hazard exists [36, 45], etc. Regardless of the usage though, it is important to match cue designs with an appropriate task.

For this study we chose the Gaze Line cue, which has been reported as a particularly effective cue for visual search tasks [22–25, 33]. Given our interest in cue target selection, we specifically opted to choose a cue that has already been proven as an effective design for visual search tasks, such as ours, and opted to implement the Gaze Line cue. This particular cue has been compared to multiple other popular cueing strategies including arrow designs (in which a 2D or 3D arrow points to target locations) [22–25], wedge designs (where a scaling triangle is positioned on screen with the tip over the target location, even if offscreen, and the base of the triangle always in the user's view) [23–25], and radar designs (where a minimap shows target and user positions) [33]. By using a well established, effective, cue for our task we can better focus on the effects of target selection techniques and subset cueing.

2.2 Adaptive Cueing

Recently adaptive techniques have gained traction for visual cueing research [23]. This includes both machine learning (ML) powered integrations [41, 42, 48], as well as more rudimentary algorithms and techniques [18, 31].

ML techniques are most commonly used for adaptive cueing implementations [41, 42, 48, 61], with target detection as an obvious use case for these ML based adaptive cueing interventions.

Raikwar et al. [41] implemented ML based computer vision (CV) techniques to detect targets in a scene for cueing through HMD cameras. However, target detection is not the only aspect of visual cueing that is ripe for adaptive exploration. Seeliger et al. [48] applied an ML model, trained on user interaction data, to a navigation task, where the ML model determined whether or not to render the assistive cue. In their work, they found the adaptive system to provide similar performance benefits to an always on system, but with a reduction in cognitive load [48].

While ML based adaptive interventions have been found to be at least as effective as always on cueing systems [41, 42, 48], it is possible to use non-ML techniques to provide similar benefits. For instance, Liu et al. [31], and Harris et al. [18], both explored the use of adaptive techniques to drive cue activation (similar to Seeliger et al. [48]), but did so without training a ML model. Instead, both of these works relied on user positional and gaze information [18, 31]. Where the user looked [18, 31], or positioned their hands [31] would cause a cue to render or hide.

Using non-ML techniques such as those presented by Liu et al. [31] and Harris et al. [18], presents some potential advantages over ML techniques. With ML techniques, a training dataset must first be acquired. For instance, Raikwar et al. [41], generated a synthetic dataset in Blender (a 3D modeling and rendering software) that was used to train their CV model, and Seeliger et al. [48] conducted a pilot study aimed at collecting detailed interaction data. While the use of ML does allow for sophisticated adaptive cueing, the process of sourcing and collecting data for model training can be costly and time consuming, whereas non-ML techniques often require far less information and effort to provide benefits. Additionally, there are growing concerns over the the environmental impacts of AI techniques leading to calls for sustainable AI [13, 50]. In addition to requiring less data, non-ML techniques often also require less computational power, improving sustainability and allowing adaptive techniques to exist on standalone VR and AR HMDs (such as the Oculus Quest line of headsets) without needing to offload computations.

While there has been some prior exploration on adaptive cueing techniques with both ML and non-ML based strategies, there exists no singular method or strategy for adding adaptive features to the visual cueing interventions. *Cue activation* [18, 48], *target detection* [41, 42], and *target selection* [22, 31] have garnered attention from researchers. However, no research, to the best of our knowledge, has compared adaptive target selection to the two most common non-adaptive approaches. With the two most common non-adaptive approaches being single-ordered selection [4–6, 10, 15, 17, 22, 24, 25, 33, 41, 43, 47, 48, 54, 56, 60] and cueing all targets simultaneously [7, 8, 14, 26, 31, 40, 62].

Target selection differs from both cue activation, and target detection. With cue activation the targets for the cues have already been set, so regardless of whether or not the adaptive system has decided to present those cues, the cued target does not change [18, 48]. In the case of target detection, the target is unknown to the system, but through adaptive means (most often ML), this target becomes known and then a static cue is instantiated to guide the user [41, 42]. *Target selection* is the use of adaptive means to choose targets from all possible targets. In this case the targets are already known and the cues are always active, but the selection of which target to guide the user towards is adaptive. Our work implements an adaptive target selection algorithm and compares this adaptive approach to the common non-adaptive approaches.

2.3 Target Selection

When determining what target to cue, most prior studies have taken one of two approaches; they either cue targets in an ordered fashion [4–6, 10, 15, 17, 22, 24, 25, 33, 41, 43, 47, 48, 54, 56, 60] or they cue all possible targets simultaneously [7, 8, 14, 26, 31, 40, 62]. Ordered targeting, cues one target at a time. Most often this is because only a single target exists in the environment at a time [4–6, 10, 15, 17, 24, 25, 33, 41, 48, 54, 56], but in situations where multiple targets exist simultaneously it is not uncommon to have a predetermined order for target selection [8, 43, 47, 60]. Often, this predetermined order is driven by the task (i.e. parts for step one must be found before parts for step two), but can also be arbitrary, where the order is predetermined by researchers with no particular method. In many of these cases, users must find and select target A before they are allowed to select target B.

When order is not predetermined by some means (i.e. task requirements, arbitrary ordering, or importance), prior work has often cued all possible targets [7, 8, 14, 26, 31, 40, 62]. In these cases the order of selection does not matter, however presenting too much information to the user at once can lead to clutter effects [37, 44, 53, 55] which in turn result in cognitive overload, thus hindering performance [46, 49, 57–59]. Instead, cueing a subset of targets may be beneficial, as a subset allows user's to attend to more than one target at a time, but limits the amount of spatial information to avoid detrimental clutter effects [37, 44, 53, 55].

Along with ordered target selection, where targets were cued in a predetermined order, and a target selection method where all possible targets were cued simultaneously, we implemented two selection methods were a subset of three targets were cued simultaneously.

2.4 Number of Simultaneous Cues

To determine the optimal number of cues to display simultaneously we turn to cognitive principles on working memory [2, 3, 9, 19, 32]. Working memory theories posit that individuals can attend to a limited amount of information at a time. Originally, this was believed to be seven plus or minus two [34], but recent evidence has suggested the true limit to be four plus or minus one item [11].

While there has been limited research on visual cueing techniques that apply working memory limits, there have been several explorations on working memory and *precueing* [1, 28–30]. Precueing tasks differ from cueing tasks (such as the one presented here), as they present a single current target to the user, alongside the next N steps, thus giving the user a glimpse at future targets. However, several precueing studies have explored the optimal number of precues to present to a user in the context of working memory limits [28–30]. Most of these studies report an optimal number of 3 precues, which helped to guide our decision to cue a subset of 3 simultaneous targets for our work.



Figure 2: A view from the user's perspective of the search environment. The blue laser is used to help with selection. The blue sphere is a marker placed at a target location. In the top half of the image a single Gaze Line cue is guiding the user to the next target location.

3 Methods

To address our guiding research questions (*Does adaptive target selection improve visual search outcomes?* and *Does cueing a subset of targets improve visual search outcomes?*), we conducted a within-subject experiment, that was approved by our institutions internal review board, with five different conditions: ordered 1 ($O1$), ordered 3 ($O3$), adaptive 1 ($A1$), adaptive 3 ($A3$), and cue all (ALL).

3.1 Apparatus

Our testbed application was developed using Unity (version 2022.2.1f). This application was then loaded onto a Meta Quest Pro HMD. The app ran standalone on the HMD (e.g. with no external PC to drive the VR experience). Relevant data (i.e. search time, accuracy, etc.) was automatically collected by this system each frame and upon completion of a search trial. Between conditions reported effort was measured using an in-HMD implementation of the Paas scale [27, 38, 39].

3.2 Task Design

For our search task participants were placed in the center of a virtual environment and given an 8m by 8m boundary to freely walk within. Several buildings were present each with 1-3 stories. Each window and doorway on these buildings served as a potential spawn point for both targets and distractors. In our environment, this afforded a total of 70 potential search points. During any given search, 10 targets and 30 distractors were present, with the precise location of these objects being controlled by a configuration file.

When a participant found a target they were instructed to use either of the two VR motion controllers, one in each hand, to point at the target location and press the trigger button to spawn a marker at that location. To aid in the pointing and selection process a blue line was rendered from the controller along it's forward direction (see Figure 2). If the participant ever placed a marker in the wrong location they were able to delete the marker by pointing at the misplaced marker and pressing the trigger button to delete the object.

Once they believed they had found all of the targets they pressed either the B or Y button (dependent on the hand used) to proceed to the next search configuration. Once all of the searches for a condition were completed, the next condition would automatically begin. For each condition the same 21 search configurations were used, but the order of completion was randomized.

3.2.1 Cue Design. For this study a single cue design was selected. We opted to implement the Gaze Line cue. This cue consists of a single red line, 0.5m thick, with one end terminating at an offset 0.5m in front, and 0.25m above the center of the user's FOV and the other end terminating at the center of the target location in 3D space. Several other studies have found the Gaze Line cue to provide significantly improved visual search results over other popular cues; including wedge, map, and arrow designs [22, 24, 25, 33]. As the focus of this study is on adaptive target selection and subset cueing, we specifically chose a well-established cue with strong prior performance for visual search tasks, rather than adding another confounding variable by testing different cue designs.

3.2.2 Adaptive Target Selection. To drive target selection for the two adaptive conditions (A1 and A3) we implemented an adaptive algorithm that prioritized cues based on the angular distance between the center of the user's FOV and the direction to each target (see Figure 3 for a diagram of our algorithm). This algorithm was used to reset the cued targets after the user placed a marker at any cued location.

First, we determine the location of each remaining unmarked target. For each of these remaining search targets we calculated the directional vector to the target (V_{TAR}). Using V_{TAR}, we then calculated the unsigned angle (θ) between the forward vector from the center of the user's FOV (V_{FOR}) and V_{TAR}. The resulting angles were then stored as a key value pair, linking each target position to their associated angle. These pairs were then sorted from smallest to largest based on the resulting angle, so if $\theta_1 < \theta_2$ then θ_1 will take precedence over θ_2. Once sorted, N total locations were selected from the pairs with the N smallest angle values, where N is the number of cues presented simultaneously to the user. From these selected pairs the target position was used to update cue visualizations.

3.2.3 Conditions. The two most common approaches to selecting targets for cueing tasks have been: single sequential ordering [4–6, 10, 15, 17, 24, 25, 33, 43, 47, 54, 56, 60], or cueing everything [7, 8, 14, 26, 40, 62]. This leads us to include a single ordered condition ($O1$), where targets are cued in a predetermined order based on a preset configuration file (although unlike prior studies, where the active target must be acted upon before moving onto the second target [8, 24, 25, 47, 54, 56], we allow participants to mark uncued

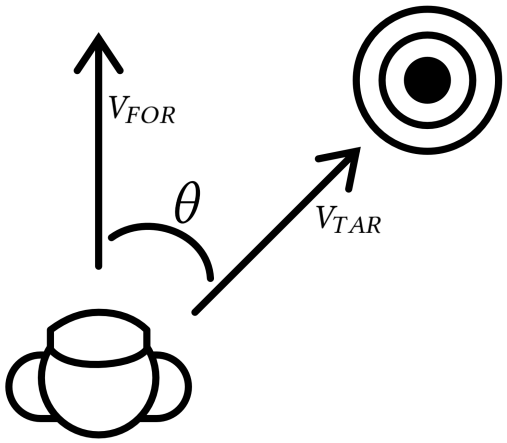


Figure 3: A visual representation of our adaptive algorithm that was implemented for our adaptive conditions (A1 and A3). To determine which target to cue, the angle (θ), between the forward (V_{FOR}) and target (V_{TAR}) vectors was calculated for each remaining unmarked target.

targets regardless of whether they are actively cued or not), and an all targets cued condition (*ALL*), where every target in the scene is cued simultaneously. However, both adaptively selecting a target (as opposed to using a predetermined order such as with *O*1) and cueing a subset (as opposed to cueing everything as with *ALL*) may provide benefits. Thus we include an adaptive condition using an angular-distance proximity heuristic (see subsubsection 3.2.2) that cues three targets simultaneously (*A*3). Using an adaptive approach, even just a simple heuristic, to cueing has been shown to improve search outcomes, even if just by reducing cognitive load [18, 31, 41, 48], and precueing studies have found three simultaneous precues to be optimal for tasks [1, 28, 29], thus we expect *A*3 to provide benefits over *O*1 and *ALL*.

However, there exists a problem with implementing just the *A*3 condition; it incorporates both an adaptive selection approach using our angular-distance proximity heuristic, and cues a subset of targets. Due to this it would be impossible to understand if potential differences between *A*3 and both *O*1 and *ALL* are due to the heuristic, or due to cueing a subset. As such, we also implemented an adaptive one condition (*A*1), where only one target is cued, but the target selection is adapted by using our angular-distance proximity heuristic, to evaluate the effects of cueing a subset, and an ordered three condition (*O*3), where three cues are displayed simultaneously, but the same predetermined order as *O*1 is used, in order to evaluate the effects of our adaptive target selection algorithm. This produces five different conditions *O*1, *O*3, *A*1, *A*3, and *ALL*. For an example of how these conditions appeared in VR for users see Figure 1.

3.3 Procedure

After obtaining informed consent from participants they completed a demographic questionnaire that collected information of interest, such as age, gender, prior experience with AR and VR, etc. During this process participants were also screened for 20/20 vision or corrected to 20/20 vision (via glasses or contact lenses) and motion sickness susceptibility.

If the participant was eligible, they completed an orientation and practice task in VR. This practice task consisted of the user searching for two targets in a sample building with two distractors present. They were allowed to engage with the orientation and practice task as long as they needed to understand the target marking and resetting interactions. Once they were comfortable with the orientation task, they began the full search task.

The five conditions (*O*1, *O*3, *A*1, *A*3, *ALL*) were counterbalanced via Latin Square to minimize any order and learning effects. Within each condition participants completed 21 total search configurations, each with 10 total targets to find. These configurations were the same for each condition, but the order of the 21 configurations were shuffled before each condition so the ordering was different for each condition and each participant. On average, completing the full experimental procedure (inluding the pre-screeing and search task) took around 45 minutes. Between each condition, the participant was asked to rate the level of effort required for the completed condition using an in-VR implementation of the Paas scale [27, 38, 39].

After completing all searches with all conditions, the participant removed the VR headset and was compensated with either a $20 gift card or extra credit in an applicable course. They were also asked to share any comments or questions with the researcher monitoring the session. Any pertinent comments or feedback was noted by the researcher.

3.3.1 Participants. A total of 23 participants (9 women, 12 men, and 2 non-binary) were recruited with an average age of 23.71(SD = 4.9). Of these 19 reported prior use of AR and all reported prior use of VR. As five conditions were utilized for this study an imbalance existed for the dataset due to the number of participants. Sensitivity analysis was conducted comparing the balanced set of 20 to the full set of 23. Results of this analysis revealed no difference in reported statistics as described in section 4.

4 Results

The average search time to find a single target out of all ten was automatically collected whenever a participant completed a search configuration. After correctly placing a marker at a target location, the time since the last placement (or the start of the search) was collected and the timer was reset, then these values were averaged for each participant. Accuracy was also automatically calculated at this point, and was simply the number of targets correctly marked divided by the number missed. During each configuration the total amount of head movement in meters and head rotation in degrees was collected. At the end of each condition participants were asked to rank the level of effort required using the Paas scale [27, 38, 39], which consists of a single Likert scale ranging from 1 to 9. See Table 1 for the results of all conditions.

Table 1: Results table for each of the five cue conditions.

Condition	Time	Accuracy	Movement	Rotation	Paas
O1	2.11s	92.33%	5.16m	655.12°	4.71
O3	1.81s	94.31%	4.44m	512.57°	4.43
A1	1.48s	94.06%	3.18m	350.53°	3.67
A3	1.38s	94.28%	2.93m	342.6°	3.52
ALL	1.51s	92.32%	3.15m	360.84°	3.43

4.1 Time

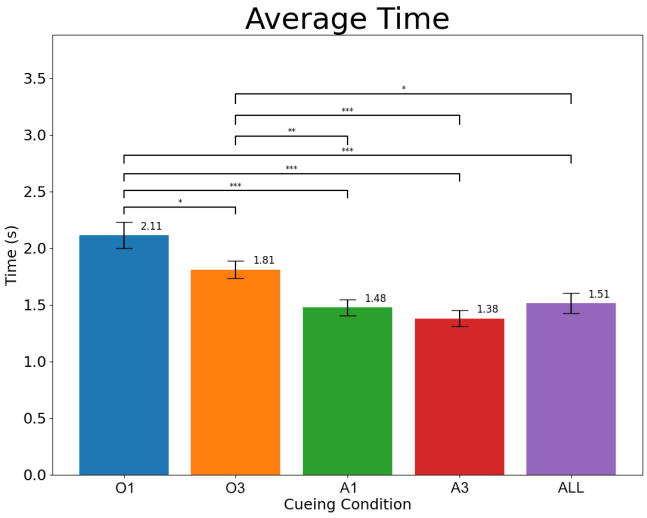


Figure 4: The average search time required to find a single target among all ten. Bars indicate standard error.

After checking data for normality, a repeated measures ANOVA was used to analyze time measures. A Greenhouse-Geisser correction was applied due to Mauchly's test revealing a violation of sphericity ($\chi^2(4) = 31.57, p < 0.001$). Post hoc analysis was conducted using Tukey's HSD with Bonferroni correction. The average search time (the time to find a single target out of all present), was found to be significant ($F(4, 88) = 22.82, p < 0.001$). A3 produced the fastest average search time with each target taking 1.38s (SD=0.34). This was followed by A1 with an average time of 1.47s (SD = 0.34), then ALL with 1.51s (SD = 0.41). O3 and O1 elicited the slowest average response time with 1.81s (SD = 0.35) and 2.11 (SD = 0.54) respectively. See Figure 4 for the full comparison.

Effect sizes were calculated using Cohen's D. A small effect was observed between the two sequentially ordered conditions ($O1$ and $O3$, $d = 0.46$), between $O3$ and $A1$ ($d = 0.67$), and between $O3$ and All ($d = 0.54$). A large effect was observed between the $O1$ and $A1$ conditions ($d = 0.98$), between $O1$ and $A3$ ($d = 1.13$), between $O1$ and All ($d = 0.87$), between $O3$ and $A3$ ($d = 0.87$).

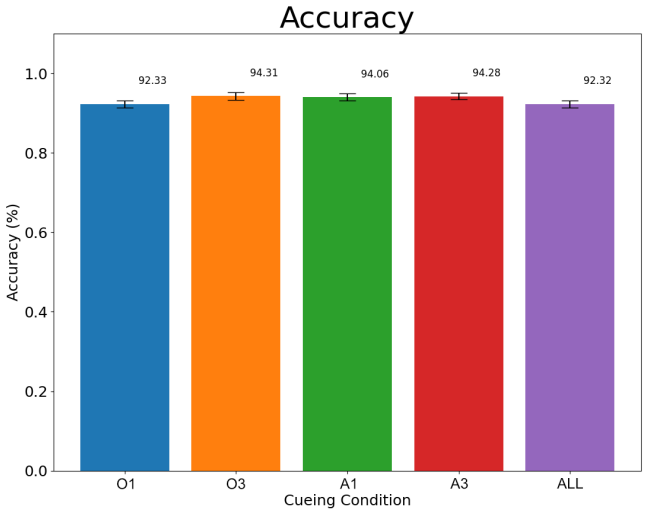


Figure 5: The accuracy produced by each of the conditions. Bars indicate standard error.

4.2 Accuracy

A repeated measures ANOVA was used to analyze accuracy data, however no significant differences emerged. A3, A1, and O3 all produced an accuracy of roughly 94%, and both O1 and ALL produced an accuracy of around 92% (see Figure 5).

4.3 Effort

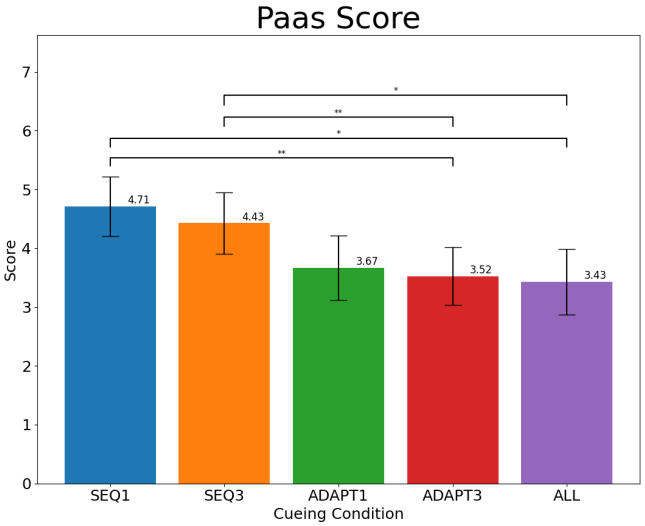


Figure 6: The subjective Paas scale rankings for each condition. Bars indicate standard error.

Due to a lack of normality expressed by the Paas scale data collected and within-subjects nature of the data Friedman's test was used for analysis. Statistical analysis revealed significant differences in reported effort ($\chi^2(4) = 18.57, p < .001$). Post-hoc analysis was conducted using a Wilcoxon Signed-Rank test (see Figure 6 for

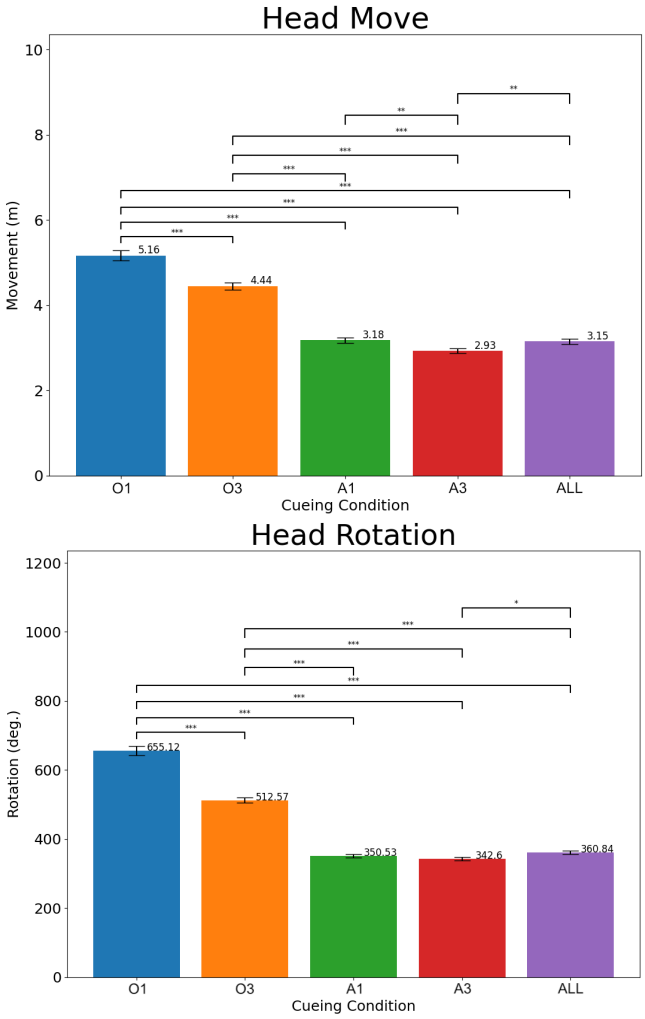


Figure 7: Total head movement and rotation produced while finding all ten targets using a particular condition. Bars indicate standard error.

comparisons). O1 had the highest reported level of effort at 4.71 (SD = 2.27), followed by O3 with a score of 4.43 (SD = 2.34), then A1 with a score of 3.67 (SD = 2.44), then A3 with a score of 3.52 (SD = 2.2), and finally ALL with a score of 3.43 (SD = 2.48).

4.4 Movement

Both head movement and head rotation measures were analyzed using a repeated measures ANOVA (see Figure 7). A Greenhouse-Geisser correction was applied to both due to Mauchly's test revealing a violation of sphericity (head movement: $\chi^2(4) = 56.41, p < 0.001$, head rotation: $\chi^2(4) = 89.95, p < 0.001$). Post hoc analysis was conducted using Tukey's HSD with Bonferroni correction. The cueing condition produced a significant effect for both Head Movement ($F(4, 88) = 36.09, p < 0.001$), and Head Rotation ($F(4, 88) = 49.79, p < 0.001$).

Participants moved the most with the O1 condition which produced 5.17m (SD = 1.79) of movement. O3 produced 4.44m (SD = 1.21) of movement. ALL produced 3.16m (SD = 0.88) of movement. Both the A1 and A3 conditions produced close to 3m of movement with A1 producing 3.17m (SD = 0.68) of movement and A3 producing the least amount of movement at 2.93m (SD = 0.76). A similar order emerged with head rotation with O1 producing the highest level of rotation (654.7°, SD = 211.32). This was followed by O3 which produced 513.07° (SD = 101.04). All produced 361.53° (SD = 61.52). A1 followed close behind, producing 350.47° (SD = 56.19). The lowest amount of rotation was produced by A3 with 342.53° (SD = 42.3).

Cohen's D was used to calculate effect size for head movement. A large effect size was observed between the *O*1 and each of the *A*1 ($d = 1.02$), *A*3 ($d = 1.12$), and *All* ($d = 0.98$) conditions with respect to head movement. A large effect size was also observed between the *O*3 and each of the *A*1 ($d = 0.89$), *A*3 ($d = 1.03$), and *All* ($d = 0.83$) conditions with respect to head movement. For head rotation, Cohen's D was also used to calculate effect size. A large effect size was observed between the *O*1 and each of the *A*1 ($d = 1.36$), *A*3 ($d = 1.41$), and *All* ($d = 1.3$) conditions with respect to head rotation and for the *O*1 and *O*3 conditions a medium effect size was observed ($d = 0.59$). A large effect size was also observed between the *O*3 and each of the *A*1 ($d = 1.38$), *A*3 ($d = 1.52$), and *All* ($d = 1.25$) conditions with respect to head rotation.

5 Discussion

This work aims to address two key questions: 1) *Does adaptive target selection improve visual search outcomes?* and 2) *Does cueing a subset of targets improve visual search outcomes?*. In our exploration of these questions several key insights emerged that should guide adaptive cue implementation, demonstrate the benefits of adaptive cueing over sequential cueing, and demonstrate the benefits of cueing more than one target simultaneously.

5.1 Design Insights

5.1.1 Cueing more and using adaptive heuristic target selection provide similar benefits. The A1 and A3 conditions provided similar reductions in search time; reducing search time per target from 1.81s and 2.11s to 1.51s or less. The effect size results suggest that providing more information provides a benefit when using sequential ordering, and that this benefit grows with more information, however using our adaptive angular-distance proximity heuristic provides an even stronger benefit. While a half second may not be consequential for all search tasks, time sensitive tasks such as search and rescue or triage benefit from any and all time advantages. While there does not appear to be a significant compounding effect between using adaptive target selection and cueing more targets, we still recommend cueing a subset with an adaptive approach to ensure maximum benefits, especially since cueing a subset with an ordered approach (O3) improved search time over cueing a single target with an ordered approach (O1), and cueing with an adaptive approach provided faster response times over ordered approaches.

5.1.2 Cueing everything is a valid alternative to adaptive techniques. In the event an adaptive heuristic cannot be utilized, cueing everything is a valid alternative. This approach has been utilized in

many prior studies [7, 8, 14, 26, 40, 47, 62], and, even with further exploration from our efforts, does not appear to significantly hinder search performance. Additionally, Paas scores revealed a reduction in reported effort between both the sequential conditions and both the *A*3 and *ALL* conditions. This is in line with several other studies that compared adaptive cueing implementations to non-adaptive implementations, which found the adaptive integration to not always provide performance benefits [48].

The only instance where using our adaptive target selection heuristic over cueing everything may be beneficial, is when movement reduction is of particular concern, as the A3 condition did reduce both head movement and rotation over the ALL condition. There may also be situations where screen clutter effects are present [37, 44, 53, 55], where cueing everything may not be possible without adverse performance effects. In our case the Gaze Line cue design has been reported in prior studies to not produce a high level of cognitive effort [22, 24, 25], which may have lead to minimized clutter effects when cueing all ten targets.

5.1.3 When order is important provide a subset of cues. In line with precueing literature [1, 29, 30], we found that cueing a subset of three targets reduced search time. There are several search tasks that require selection of targets in a particular order, while our task allowed users to select targets in any order, the reduction in search time from our O1 to our O3 condition highlights the benefit of giving users information on future targets. Most likely, this reduction was produced by giving the user spatial information that they could use to better plan out their selection approach, as opposed to O1, where the user may have attended only to the cue and missed other targets on the way to the cued location.

5.1.4 Accuracy may be more impacted by cue design. Several prior works have found cue design factors to impact accuracy [22–25, 54]. However, our data demonstrated no such differences between our conditions. This suggests that cue design may be more impactful for accuracy. As such, cue design should be considered alongside adaptive implementations to maximize performance outcomes.

5.2 Research Questions

5.2.1 Does adaptive target selection improve visual search outcomes? Our data does demonstrate a benefit to search outcomes when using an adaptive target selection heuristic over an ordered selection technique. Using an adaptive heuristic reduces the search time and reduces user movement over both of our ordered implementations. What was unexpected, however, was the lack of differences between our adaptive approaches and cueing all targets simultaneously, positioning both adaptive target selection and cueing everything, as similarly valid approaches to target selection for visual search tasks.

5.2.2 Does cueing a subset of targets improve visual search outcomes? Cueing three targets instead of one did improve upon search time for our ordered conditions, however this reduction was not significant when comparing the adaptive conditions. Similarly, cueing all targets provided a benefit over cueing a single ordered target. Due to this we argue that there are some benefits to cueing more than one target, however the benefits from cueing multiple targets and using adaptive target selection do not appear to compound.

5.3 Limitations and Future Work

In our work we focused on only the Gaze Line cue design. While this cue has been proven effective for visual search tasks [22, 24, 25, 33], there exist a plethora of other cue designs that work well for visual cueing. As such, using these other designs may lead to slightly different outcomes, especially if those cues are more prone to cognitive overload effects from visual clutter [37, 44, 53, 55].

We also only apply adaptive cueing to one element of visual cueing; target selection, however there are plenty of other aspects of visual cueing that can be further explored such as target identification [41, 42], or cue activation [18, 48]. Our angular-distance proximity heuristic is also only one method for implementing adaptive cueing into VR, however there exist other, more robust, techniques, such as ML based systems [41, 48], that may provided more beneficial outcomes. Furthermore, our *ALL* condition was only tested with 10 total targets, however searching for significantly more may lead to dramatically increased cognitive load [38, 46, 49] and clutter effects [37, 44, 53, 55] that may in turn reduce the effectiveness of cueing all targets. Similarly, the cue design and environment may further compound these effects.

Theories on working memory limits posit that we can attend to 4 plus or minus 1 items simultaneously, meaning we can attend to a range of 3 to 5 items [9, 11]; however our work only incorporates the low end of this limit into our design (3 items). Due to these limits we recommend future work explore the difference between cues for adaptive target selection, other areas where adaptive techniques can be beneficial, and how working memory limits may interact with the insights provided by this work.

6 Conclusion

This work presents a comparative study on five different cueing strategies that analyzes an adaptive target selection heuristic, two common non-adaptive target selection techniques (single-ordered targeting and cueing all targets), and the effect of cueing a subset of targets. In doing so we aim to address two key questions: *Does adaptive target selection improve visual search outcomes?* and *Does cueing a subset of targets improve visual search outcomes?*. Our findings support the use of both adaptive techniques for target selection and cueing multiple targets simultaneously while providing several key insights.

Our results suggest that cueing more targets and using an adaptive target selection angular-distance proximity heuristic can provide similar benefits to visual search performance. In the event that adaptive target selection cannot be integrated into cueing, cueing all targets simultaneously appears to be a valid alternative approach. However, if target selection order is important, such as for an assembly task, providing a subset of cues is particularly beneficial. While response time and movement did appear to be affected by adaptive cueing and cueing more, accuracy and mental effort may be more heavily impacted by cue design; further highlighting the importance of prior cue design work. These insights should guide future research and provide practitioners with avenues to improve upon visual cueing outcomes for visual search tasks.

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