

# The Low Prevalence Effect with Random Motion Stimuli in a Visual Search Task

**Chad Peltier (peltie11@gmail.com)**

Leidos, Inc., 1202 1750 Presidents Street  
Reston, VA 53706 USA

**Sylvia Guillory (sylvia.b.guillory.civ@health.mil)**

Naval Submarine Medical Research Laboratory, Box 900, Naval Submarine Base, New London  
Groton, CT 06349 USA

**Krystina Diaz (krystina.l.diaz.ctr@health.mil)**

Naval Submarine Medical Research Laboratory, Box 900, Naval Submarine Base, New London  
Groton, CT 06349 USA

**Jeffrey Bolkhovsky (jeffrey.b.bolkhovsky.civ@health.mil)**

Naval Submarine Medical Research Laboratory, Box 900, Naval Submarine Base, New London  
Groton, CT 06349 USA

## Abstract

The low prevalence effect (LPE), a decrease in target detection performance as target prevalence decreases, is a concern in real-world visual search tasks, such as baggage screening. Unfortunately, much of the research into the LPE and its potential countermeasures may not represent the challenges of other real-world search tasks, such as sonar and security monitoring, in which objects in the search environment exhibit movement. Additionally, target (e.g., submarine) and non-target (e.g., merchant ship) movement may interact with target prevalence to further decrease target detection performance, but these factors have not been systematically manipulated to determine their effects. In Experiment 1, high and low prevalence targets occurred in search conditions with static or randomly-moving objects. Although there was no significant interaction effect detected between target prevalence and motion, these conditions independently contributed to significantly lower hit rates. In Experiment 2, a higher prevalence target was included as an attempted LPE countermeasure. Observers searched for a relatively high and a low prevalence target in the moving search task. The addition of a higher prevalence target improved target detection overall in a search environment with moving objects, serving as a possible countermeasure to the LPE.

**Keywords:** Dynamic; visual search; low prevalence effect; movement; random motion

## Introduction

Visual search is a task in which an observer searches for a target, ranging from the innocuous—looking for a friend among a group of people—to the potentially threatening—a gun in luggage. These searches often involve distractor objects, or task-irrelevant non-target objects, such as other people in the crowd or clothing in luggage. In laboratory settings, visual search is frequently studied using static images with target items presented on 50% or more of the search trials (Oh & Kim, 2004; Palmer et al., 2011; Wolfe et al., 2010). For search tasks with these parameters, accuracy is generally high, and reaction times (RTs) for target-present

and/or target-absent responses scale with the number of search items on a trial display—the set size. In real-world visual search tasks, such as in security monitoring, sonar operating, and life-guarding, targets are infrequent, may appear in conjunction with other targets, and can move in different directions. Each of these factors (target prevalence, multiple targets, and dynamic movement) can have independent effects on target detection speed and accuracy.

Target prevalence is the rate at which targets appear within visual search tasks. It is common to observe the low prevalence effect (LPE)—a decrease in both target detection accuracy and target-absent reaction time as target prevalence decreases. This effect is attributable to two causes related to information accrual during search: a conservative shift in decision-making criterion and a decreased quitting threshold (Green & Swets, 1966; Wolfe & Van Wert, 2010). A conservative shift in the decision-making—the rule that an observer employs to decide a target present or absent response—results in identification errors. A decrease in an observer's quitting threshold—the threshold of stopping the search (perhaps prematurely)—results in selection errors, with the observer inspecting fewer items in a search task before quitting the search. Combined, these effects may reduce the odds of finding a low prevalence target by 80% or more relative to an identical target in a higher-prevalence scenario (Ishibashi et al., 2012).

The relative prevalence of two different targets within the same search task can also affect an observer's behavior and performance. When two different targets of two different prevalence rates appear within the same search task (but not in the same trial), the low prevalence target is missed more frequently than the high prevalence target (Godwin et al., 2015). Similar work has shown that when the overall target prevalence is 50%, but targets of different types and prevalence rates occur on the same trial, the relative prevalence effect remains such that the infrequent targets are

missed more often than the more frequent targets (Wolfe et al., 2005).

Observing target detection performance is further complicated when accounting for types of motion. Motion is the ongoing change in position of search stimuli as the stimuli move throughout the observer's area of view. The search objects may move around, going on and off the screen or view, or they might be fixed and motionless, as in images or luggage scans. Each of these types of motion prompts observers to develop varied search methods or strategies. In a static search, a form of memory known as inhibition of return (IOR) aids the observer in memorizing the fixed locations of search stimuli. This strategy reduces the likelihood of an observer revisiting a previously inspected item or area, facilitating search towards new items and areas. In dynamic searches, however, given that humans have a limited ability to track multiple moving objects (Pylyshyn, 2001; Pylyshyn & Storm, 1988), stimuli movement may result in a less efficient search, as observers re-inspect items due to a lack of IOR (Wang et al., 2010). It is therefore expected that moving stimuli make search more difficult and/or less efficient because randomly-moving stimuli do not permit the benefits of IOR. However, a study measuring search slopes—the change in accuracy/reaction time with the number of items in the search display—as a measure of search efficiency between dynamic and static conditions, found no difference between conditions (Hulleman, 2009). Although, these results could be attributed to the relative ease in discriminating between the study's targets (Humphreys et al., 1989). Other research has found that searching for moving targets was more challenging than searching for stationary targets (Kunar & Watson, 2011). In addition to these varied results, a scarce number of studies have attempted to elucidate potential interaction effects of motion on prevalence where the quitting threshold may be shifted higher in search scenarios involving dynamic moving objects, as observers may be tracking objects which slow the accumulation of information towards the response boundary (Shi et al., 2020).

Research manipulating target prevalence and motion finds that the LPE exists in both static and moving conditions (Wang & Sun, 2015). These results also showed no interaction between prevalence and movement. A limitation of this conclusion, however, is that in their movement condition, all the stimuli moved in the same direction such that while the stimuli moved, they maintained their relative spatial distribution. Other work has shown that search is more effective in moving stimuli when they maintain their relative positions to each other compared to when they move in random directions (Alvarez et al., 2007). This could indicate that an interaction between prevalence and ballistic motion in random directions is possible, such that random motion exacerbates the LPE.

The current study investigated the potential interaction between target prevalence and object motion. To do so, we explored the effects of target prevalence using a single target in a visual search task with visual stimuli that moved in

random directions, with two levels of target prevalence (high and low) and two levels of stimuli motion (no motion and random motion). Next, in Experiment 2, a second target was added to the search, increasing the overall target prevalence of the task to assess the impact that a higher prevalence target has on a lower prevalence target as a LPE countermeasure in a dynamic search environment.

## Experiment 1

In Experiment 1, we compared performance in search conditions containing static objects (no motion) and moving objects (motion) to identify differences in measures of search performance at high (50%) and low (10%) target prevalence.

### Method

**Participants** Participants were recruited online using Amazon Mechanical Turk (MTurk) and were tested online using E-prime<sup>®</sup> Go software (Psychology Software Tools Inc., Pittsburgh, PA, USA). Participants were compensated \$6.00 USD for their participation in the study. Data were collected from 68 participants, who were randomly assigned to complete a visual search task in one of four possible conditions. A final sample size of 60 participants was used in the data analysis, as eight were excluded for not meeting the performance criteria thresholds (exclusion criteria detailed in the result section). Of the remaining 60 participants, 34 participants completed the visual search task with static stimuli—18 at high target prevalence (HP) and 16 at low target prevalence (LP)—and 26 participants completed the task with dynamic (random motion) stimuli—14 at HP and 12 at LP. All procedures were approved by the Institutional Review Board (IRB).

**Experimental task** Participants were instructed to search a display of 25 items for a target letter “T” among non-target offset “Ls” (radius: 18 pixels on a 27-inch monitor with screen resolution 1440 × 900 pixels). The items could be rotated 0°, 90°, 180°, or 270°, and were black in color. The objects appeared scattered within a visible square (800 × 800 pixels) outlined in white, on a gray background. A white fixation cross was featured at the center of the display. On each trial, the search display was visible for 7000 ms and was followed by a white screen for 500 ms.

Participants indicated a target-present response by pressing the space bar on the computer's keyboard. Participants made no input response for a target-absent trial. Similar to tasks assessing vigilance and attention, such as the continuous performance task (CPT), this experiment was based on a go-no go design, with responses to infrequent targets while monitoring and withholding responses to regular non-targets (Roebuck et al., 2016). Each participant completed 250 trials presented in a random order. In the HP condition, 50% of the trials featured a target, and in the LP condition, 10% of the trials contained a target. In the no motion, static condition, observers searched an image of stationary objects (7000 ms) before a white screen was displayed briefly (500 ms), and

then a new search image was presented. Neither of the conditions (motion and no-motion) were self-paced; rather, the trial would advance following the finite stimulus duration of 7000 ms.

In the motion condition, the same number of stimuli were always present on the display, but they were in constant motion so that their relative positions changed constantly in a ballistic trajectory of a linear random path, with all objects moving at the same constant speed (2.5 pixels per frame). When the objects collided with each other or with the central fixation cross, they would ricochet and change to a different linear path (Souza & Oberauer, 2017). When an object reached the search display boundary, the object would reappear on the opposite side and continue moving in the same direction. In all task conditions, only a single target could be present during a trial.

**Procedure task** Participants performed the visual search task on their personal computers. Participants were randomly assigned to one of the four task conditions: static stimuli with an HP target (no motion-HP), static stimuli with an LP target (no motion-LP), moving stimuli with an HP target (motion-HP), and moving stimuli with an LP target (motion-LP). Before starting the task, participants completed ten practice trials that reflected the participant’s task condition (Figure 1).

**Statistical analysis** Four measures were used to evaluate performance on the visual search task: target detection hits (true positive/all positives), correct rejections (CR) (true negative/all negatives), target hit reaction time (RT), and the signal detection measure  $d'$ . The  $d'$  measure used to quantify the ability to discriminate targets and non-targets (Wickens, 2002). An analysis of variance (ANOVA) with factors Display Type (no motion, motion) and Target Prevalence (HP, LP) was conducted. Independent analyses were conducted for each dependent measure. Significant interaction effects were followed-up with a post-hoc test using pairwise comparisons with Bonferroni correction. Analyses were conducted using SPSS version 23 (IBM Corp) with an  $\alpha$  level  $p = .05$  with 2-tailed testing.

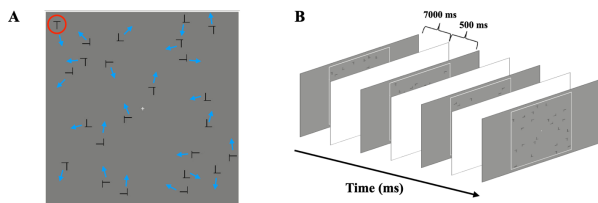


Figure 1. Experimental Set-up (A) The visual search display. In the example only, the target, “T”, is circled in red, where those trials are designated as target-present trials, and the blue arrows (not present during the actual task) indicate the movement of stimuli in the motion condition. (B) Task schematic. The search display was visible for 7000 ms and was followed by a blank screen (500 ms).

## Results

Participants were excluded from analysis for not completing the full task, i.e., completing less than 250 trials or failing to make any response ( $n = 8$ ). Average behavioral results for each individual task condition are summarized in Table 1 and statistical analysis results are summarized in Table 2 and Figure 2.

A significant main effect of target prevalence was found such that visual search with an HP target (mean  $\pm$  standard error;  $0.47 \pm 0.03$ ) resulted in a higher proportion of hits than an LP target ( $0.37 \pm 0.04$ ). A significant main effect of Display Type revealed that, on average, target hits in the no motion condition ( $0.53 \pm 0.03$ ) were greater than in the motion condition ( $0.31 \pm 0.04$ ). No significant interaction effect was detected.

Correct rejection performance was significantly higher in the no motion ( $0.93 \pm 0.03$ ) condition compared to the motion ( $0.84 \pm 0.03$ ) condition. The main effect of Target Prevalence was not statistically significant. The interaction between Display Type and Target Prevalence was also significant. Post-hoc independent sample t-tests showed that there was a significant difference in correct rejections among the HP motion and no motion condition ( $p < .001$ ), but no significant difference between motion and no motion with an LP target ( $p = .94$ ).

Reaction times were significantly slower in the no motion ( $1866.7 \pm 118.54$  ms) than the motion condition ( $1255.13 \pm 142.84$  ms). No other significant main effects or interactions were detected.

A main effect of display type ( $p < .001$ ) found that the no motion condition had an increased sensitivity in comparison to the motion condition. No other significant main effects or interactions were detected.

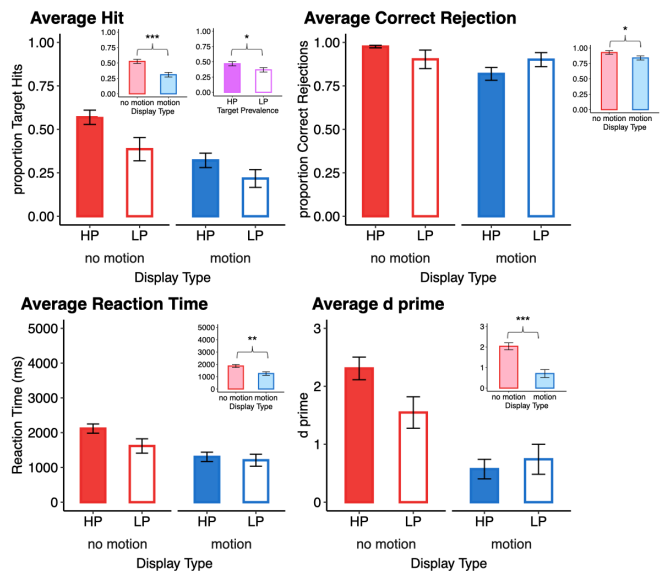


Figure 2. Experiment 1 results comparing motion and no motion at low and high target prevalence. (Top row). Left: Average target hits for no motion (red) and no motion (blue)

condition for the high prevalence (HP, 50%) target (filled bars ■) search and low prevalence (LP, 10%) target search (open bars □) with inlay images of the main effects of Display Type and Target Prevalence. Right: average correct rejection performance. (Bottom row). Left: Average reaction and Right: average  $d'$  score. Significant results  $p < .05$  are indicated in bold font and an asterisk (\*),  $p < .01$  as two asterisks (\*\*), and  $p < .001$  as three asterisks (\*\*\*). Error bars indicate  $\pm 1$  standard error (SE).

Table 1: Performance Measures Mean (Standard Error)

Display type Target prev.	Hits	CR	RT (ms)	$d'$
no motion	.57	.98	2116.83	2.31
HP (50%)	(.04)	(.04)	(162.63)	(.23)
no motion	.48	.88	1616.57	1.76
LP (10%)	(.05)	(.04)	(172.49)	(.25)
motion	.37	.79	1303.96	.65
HP (50%)	(.05)	(.04)	(184.40)	(.26)
motion	.25	.88	1206.30	.77
LP (10%)	(.05)	(.05)	(218.19)	(.28)

Table 2: Analysis of variance (ANOVA) Summaries

Hits	df	F	$p$
Target Prevalence	1,56	4.12	<b>.047*</b>
Display Type	1,56	18.95	<b>&lt;.001*</b>
Interaction	1,56	0.08	.78
<b>Correct Rejections</b>			
Target Prevalence	1,56	0.004	.95
Display Type	1,56	4.07	<b>.048*</b>
Interaction	1,56	4.66	<b>.04*</b>
<b>Reaction Time</b>			
Target Prevalence	1,54	2.59	.11
Display Type	1,54	10.86	<b>.002*</b>
Interaction	1,54	1.18	.28
<b><math>d'</math></b>			
Target Prevalence	1,56	0.71	.43
Display Type	1,56	26.89	<b>&lt;.001*</b>
Interaction	1,56	1.65	.21

Significant results ( $p < .05$ ) are indicated in bold font with an asterisk (\*)

## Discussion

Experiment 1 showed: 1) low target prevalence significantly reduced hit rate relative to high target prevalence, 2) random object motion significantly reduced hit rate relative to no motion, 3) random object motion significantly reduced the time it took to make a target-present response, and 4) prevalence and motion did not interact to

further reduce hit rates but did interact to increase the potential for false alarms. Demonstrating that random object motion reduced target detection performance, both in terms of accuracy and time to target, aligned with most prior research. A novel finding was that the negative effects of low prevalence and random motion were additive, but not highly interactive.

In terms of hit rates, it was found that each variable independently contributed to reducing hit rates. Confirming that LPE exists with randomly-moving objects adds to the existing literature on how consistent low prevalence can affect target detection performance.

Random object motion having a significant detrimental effect on target detection accuracy, independent of target prevalence, aligns our work with that of Kunar and Watson (2011). One might expect that random motion prevents the inhibition of return (IOR) benefits and makes searching longer and/or less efficient. When combined with time limits, a less efficient search would lead to fewer novel item inspections and lower target detection rates. However, our results show that random motion accelerates reaction times to target-present responses, an apparently incongruous result. It is possible that participants are making a speed accuracy trade-off, hastening their responses in the random motion conditions at the cost of lower detection rates. What may be happening, though, is that the motion conditions present such a challenge to participants (who exhibited only a 25% hit rate in the low prevalence-motion condition, for example) that they are guessing more frequently and faster than in the no motion conditions, and are basing these guesses on their perceived target prevalence (Peltier & Becker, 2017). Assuming this is true, one would predict that under low prevalence conditions, there would be fewer target-present guesses, leading to a higher miss rate and higher correct rejection rate, with the opposite pattern at high prevalence. This prediction aligns with our results, and is particularly prominent in the correct rejection data, for which a significant Display Type and Motion interaction was detected, and the high prevalence-motion condition had only a 79% correct rejection rate—a lower correct rejection rate than the other three conditions in our overall task. This interpretation is also supported by the drastic reduction in target-present reaction times between the motion and no motion conditions. Therefore, we think it is very likely that the motion conditions add a large degree of difficulty to high and low prevalence visual search tasks. If this is true, then the low hit rates we observed under random motion may be inflated by target-present guesses in which the subject did not actually identify a target, but guessed it was there. This raises further concerns for real-world scenarios where one does not only need to “respond” if a target is present, but also identify the targets’ location. A security guard merely reporting that they see someone with a gun, without identifying who or where that person is, would not be able to effectively stop that threat. Similarly, a target-present guess that is a false alarm may be disastrous (e.g., mis-targeting a neutral ship as an adversary ship).

Lastly, our results show that prevalence and motion do not interact in terms of target detection, but their effects are additive, i.e., lower target prevalence and random motion both independently lower target detection accuracy and contribute to the low prevalence random motion condition showing the lowest target detection accuracy. However, we encourage interpreting this result with caution. If it is true that observers were making frequent guesses in their responses due to the challenging nature of the random motion searches, then our results may not paint an accurate picture. If these results do accurately capture the lack of interaction between prevalence and motion, they demonstrate that the addition of one of these conditions does not affect the other.

Research systematically investigating the effects of target prevalence and random motion is lacking, despite its importance for real-world observers. While Wang and Sun (2015) manipulated prevalence and motion, their experimental manipulation lacked random motion. Multi-element asynchronous dynamic (MAD) search research (Scarince & Hout, 2016), examines randomly moving objects and indirect manipulations of target prevalence but prevalence and motion were not directly crossed. Another study manipulated event prevalence in a multiple object tracking experiment and found that low prevalence target detection performance was worse than high prevalence target detection performance in a randomly-moving environment, but did not have a matching static task to establish the independent effects of display type, or their potential interactions with target prevalence (Racioppo, 2020). Finally, another set of researchers manipulated target prevalence in a moving driving simulation, but also lacked a matching static condition to investigate a potential interaction (Beanland et al., 2014). To our knowledge, the current study's initial experimental results represent the first systematic investigation of prevalence and motion. Follow-up investigations with additional variation beyond what is used here (e.g., realistic objects, additional prevalence rates, multiple targets, self-terminating trials, prolonged task time) are necessary to corroborate these effects and determine the bounds of these results' generalizability.

Our results from Experiment 1 show that target detection accuracy is lowest in the low prevalence, random motion condition. This implies that methods are needed to improve hit rates (and decrease the potential for greater false alarm rates) in low prevalence, moving conditions for the real-world tasks to where such conditions exist. The methods that have been successful in reducing the LPE in static conditions may serve as starting points for improving performance in low prevalence moving conditions, but given the addition of motion, we must determine if the same methods are appropriate and effective.

## Experiment 2

The preceding experiment revealed that behavioral performance during visual search comprised of dynamic moving stimuli resulted in lower target identifications compared to visual search with static stimuli. In Experiment

2, participants were tasked with searching for two targets of differing prevalence. One target was presented at a higher prevalence rate (40%) than the other target (10%) to examine how the presence of a higher prevalence target impacted search performance for the lower prevalence target.

### Method

**Participants** Eighteen participants were recruited and participated in a visual search task with moving stimuli featuring two targets. As in Experiment 1, individuals were recruited from MTurk, tested through E-Prime, and compensated \$6.00 for their participation. The performance of these individuals was compared with the 12 participants that completed the low prevalence visual search task with dynamic moving stimuli in Experiment 1, permitting the investigation of whether a high prevalence but unique target would impact low prevalence target detection rates.

**Experimental task** Experiment 2 used the same visual search paradigm as the moving stimuli condition from Experiment 1 except that the participants were tasked with searching for two different targets. Participants searched for the letter's "T" and "L," among non-target, distractor objects of offset "Ls." The target "T" appeared in 25 trials (10%) and the target "L" in 100 (40%) trials, out of 250 total trials. The total target prevalence of the task was 50%. Only a single target could be present in a given trial. Target-present responses were made by pressing the space bar, and target-absent responses were denoted by no input response.

**Procedure** The procedure was the same as in Experiment 1 except that there was a single task condition, which consisted of two targets at two different prevalence rates (10% and 40%).

**Statistical analysis** LP performance (hits, correct rejections, RT, and  $d'$ ) was analyzed in an independent samples t-test comparing the two-target and single-target task (from Experiment 1) conditions. Only the results for the low prevalence ("T") target were presented, to observe the effects of multiple targets on a lower prevalence target.

### Results

The group performance is presented in **Table 3** and **Figure 3**. There was a significant increase in the LP target hits when search involved a second, higher prevalence target. However, there was also a significant decrease in correct rejection performance. There was no statistically significant difference detected between the two- and single-target searches for reaction time or  $d'$  measures (**Table 4**).

Table 3: Mean (SE) Performance

	two targets	single target
Hits	.44 (.05)	.25 (.05)

CR	.69 (.06)	.88 (.05)
RT (ms)	1397.85(136.25)	1206.30 (204.14)
$d'$	.52 (.16)	.77 (.30)

Table 4: t-test summaries

	df	t	$p$
Hits	28	-2.66	<b>.01*</b>
CR	28	2.41	<b>.02*</b>
RT (ms)	26	-0.81	.43
$d'$	16.94	0.71	.49

*Significant results ( $p < .05$ ) are indicated in bold font with an asterisk (\*)*

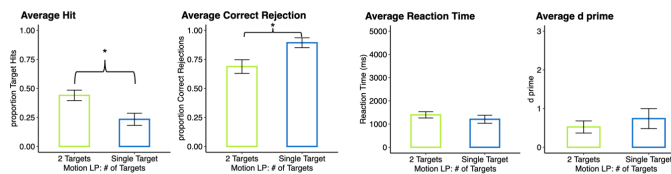


Figure 3. Experiment 2 results comparing LP conditions with either 2 or a single target. (From left to right) Average hit rate, average correct rejection, average reaction time, and average  $d'$  prime score of the LP target of a two-target search (green) and LP target of a single target search (blue). Significant results ( $p < .05$ ) are indicated in bold font and an asterisk (\*). Error bars indicate  $\pm 1$  standard error (SE).

### Discussion

Experiment 2 results showed that adding a uniquely-defined high prevalence target has a positive effect on the detection rate of low prevalence targets, increasing the low prevalence detection rate from 25% to 44%. There was also a significant reduction in correct rejections with the addition of a second target, decreasing correct rejections from 88% in the single target condition to 69% in the two-target condition. This pattern of results is consistent with general prevalence effects: as overall target prevalence increases, hits increase and correct rejections decrease (Mitroff & Biggs, 2014; Wolfe & Van Wert, 2010). This increase in target detection may not be related to the addition of a second target, as the literature finds a dual-target cost, which is a cost in response accuracy when searching for multiple targets simultaneously (Menner et al., 2007; Stroud et al., 2012).

From an applied perspective, the finding that the addition of a second, higher prevalence target can increase low prevalence target detections under moving conditions is a step toward improving real-world performance under these conditions. This method of adding a higher prevalence secondary target to boost detections of a lower prevalence target aligns with prior research with static objects (Wolfe et al., 2007). As Wolfe et al. found, the presence of a high prevalence target in addition to the low prevalence target

increased low target detections at the cost of fewer correct rejections. Though the decreased correct rejection rate is potentially discouraging from the standpoint of wanting a consequence-free solution to the LPE involving object motion, the similar pattern of results between the static Wolfe et al. stimuli and the moving Experiment 2 stimuli within the current study suggests that some visual search countermeasures to the LPE in static searches may be appropriate in random motion searches.

### General Discussion

The primary aim of this study was to examine whether a search environment featuring moving stimuli would exhibit low prevalence effects similar to those reported in static stimuli search tasks. The second aim was to determine the influence that a second, relatively higher prevalence target, had in the same type of dynamic search for a low prevalence target. Experiment 1 found that random motion and target prevalence do not interact to affect target detection performance. However, these conditions are additive in that lower target prevalence and motion both independently decrease target detection performance, leading to the lowest hit rate in the low prevalence, random motion condition. This presents a challenge for real-world situations, such as sonar or security monitoring, where targets are rare, and objects can move continuously and randomly. Experiment 2 used a method to improve search that has been successfully implemented in low prevalence static searches. Adding a uniquely defined higher prevalence target in addition to the low prevalence target, thereby increasing the overall target prevalence, increased the hit rate for the low prevalence target. Unfortunately, as was found when this method was used in static searches, adding a higher prevalence target led to lower correct rejection rates for the original low prevalence target. This decrease in correct rejection rates may appear innocuous, but within a military setting such as sonar tracking, misclassifying a non-threat vessel as an adversary can lead to severe consequences.

A limitation of the current research is that targets did not overlap in a trial—a characteristic that may be unrealistic in a real-world setting. The negative effect of multiple targets possibly cooccurring in a single search display is referred to as “subsequent search miss.” This effect describes missing other cooccurring targets after another target has been detected in the search display (Adamo et al., 2021; Biggs, 2017; Cain et al., 2011). The decrease in performance has reportedly been worse in search displays with randomly moving objects (Stothart et al., 2018). Future research should investigate the interaction between moving objects, low prevalence, and multiple targets that co-occur.

The current study provides an initial step in understanding search behavior in situations with moving objects and low prevalence targets, and demonstrates there are clear benefits to target detection rates when observers are instructed to search for a higher prevalence target.

## Acknowledgments

The views expressed in this report reflect the results of research conducted by the author(s) and do not necessarily reflect the official policy or position of the Department of the Navy, Department of Defense, nor the U.S. Government. This work was supported by funding work unit number **F2001** with funding source **Office of Naval Research (ONR)**. The study protocol was approved by the Naval Submarine Medical Research Laboratory Institutional Review Board in compliance with all applicable Federal regulations governing the protection of human subjects, protocol number **NSMRL.2020.0021**. Some of us are military service members or federal/contracted employees of the U.S. Government. This work was prepared as part of our official duties. Title 17, U.S.C., §105 provides that copyright protection under this title is not available for any work of the U.S. Government. Title 17, U.S.C., §101 defines a U.S. Government work as work prepared by a military Service member or employee of the U.S. Government as part of that person's official duties.

Portions of this work were presented as a poster at the 2022 annual meetings of the Vision Science Society, St. Pete Beach, FL; the Military Health System Research Symposium, Kissimmee FL; and the Department of Defense Human Factor Engineering Technical Advisory Group meeting, Oklahoma, OK.

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