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Modeling Lag-2 Revisits to Understand Trade-Offs in Mixed Control of Fixation Termination During Visual Search

Hayward J. Godwin, Erik D. Reichle, & Tamaryn Menneer

*Psychology*

*University of Southampton, UK*

Author Note

Correspondence regarding this article should be addressed to Hayward J. Godwin, University of Southampton, Psychology, Highfield, Southampton, Hampshire, SO17 1BJ. Tel: +44(0)2380 595078; Email: [hayward.godwin@soton.ac.uk](mailto:hayward.godwin@soton.ac.uk). The research described in this article was supported by a National Institutes of Health grant (HD075800) awarded to the second author.

# Abstract

An important question about eye-movement behavior is when the decision is made to terminate a fixation and program the following saccade. Different approaches have found converging evidence in favor of a mixed-control account, in which there is some overlap between processing information at fixation and planning the following saccade. We examined one interesting instance of mixed control in visual search: *lag-2 revisits*, during which observers fixate a stimulus, move to a different stimulus, and then revisit the first stimulus on the next fixation. Results show that the probability of lag-2 revisits occurring increased with the number of target-similar stimuli, and revisits were preceded by a brief fixation on the intervening distractor-stimulus. We developed the *Efficient Visual Sampling* (*EVS*) computational model to simulate our findings (fixation durations and fixation locations), and to provide insight into mixed control of fixations and the perceptual, cognitive, and motor processes that produce lag-2 revisits.

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We make eye movements in order to bring the limited-resolution fovea to focus on areas or objects within our environment and process them in detail. Eye movements consist of *fixations* (periods of time when the eyes are relatively still) and *saccades* (periods of time when the eyes are moving). It is only during fixations that visual input is available. We make, on average, 3-5 fixations, interspersed with saccades, every second (for a review, see Rayner, 2009). Given the importance of fixations in focusing on behaviorally relevant objects or stimuli, it is important to understand the processes that determine both when saccadic programming will be initiated and where the eyes will be moved. In the present study, we explore the oculomotor and task-contextual parameters involved in the termination of fixations and saccadic planning in visual search. Although studied extensively in the context of eye movement behavior and reading, the issue of fixation termination has received surprisingly little attention in visual search studies (Reingold & Glaholt, 2014). In particular, we focus on errors made in this task in order to better understand the processes involved in controlling eye movements. Specifically, these errors consist of early termination of fixations that then necessitate revisits to a previously fixated stimulus. By understanding the factors that cause these errors, and by modeling the parameters required to simulate them, we therefore use these errors to gain a general understanding of the mechanisms that mediate eye-movement control in visual search tasks.

**Accounts of Fixation Termination**

There has been extensive debate regarding the mechanisms that govern when the eyes are moved to new locations during a variety of tasks. The focus of this debate has been related to the question: When, during a fixation, is a saccade to move the eyes to a new viewing location programmed? This question is important because saccades are ‘ballistic’: After the program to initiate a saccade has been sufficiently completed, it cannot be halted (W. Becker & Jürgens, 1979). Attempts to understand how this happens are complicated by the fact that not all saccades require the same amount of time to program; for example, the time taken to program and initiate a saccade varies with the length of the saccade (Bartz, 1962; Hackman, 1940; Kalesnykas & Hallett, 1994).

Generally speaking, theoretical accounts of how people decide when to move their eyes can be grouped into three broad categories. First, there are *direct-control* accounts (Rayner, 1978), wherein decisions about when to terminate fixations are under the direct control of online cognitive processing. Under a strict direct-control account, saccadic programs are only initiated after the analysis of the visual information at the point of fixation has been completed. Second, there are *indirect-control* accounts, wherein fixations are terminated after some “default” amount of time has elapsed (Engel, 1977; Vaughan, 1982). These accounts therefore posit that saccadic programs are initiated after some amount of time has passed during a fixation, so that the decision about when to terminate a fixation is made in an indirect fashion. The default time is set according to, for example, experience with task difficulty. Third, there are *mixed-control* accounts that posit a loose coupling between on-going cognitive processing and decisions about when to move the eyes (Rayner & Pollatsek, 1981). Under mixed-control accounts, saccadic programming is triggered after some portion of the processing of the visual input is complete, so that saccadic programming and processing of the visual input overlap in time. This latter assumption presumably reduces the ‘dead time’ that would otherwise occur under strict direct-control accounts (i.e., reducing the waiting for visual input to be processed and *then* programming a saccade; Hooge & Erkelens, 1996). Thus, according to the mixed-control accounts, only a portion of the time spent during a fixation is determined by online cognitive processing.

In the context of visual-search tasks, there have been several approaches taken in the study of how fixations are terminated, providing varied amounts of empirical support for each of the three aforementioned accounts of fixation termination. For example, Hooge and Erklens (1996) found that participants did not modulate their fixation durations based upon the difficulty of searching on a trial-by-trial basis, suggesting that durations were set by some type of fixed rate parameter. However, in contrast to this, it has been found that fixation durations *do* increase when participants fixate target-similar objects, compared with target-dissimilar objects (S. I. Becker, 2011; Luria & Strauss, 1975; Reingold & Glaholt, 2014), suggesting that fixation durations are, in fact, under the active control of the visual information at fixation (in line with direct- and mixed-control accounts). And in a later study, Hooge and Erklens (1998) also found that participants did not reduce their fixation durations when given less time to search, and it was argued that this occurred because fixation durations were set by a fixed parameter and were, as a consequence, not modulated when participants were given a briefer period of time to search. However, participants may have reduced their fixation durations if they had been instructed to deliberately search more rapidly rather than simply being allowed to search for a limited time (e.g., such speed-ups occur when participants are instructed to "skim" text; see Fitzsimmons, Weal, & Drieghe, 2014).

Fixation durations have also been examined in scene perception and search tasks using the *scene-onset-delay paradigm* (Rayner & Pollatsek, 1981). Although initially developed to study oculomotor control during reading, where it has provided evidence for mixed control of fixations, the paradigm has also been adapted to visual-search and scene-perception tasks (Henderson & Pierce, 2008; Henderson & Smith, 2009; Pannasch, Schulz, & Velichkovsky, 2011). During each trial, a scene or display is first presented, and participants then engage with that scene. Then, after a pre-defined number of fixations have been made, the display is removed from view for a brief interval of time. After a second interval of time has elapsed with a blank screen, the original display is then re-instated. The results of such experiments have revealed two distinct populations of fixation durations within the display-absent intervals. The first were very short in duration, most likely because the saccades terminating these fixations had already been initiated, suggesting that these saccadic programs had *not* been under direct cognitive control. In contrast, the second population of fixations were longer in duration, suggesting that the saccades terminating these fixations had been delayed by visual processing and thus were under some degree of direct cognitive control. However, one limitation of this interpretation is that analyses of the fixation-duration distributions completely ignore the question of *what* is being processed during the intervals when the scene information is removed from view. With this in mind, Godwin, Benson, and Drieghe (2013) used a variant of the scene-onset-delay paradigm combined with a simple visual-search task and found evidence that the elongated fixations observed using this paradigm reflect participants’ active attempts to continue processing the now-absent information, rather than their passive ‘waiting’ for the scene to return. This evidence therefore further suggests that the longer fixations observed in the scene-onset-delay paradigm reflect online cognitive processing. Overall, the findings from the scene-onset-delay paradigm provides strong evidence in favor of mixed-control accounts.

**A New Approach: Using Lag-2 Revisits to Understand Trade-Offs in Fixation Termination**

Although the studies summarized above have predominantly provided evidence for mixed control of when fixations are terminated, this evidence is by no means conclusive. To examine the issue in more detail, in the present article we adopt an alternative approach—one of examining the errors that occur in visual search when participants fixate but then erroneously move their eyes away from the target object. This approach is particularly useful since eye-movement behavior can be aligned with correct versus incorrect responses because the target is the only object in the display that we can be sure that participants have veridically identified (i.e., by indicating that it is the target). It has long been noted that participants often directly fixate the target but then continue searching, ultimately failing to detect the target, both in simple tasks involving search for abstract shapes as well as more complex tasks such as radiographic image screening (Engel, 1977; Gould & Cairn, 1973; Hooge & Erkelens, 1996; Nodine & Kundel, 1987). This behavior has been referred to as an error of *perceptual identification* (Cain, Adamo, & Mitroff, 2013; Schwark, MacDonald, Sandry, & Dolgov, 2013) and typically occurs when the first fixation upon the target is very brief. The brief nature of fixations upon targets that are missed has been taken to suggest that the processes involved in object identification either incorrectly identified the target as a distractor or failed to identify the target completely (Nodine & Kundel, 1987).

The finding that fixations on missed targets are of similar duration to fixations on distractors (Nodine & Kundel, 1987) is seemingly paradoxical and raises the question: Why might missed target objects be fixated for a similar duration as correctly-rejected distractors? One way to answer this question is to turn to a number of models of visual search that have represented object identification as part of a random-walk process (Ratcliff, 2006; Wolfe, 2007). Under a random-walk process, objects are identified within the system as information about their identity accumulates until a threshold is reached; there is one threshold for deciding that an object is a target, and a separate threshold for deciding that an object is a distractor. Therefore, under a random-walk account, targets that are missed and categorized as distractors exhibit the same fixation durations as distractor objects because the search system has reached the ‘distractor’ threshold erroneously, causing targets to be missed.

The existence of perceptual identification errors has been used as evidence against strict direct-control accounts, with such occurrences being regarded as a natural by-product of the fact that fixations can be terminated by an indirect mechanism (e.g., an autonomous timer) that drives fixations to new locations irrespective of whether or not the processing of an object at a given fixation location has been completed. However, more recent studies (Godwin, Menneer, Riggs, Cave, & Donnelly, 2015; Hout, Walenchok, Goldinger, & Wolfe, in press) have found that perceptual identification errors are more likely to occur when the target is presented on a small proportion of trials (5% of trials) compared with a higher proportion of trials (45%), perhaps because of priming from target repetition and/or expectations about the likelihood of a target being presented (Godwin, Menneer, Riggs, Taunton, et al., 2015). This finding suggests that failures to detect the target upon fixating it may reflect object identification failures rather than being a consequence of some indirect mechanism, as predicted by indirect-control accounts. In other words, these failures to identify targets could be the result of online cognitive processing, as opposed to reflecting reliance upon a default timer to terminate fixations.

In a similar vein, there have also been reports that participants often fixate a stimulus (e.g., a search target), move their eyes to a second stimulus (e.g., a distractor), and then rapidly move their eyes back to the first stimulus (Engel, 1977; Gould, 1967; Hooge & Erkelens, 1996). This pattern of eye movements (illustrated in Figure 1) has been referred to as *lag-2 revisits* (Peterson, Kramer, Wang, Irwin, & McCarley, 2001) and they are quite common, occurring on as many as 20% of trials (McCarley, Wang, Kramer, Irwin, & Peterson, 2003; Peterson, Beck, & Vomela, 2007). It was initially argued that such lag-2 revisits were, as with perceptual identification errors, a by-product of a direct-control mechanism, wherein the default timer to terminate a fixation is triggered before object identification is complete (or because an object is identified after the following saccade is initiated). However, as with perceptual identification errors, there is evidence to suggest that lag-2 revisits are the result of online cognitive processing, rather than being a consequence of an indirect control mechanism. Indeed, it has been argued that lag-2 revisits reflect the willful re-examination of stimuli, and arise because of cognitive processing, because the majority of them are made in response to the target or stimuli that are similar to the target (Heße, Wienrich, Melzer, & Müller-Plath, 2009). This observation has lead to the “miss + realization” account of lag-2 revisits—that they occur because a target is not identified as such when it is initially fixated, thus necessitating that they be refixated (Peterson et al., 2001). By this account, targets are not identified during their initial fixation because those fixations are brief, thereby affording too little time for accurate identification.[[1]](#footnote-1).

*[Insert Figure 1 around here]*

Lag-2 revisits can readily be explained by a ‘miss + realization’ account if one also assumes some degree of error in the systems that support visual search. For example, the object-identification system is prone to error, as evidenced by the simple fact that targets that are directly fixated are sometimes missed (as discussed above). Similarly, the oculomotor system is also prone to error; for example, saccades often miss their intended targets, resulting in rapid corrective saccades to the intended target locations (e.g., see Trukenbrod & Engbert, 2007). Furthermore, the oculomotor system is biased to make numerous rapid saccades, correcting errors when necessary, rather than making slower, more accurate saccades (e.g., see Wu, Kwon, & Kowler, 2010). With that in mind, under a mixed-control account, which assumes that there is at least some overlap between object identification and saccade planning (both of which take varying amounts of time to complete), lag-2 revisits may actually be beneficial in terms of allowing search to proceed at a faster rate, albeit with a reduction in how accurately targets can be identified during their initial fixation.

The beneficial nature of lag-2 revisits becomes apparent if we consider just how rarely targets occur, even in standard visual-search tasks. For example, although targets are typically presented on 50% of trials, in a search task with a set-size of 16 objects, the probability that any of the objects will be a target is only *p* = 1/32 = 0.03. Put another way, in an exhaustive search, only 3% of the objects fixated will end up being a target. It is therefore not too surprising that lag-2 revisits are so common: The systems involved in search can increase the rate of search by correcting (as necessary) those fixations that miss the rarely-encountered targets. By this account, lag-2 revisits can be conceptualized as a speed-accuracy trade-off, with any costs associated with the occasional failure to identify targets when they are first fixated being paid to more rapidly explore the environment.

**The Present Study**

In the present study, we sought to use lag-2 revisits to better understand how trade-offs in the mixed control of fixation termination guide the eyes during visual search. To that end, our goals were to manipulate the probability of lag-2 revisits occurring, and to then provide a computational account of this behavior. The computational account is vital in determining the parameters that are necessary to produce lag-2 revisits and fixation-duration control more generally. Importantly, we wanted to test whether a global parameter was required to simulate the fixation behavior, and if so, what form this parameter takes. That is, if lag-2 revisits are a form of trade-off between the overall rate of search and the accuracy in target detection on the first fixation, then participants should be less likely to make lag-2 revisits when the objects being fixated are more likely to be a target (Godwin et al., 2015; Hout et al., in press). If so, then this would provide evidence of a new, previously unknown global parameter (the value of which is affected by the probability of any fixated object being the target) influencing the push-pull relationship between online cognitive processing and the drive to program and initiate new saccades in order to proceed with search.

Our basic method entailed having participants search for a single colored *T*-shape amongst nineteen colored *L*-shapes. One target was presented on every trial, such that participants knew in advance that one of the stimuli would be the target (i.e., this enabled participants to form a more accurate estimation of the probability that any object fixated would be the target). The key manipulation was the number of *target-similar* distractors in each display. It is well documented that both visual and semantic similarity are important determinants of eye-movement behavior during search (S. I. Becker, 2011; Godwin, Hout, & Menneer, 2014; Luria & Strauss, 1975; Stroud, Menneer, Cave, & Donnelly, 2012). In our experiment, target-distractor similarity was defined in terms of color: Target-similar distractors were the same color as the target, thus often warranting direct fixations, whereas target-dissimilar distractors differed from the target in color, and therefore did not warrant direct fixations. We used a set-size of twenty throughout all trials. There were also two conditions presented in separate blocks of trials. In the *few-distractors* condition, only four distractors were the same color as the target, while in the *many-distractors* condition, fifteen distractors were the same color as the target.

We predicted an increased number of lag-2 revisits in the many-distractors condition because of a decreased probability of any given stimulus being a target (*p* = 1/16 = 0.0625) relative to the few-distractors condition (*p* = 1/5 = 0.2). However, with the wide array of processes that influence oculomotor control during visual search, it is entirely possible that any differences between the few-distractors and many-distractors might instead—or additionally—reflect target-monitoring accuracy and constraints of the oculomotor system. There is, for example, an alternative explanation for increased lag-2 revisits in the many-distractors condition: Because fixation durations tend to decrease prior to shorter saccades (Bartz, 1962; Hackman, 1940; Kalesnykas & Hallett, 1994), fixations in the many-distractor condition may provide less time for target identification, thereby increasing the number of lag-2 revisits.

To address this possibility, we adapted our previous model of eye-movements in visual search (Godwin, Reichle, & Menneer, 2014) to include the oculomotor control factors that may influence the propensity to make lag-2 revisits, while accounting for the observed data. The key question that we answered using the model was whether or not, in order to provide an adequate simulation of our participants’ data, the model required a global parameter to modulate the probability of lag-2 revisits. If so, this would demonstrate that the mixed control of eye movements during visual search is clearly influenced by global parameters such as target likelihood. Although most of our discussion above has focused on lag-2 revisits to target objects only, we also expected there to be an increased likelihood of lag-2 revisits to distractor objects as the number of target-similar stimuli increased, although we did expect lag-2 revisits to be comparatively rare for distractors. This expectation served as a useful test of our assumption that a global parameter influenced search behavior, since that same global parameter should influence the likelihood of lag-2 revisits for both targets and distractor objects.

Additionally, the experimental data and the model were also used to evaluate the “miss + realization” account of lag-2 revisits (Peterson et al., 2001) by examining fixation durations on each stimulus type. If lag-2 revisits are due to participants failing to fully identify a target when it is initially fixated, then those fixations should be the same duration as fixations on distractors because both types of stimuli should have presumably been processed to the same degree prior to fixation termination, and there is no reason for the fixation duration to differ when the target has not been identified. Furthermore, fixations on the distractors immediately prior to lag-2 revisits should be relatively short in duration because of the realization that the search target requires re-inspection (indeed, these would be a form of corrective saccades, see Trukenbrod & Engbert, 2007). We therefore compared the mean fixation durations on distractors to both the initial target fixations and the fixations on distractors immediately prior to lag-2 revisits.

**Method**

**Participants**

Sixteen undergraduate participants with normal or corrected-to-normal color vision took part in the study either for course credit or payment. We chose a sample size of sixteen based on our previous study (Godwin, Reichle, & Menneer, 2014).

**Apparatus**

We recorded eye-movement behavior using an Eyelink 1000, operating at 1,000 Hz. Participants viewed the displays binocularly but only the right eye was tracked. The tracker was calibrated using a nine-point calibration, and the calibration was accepted only if the average calibration error was lower than 0.5° of visual angle, and if no calibration point had an error in excess of 1° of visual angle. Before each trial, a drift correction procedure was performed, and calibration was re-checked after a break every 50 trials.

The stimuli were presented to participants using a 21” ViewSonic P227f CRT monitor operating at a refresh rate of 100 Hz with a resolution of 1024 × 768 pixels. Participants were seated at a distance of 71 cm from the display in a dimly lit room. The head position of participants was stabilized using a chinrest, and participants provided their responses regarding the orientation of the target (left or right) using a response box. Following an incorrect response, a tone sounded from the computer.

**Stimuli**

The stimuli were T- and offset L-shapes. The T-shape was designated as the target and the L-shapes were designated as distractors. We set the shapes to be small, approximately 0.3° of visual angle in size, in line with previous studies (Hooge & Erkelens, 1996), and to promote the need to fixate the stimuli in order to identify them (see also Godwin et al., 2013). The L-shapes were randomly rotated by 0˚, 90˚, 180˚, or 270˚, and then placed at a random location upon a virtual 5 × 5 grid. The T-shape could be oriented to the left or to the right. Twenty stimuli were displayed on each trial, and each stimulus was jittered randomly ±1.2° along the x- and y-planes within the boundaries of their virtual grid cells.

The target and distractor colors were chosen from previous studies that we have conducted (Menneer, Barrett, Phillips, Donnelly, & Cave, 2007) from previous studies that participants are very unlikely to fixate the dissimilar-colored distractors (Stroud et al., 2012). To be certain that the results were not specific to our distractor/target color combination, half of the participants were asked to search for a blue target amongst orange distractors while the remaining half of the participants were asked to search for an orange target amongst blue distractors. However, the research questions are not concerned with differences between the target colors, and as such data were collapsed across target color for analyses.

**Design and Procedure**

The study consisted of two blocks (few-distractors and many-distractors) of 100 trials each, with both being preceded by 20 practice trials. A target was presented on 100% of trials. On 50% of trials, the target was oriented to the left; on the remaining 50% of trials, the target was oriented to the right. Participants were asked to respond as rapidly and as accurately as they could with the correct orientation of the target. There were always 20 items (19 distractors and one target) on each trial. In the few-distractors trials, four distractors were the same color as the target, while in the many-distractors trials, fifteen distractors were the same color as the target. The order of the blocks was counterbalanced across participants. Each trial began with the presentation of a cue depicting the target at the center of the display. After a stable fixation upon the cue had been registered for 500 ms, the trial display was presented. The display was visible until the participant responded.

**Results**

For all results reported below, any proportion-based data were arcsine square-root transformed prior to being analyzed, to normalise the binomial distribution of the data. However, we report the raw means for the purposes of descriptive statistics. All post-hoc *t*-tests had their *p*-values were Bonferroni-corrected prior to being reported. We report generalized *η*2 (ges) as a measure of effect size (Bakeman, 2005).

**Data Preparation**

We removed any fixations that had a duration of less than 80 ms or greater than 1,200 ms, resulting in the removal of approximately 4% of fixations from the raw dataset. We also removed data from incorrect-response trials, leaving a raw dataset of approximately 40,000 fixations.

**Probability of Making a Lag-2 Revisit**

We examined the tendency of participants to make lag-2 revisits by dividing the number of lag-2 revisits made on each object type by the number of times each object type was presented (i.e., this was calculated separately for targets and distractors). The resultant measure gave us an index of the probability that participants would make a lag-2 revisit. We examined the probability that participants made a lag-2 revisit using a 2 (Condition: Few- vs. Many-Distractors) × 2 (Stimulus Type: Target vs. Distractor) within-participants ANOVA. Note that this ANOVA included both target and distractor objects, enabling us to be more certain that any shift in behavior as a result of a global parameter change between conditions had an effect upon both target and distractor objects. This analysis revealed effects of Condition [*F*(1, 15) = 111.26, *p* < 0.0001, ges = 0.47], of Stimulus Type [*F*(1, 15) = 231.76, *p* < 0.0001, ges = 0.84], and an interaction between the two factors [*F*(1, 15)=26.25, *p* < 0.0001, ges = 0.19], see Figure 2.

A series of post-hoc paired *t*-tests revealed that target stimuli were more likely to receive a lag-2 revisit than distractor stimuli in both the conditions [*t*s > 9.6, *p*s< 0.0001], and that participants were more likely to engage in lag-2 revisits to both target and distractor stimuli in the many- than few-distractors condition [*t*s > 7.9, *p*s < 0.0001]. These results are consistent with our predictions: Participants were more likely to make lag-2 revisits when there were more stimuli in the displays that matched the target color and thus required examination.

*[Insert Figure 2 around here]*

**Fixation-Duration Measures**

To test the predictions from the miss + realization account of lag-2 revisits (Peterson et al., 2001), we compared both the first target fixation durations (“1st on Target” in Figure 1) and the intervening distractor fixation durations preceding lag-2 revisits (“Intervening” in Figure 1) to the mean of the final 1-3 fixation durations (depending on the number of fixations that occurred during a trial) on distractor objects (“Distractor” in Figure 1)[[2]](#footnote-2). These comparisons were made using a 2 (Condition: Few- vs. Many-Distractors) × 2 (Fixation Type: Distractor vs. Intervening-Distractor vs. 1st-on-Target) within-subjects ANOVA. This analysis revealed effects of Condition [*F*(1, 15) = 14.07 , *p* = 0.002, ges = 0.08] and Fixation Type [*F*(2, 30) = 15.77, *p* < .0001, ges = 0.22] only. Subsequent *t*-tests revealed that, as predicted, first-on-target fixations were of equal duration to single fixations on distractors (*t* < 1), suggesting that participants had indeed failed to identify the targets during their initial fixations prior to lag-2 revisits. Furthermore, the intervening fixation durations on distractors prior to a lag-2 revisit were shorter than the other two types of fixation (*t*s > 4, *p*s < 0.0001), suggesting that, as predicted, these fixations were brief due to the ‘realization’ that a possible search target had been missed and thus required re-inspection.

*[Insert Figure 3 around here]*

**Simulating Lag-2 Revisits**

**Model overview.**

The model that was used to simulate lag-2 revisits is an extension of one reported by Godwin, Reichle, and Menneer (2014) that consists of five simple assumptions (described below) about how saccade targets are selected and saccades are programmed in the context of performing visual search tasks. Three simulations using this model are reported below. The results of these simulations are labelled “0-*ε*”, “1-*ε*”, and “2-*ε*” in Figures 2-5 and they are respectively intended to show how well the model fits the results of our experiment using 0, 1, or 2 different values of a parameter, *ε*, that represents the probability of failing to detect a target when it is initially fixated in the few- versus many-distractor conditions. (Table 1 displays the values of these and all of the other the parameters that allow the model to most accurately fit the empirical data in each simulation.)

**Model fitting approach.**

For each simulation, the best-fitting parameter values were obtained across four successive grid searches. The first grid search used 1,000 statistical subjects per condition and permutation of parameters, with the values of the six parameters being varied across the following domains using the indicated increments: *θ* ∈ [0.1, 0.5], increment = 0.1; *κ* ∈ [4, 7], increment = 1; *τ*1 ∈ [140, 170], increment = 10; *τ*2 ∈ [1, 5], increment = 1; *ε* ∈ [0.78, 0.99], increment = 0.01; *NFixations* ∈ [20, 50], increment = 10. The second grid search was then centered on the best-fitting values of the first grid search, using 2,500 statistical subjects per condition and parameter permutation and the following increments: *θ* = 0.05; *κ* = 1; *τ*1 = 2.5; *τ*2 = 0.5; *ε* = 0.01; *NFixations* = 5. This procedure was then repeated using the indicated number of statistical subjects and parameter increments for the third (number subjects = 5,000; *θ* = 0.05; *κ* = 1; *τ*1 = 1; *τ*2 = 0.05; *ε* = 0.01; *NFixations* = 5) and fourth (number subjects = 10,000; *θ* = 0.01; *κ* = 1; *τ*1 = 1; *τ*2 = 0.25; *ε* = 0.01; *NFixations* = 1) grid searches. Goodness of fit was calculated by first normalizing the mean probabilities of making lag-2 revisits to targets and distractors in each condition, as well as the mean durations of initial target fixations and the first 1-3 distractor fixations. The values were normalized by dividing the absolute differences between each of the observed and simulated means by their corresponding observed standard deviations, thereby allowing different dependent measures (i.e., fixation probabilities and durations) to be compared using a common scale (i.e., *z*-scores). Goodness of fit was then calculated as the mean absolute difference between the observed and simulated normalized values of these measures. In the simulation involving only a single value of *ε* (i.e., 1-*ε*), a single best-fitting value was obtained for the few- and many-distractor conditions. In the simulation involving no failure to detect targets (i.e., 0-*ε*), the value of *ε* was fixed equal to 0 (i.e., targets were always identified when they were initially fixated). In this final simulation, the goodness of fit measure did not include lag-2 probabilities for targets or initial target fixation durations because the model makes no predictions for these measures (because targets are always identified when they are first fixated).

**Model assumptions.**

The core assumptions of the model are that the programming of saccades can be adjusted to reflect the overall demands of the task being performed (consistent with the global-timing account), but that this saccadic programming is conducted in the service of efficiently identifying individual stimuli (similar to the miss + realization account; Peterson et al., 2001), and is also subject to inherent limitations of the visual and oculomotor systems. As such, the model’s assumptions provide a description of how humans performing a visual search task might coordinate various perceptual, cognitive, and motor processes to efficiently sample visual information in the service of searching for a target as rapidly and accurately as possible given the constraints of limited visual acuity, the costs associated with selecting saccade targets and moving the eyes, and so on. For those reasons, we will now refer to this model as the *Efficient Visual Sampling* (*EVS*) model.

The first assumption of the EVS model is that potential saccade targets are selected probabilistically, on the basis of their proximity to the current fixation location. However, for any given saccade, only a subset *N* of the stimuli in the display will be eligible as potential saccade targets. These *N* stimuli are those that are the same color as the target, and that are not at locations that have been previously fixated (and thus being represented in working memory to prevent revisits). The probability of selecting stimulus *y* as the next saccade target from the current fixation location *x* is therefore specified by Equation 1:

(1) 

In Equation 1, *Δx,y* is the Euclidean distance between locations *x* and *y*, *Δ*max[*x,i*] is the Euclidean distance between location *x* and the most distal eligible stimulus, *i*, and the free parameter *θ* ensures that the most distal stimulus has some non-zero probability of being selected.

The second assumption is that—as already mentioned—previously fixated locations are actively maintained in some type of visual-episodic working memory to prevent the same locations from being repeatedly fixated. Although the issue of memory for already-fixated objects or locations in search has been controversial (e.g., Horowitz & Wolfe, 1998), there has been an emerging consensus that search utilizes a limited-capacity memory record for already fixated locations (Peterson et al., 2007, 2001). For simplicity, working memory is a buffer of fixed capacity *κ*, with one of the previously fixation locations being randomly selected for replacement by the current fixation location whenever the number of previously fixated locations exceeds *κ*.

The third assumption is that saccadic programming latencies increase linearly with the number of eligible saccade targets in the display, *N*, as described by Equation 2:

(2) 

In Equation 2, *τ*1 and *τ*2 are free parameters that respectively represent the minimum saccadic programming time and how much this time increases with the number of eligible saccade targets, *N*.

The fourth assumption is that participants fail to correctly identify a target while it is being fixated with some globally-applied probability, *ε*, that reflects some criterion of accuracy. The best-fitting values of this parameter thus provide an estimate of a subject’s expectation about each given stimulus in a display being a target, and as such varies as a function of the number of distractors. To determine the necessity of this assumption, we completed three simulations of our experimental data: Whereas the first (i.e., 0-*ε*) simulation simply did not include this criterion-of-accuracy assumption (i.e., targets were always identified when they were initially fixated), the second (i.e., 1-*ε*) simulation used one best-fitting value of *ε* to simulate both the many- and the few-distractor conditions, while the third (i.e., 2-*ε*) simulation used a separate value for each condition (i.e., the parameter was allowed to change between many- and few-distractor conditions).

The fifth assumption is that the failure to identify a target as such while it is being fixated automatically results in the initiation of a saccadic program to move the eyes back to the target (i.e., a revisit). Because the target is pre-specified, the number of eligible saccade targets is reduced to 1 (i.e., *N* = 1), which in turn causes a reduction in the time spent fixating intervening distractors during target revisits (i.e., see Equation 2). Also note that this assumption overrides the normal prohibition against moving the eyes back to a previously fixation location.

Finally, the last assumption is that subjects continue their target search for some pre-specified number of fixations, *NFixations*, that reflects the degree to which subjects are willing to persist in their searches despite (often numerous) failures to locate a target. Although specific best-fitting values of *NFixations* were used in the simulations reported below, the simulation results are robust using any value in excess of approximately 20 (i.e., values in excess of 20 give very similar fits of the observed data and are thus very difficult to differentiate).

Figures 2-5 show the observed and simulated mean values of the various dependent measures as a function of condition (i.e., the number of target-color distractors), with the latter being reported for the 0-*ε*, 1-*ε*, and 2-*ε* simulations. These dependent measures include the probability of revisiting the targets and distractors (Figure 2), the fixation durations on distractors, initial fixation durations on targets, and intervening fixation durations prior to target revisits (Figure 3), the number of fixations per trial (Figure 4[[3]](#footnote-3)), and overall trial accuracy (Figure 5[[4]](#footnote-4)). The simulated means were obtained using 10,000 statistical trials and using best-fitting parameter values that were obtained by minimizing the mean absolute deviation between the normalized observed and simulated revisit probabilities and fixation durations (i.e., the means shown in Figures 2 & 3) across multiple grid-searches of the parameter space (see ‘Model fitting approach’ above). The best-fitting parameter values for the three reported simulations are listed in Table 1. Because even a cursory examination of Figures 2-5 indicates that the 2-*ε* simulation provides the best account of our data, we will also focus our discussion below on this result, limiting our discussion of the other simulations (with their more limited assumptions about the criterion of target identification accuracy) to an brief explanation of why they are insufficient to explain the full observed pattern of results.

**Table 1.**

Best-fitting parameter values for the 0-, 1-, and 2-*ε* simulations.

|  |  |  |  |
| --- | --- | --- | --- |
| Parameters | Simulations | | |
| 0-*ε* | 1-*ε* | 2-*ε* |
| *θ* | 0.25 | 0.1 | 0.38 |
| *κ* | 6 | 6 | 5 |
| *τ*1 | 151 | 152 | 154 |
| *τ*2 | 3.5 | 3.5 | 3 |
| *ε* | 0 | 0.08 | 0.07, 0.19 |
| *NFixations* | 60 | 55 | 26 |

*Note*: The two indicated values of *ε* in Simulation 2-*ε* are for the few- and many-distractor conditions, respectively.

*[Insert Figure 4 around here]*

*[Insert Figure 5 around here]*

As Figures 2-5 show, the 2-*ε* simulation accurately reproduces the observed patterns in the aggregate data for all four dependent measures. In fact, the only discrepancies between the observed and simulated means is that the model consistently under-predicts the number of fixations per condition (see Figure 4) and over-predicts accuracy (Figure 5). The first discrepancy probably reflects the simple fact that the model’s saccades are completely accurate (i.e., not prone to saccadic error), which in turn means that—in contrast to the observed data—refixations within the same individual stimulus are not scored as discrete fixations. One might therefore predict that a version of the model that included some degree of saccadic error would predict more fixations and thus bring the model’s predictions about this dependent measure more in line with what was observed in the actual experiment. Similarly, the fact that the model over-predicts accuracy reflects the fact that model continues scanning the search display until the target is located, only terminating a trial (which is scored as an error with *p* = 0.5 because of the binary nature of the decision) if the number of fixations exceeds 26 (the value of the *NFixations* parameter). In contrast, humans are subject to lapses of attention and fatigue, which are both likely to inflate the error rate due to, for example, simple guessing. One might therefore predict that a version of a model that included some degree of guessing might increase its capacity to accurately simulate response accuracy, but at the obvious cost of increasing the model’s complexity. Given that our relatively simple model accurately captures the eye-movement measures, however, we have opted to forgo further modifications until they are motivated by something other than the goal of simply fine-tuning the model’s overall goodness-of-fit.

Finally, by comparing the 2-ε simulation to the other two, it is possible to make inferences about why the assumption of a target identification accuracy criterion is both necessary and varies as a function of the number of distractors. The first point to note in this regard is that the assumption does not appear necessary to explain the observed number of fixations (Figure 4) or response accuracy (Figure 5); the other assumptions of the model are sufficient to explain those behaviors. However, some type of target-identification criterion does appear necessary to explain both the probabilities of making lag-2 revisits (Figure 2) and the pattern of fixation durations (Figure 3). That is, without the assumption that targets are sometimes misidentified (i.e., the 0-*ε* simulation), the model predicts no lag-2 revisits to targets, making it impossible to generate predictions about the durations of initial target fixations or intervening fixations on distractors. And similarly, without the assumption that this criterion can be set to reflect the expected number of distractors (i.e., the 1-*ε* simulation), the model fails to explain why the number of lag-2 revisits is modulated by the number of distractors and how this, in turn, affects expectations of a given stimulus being a target.

**Discussion**

There has been extensive debate regarding when the decision is made to terminate a fixation. Much of this work has focused on reading and scene perception tasks, with surprisingly little work focusing on fixation termination in the context of visual search tasks (Reingold & Glaholt, 2014). At the heart of the debate regarding fixation termination is the question: When, during a fixation, is the subsequent saccade is programmed? Indirect control accounts (Engel, 1977; Vaughan, 1982) hold that the decision to terminate fixations is set in advance, according to a default timing mechanism. Direct control accounts (Rayner, 1978) hold that saccades are only programmed once processing of the visual information at the point of fixation is complete. Finally, mixed-control accounts (Rayner & Pollatsek, 1981) hold that there is at least some overlap between the processing of visual information at fixation and the onset of saccadic programming. A number of converging approaches, including those that have examined both fixation durations (e.g., Henderson & Pierce, 2008) and object identification (e.g., McCarley et al., 2003), have agreed upon the notion that fixations are terminated by a mixed-control mechanism.

In the present study, we sought to gain new insights into the mixed control of fixation termination by focusing on lag-2 revisits during visual search, given that lag-2 revisits are argued to occur due to early termination of fixations (i.e., before the stimulus is processed sufficiently for identification). Despite being commonplace in visual-search tasks, lag-2 revisits have, to date, only been explicitly examined in a handful of studies (McCarley et al., 2003; Peterson et al., 2007, 2001). Thus far, it has been argued that lag-2 revisits are the result of online cognitive processing failing to initially identify a target stimulus, followed by the rapid ‘realization’ of the error and the making of a corrective saccade back to the target (Peterson et al., 2001).

We reasoned that lag-2 revisits could be conceptualized in terms of a speed-accuracy trade-off in oculomotor control, and developed an experimental approach that was designed to modulate the trade-off directly. It has been well-established that the oculomotor system tends to make numerous saccades interspersed with brief fixations, correcting any errors where necessary, as opposed to making fewer, slower fixations, with comparatively fewer errors (Trukenbrod & Engbert, 2007; Wu et al., 2010). With that in mind, we considered the fact that, during a visual search task, the probability of fixating an object that is the search target is rather low. Returning to the example used in the Introduction, on average, in a search experiment in which a target is presented on 50% of trials, with a set-size of 16, the probability that any given object will be the target is 0.03. We therefore suggested that it is perhaps not surprising that lag-2 revisits are so common because the probability of fixating a target object is very low indeed.

To experimentally test whether the occurrence of lag-2 revisits is dependent on the probability of a stimulus being a target, we manipulated the number of distractors that were likely to be the target (because they matched the target color). Given that target-color objects would be the objects to which attention is guided (Wolfe, Cave, & Franzel, 1989), and therefore be the objects that are fixated, we also therefore manipulated the probability that a given fixated object would be the target. In the few-distractors condition, there was a 0.2 probability that a fixated object was the target, while in the many-distractors condition, there was only a 0.0625 probability than a fixated object was the target. In line with our predictions, we found that, when there were many distractors to examine, the probability of lag-2 revisits increased. To our knowledge, this is the first such demonstration of an effect of this type; that is, it has not been previously shown that the number of stimuli examined during search can directly influence the propensity to make lag-2 revisits.

With regard to addressing the issue of oculomotor control during visual search, there are two key questions that arise from this novel finding. Firstly, did participants adapt their eye-movement behavior in accordance with the probability that a fixated (target-color) item would be the target? Secondly, what assumptions and associated parameters are required about eye-movement control and task demands in order to simulate the specific pattern of eye movements associated with lag-2 revisits?

To answer these questions, we extended a model that we have previously used to examine visual search (Godwin et al., 2014), thereby developing a more comprehensive model of visual search—the EVS model. To our knowledge, this is the first and only model of oculomotor behavior in visual search that is able to capture lag-2 behavior, both in terms of the probabilities of lag-2 revisits occurring and their associated pattern of fixation durations. Our model also captured lag-2 revisit probabilities for distractor objects, which, despite receiving lag-2 revisits less often than target objects, still showed an increased rate of lag-2 revisits in the many-distractors compared with the few-distractors condition. In order to adequately simulate our data, we discovered that the model requires a global parameter that represents a shift in the participants’ expectation about the likelihood of a target being presented in each of the two conditions (i.e., many vs. few distractors). However, this global parameter was required to vary across conditions to better simulate the observed data. The implication of the simulation for our first question is therefore clear: According to the EVS model, lag-2 revisits require a global parameter, but one that is context-dependent in representing the participant’s expectations about the likelihood of a stimulus being a target. As such, our account differs from the more traditional global-timing account, wherein decisions about how long to fixate each stimulus are determined by a parameter that controls the mean duration of fixations (Engel, 1977; Vaughan, 1982). In other words, according to our account, it is the participants’ expectations about the likelihood of any given stimulus being a target (i.e., the values of *ε*) and not the time required to program saccades (i.e., the values of *τ*1 and *τ*2) that varies across our experimental conditions.

The fact that the assumptions of our model were also sufficient to produce the pattern of fixation durations that was associated with lag-2 revisits also allows us to—at least tentatively—answer our second question. According to the EVS model, the reduction in the duration of fixations on intervening distractors is due to the fact that the location of the next saccade target is known in advance because it is the stimulus that has just been inspected, and thus does not have to compete for selection with other potential saccade targets (see Equation 2). This lack of competition results in a reduction of the time required to program the saccade from the intervening distractor and thus faster termination of the fixation on that location. As such, our account is consistent with the miss + realization account offered by Peterson et al. (2001) but provides a precise hypothesis about why the intervening fixation is reduced in duration—that is it reflects the lack of competing saccade targets that comes from foreknowledge of where the eyes are to be directed next.

Taken together, our results and model provide new insights into the mixed control of fixation termination during visual search. We have shown that the estimation of the probability that any object will be the target can have a direct and significant influence on oculomotor behavior. Moreover, it is also worth noting that the behavior appears systematic in the sense that participants were, on average, approximately three times more likely to make a lag-2 revisit in the many-distractors than the few-distractors condition, while the probability that any object was the target was approximately three times lower in the many-distractors than the few-distractors condition. Overall, it is clear that the visual search and oculomotor system together take into account the likelihood that any fixated object will be the target, and adjust the oculomotor control and termination of fixations accordingly. A fruitful avenue for future research would be to better understand the mechanics and nuances associated with how the visual search system estimates, and responds to, the likelihood that currently-fixated objects could be the target. For example, it would be interesting to map out the propensity to make lag-2 revisits as a function of a much broader range of target/distractor ratios.

Our results have a number of broader implications. First, and perhaps most importantly, our results are important not just to the study of oculomotor control in visual search, but also to a wide array of visual-search tasks. It has been standard practice for decades in visual search tasks to vary the set-size of displays (Treisman & Gelade, 1980) so that changes in reaction time over set-size are then assessed using RT/set-size slopes as a measure of search efficiency (Wolfe, 1998). One important assumption of this approach is that increasing the set-size in turn increases the number of stimuli that have to be examined. However, in the present experiment we have demonstrated that varying the number of search-relevant stimuli changes the probability of a target being missed, which arises due to a fundamental shift in the nature or extent of information processing during search. Caution must therefore be taken when interpreting set-size data by considering whether results are influenced by an expectation of the likelihood that any stimulus being a target. This issue is important both for behavioral models of search behavior (e.g., Wolfe, 2007), as well as eye movement models of search behavior (e.g, Zelinsky, 2008). To date, our model is the first and only model of visual search to encapsulate global shifts of information-processing based upon the number of search-relevant stimuli. An important caveat is that in standard visual search tasks, targets are presented on 50% of trials, rather than the 100% used here, so this may influence the propensity of participants making lag-2 revisits, although we leave this for future studies to explore in detail.

Second, our results can also help to offer new insights into how participants fail to detect targets in visual search. It has been noted that targets are often missed as a consequence of failures of perceptual identification (Cain et al., 2013; Schwark et al., 2013) – that is, even after fixating the target object, the target is still missed by participants (Engel, 1977; Godwin, Menneer, Riggs, Cave, et al., 2015; Godwin, Menneer, Riggs, Taunton, et al., 2015; Gould & Cairn, 1973; Hooge & Erkelens, 1996; Hout et al., 2015; Nodine & Kundel, 1987). These failures have important societal consequences, such as in radiographic image screening, where tumors can go undetected and missed by searchers. It may be the case that, if searchers can be encouraged or trained to make more lag-2 revisits in tasks of this type, or to slow search on each area of the display to promote target identification, then targets may be less likely to be missed.

Third, our study contributes to the notion that, contrary to what might be expected, the eyes may be somewhat decoupled from ongoing object identification processes during visual search. As we noted in the Introduction, a number of models of search have treated the object identification process during search as a random-walk process (Ratcliff, 2006; Thornton & Gilden, 2007; Wolfe, 2007). It would be tempting to assume from these models—which were largely built upon behavioral, rather than eye-movement datasets—that object identification begins once a fixation lands on an object, and ends once the eyes leave that object. But what we have again highlighted here is that object identification is not always complete before a decision has been made to move the eyes away from an object, and the identification process may continue after the eyes have left the object. For the most part, this is not problematic for the search system, since the majority of objects in a display are distractors and therefore do not require a lag-2 revisit. Our findings therefore contribute to a growing body of evidence about the timing of object identification during search. Much work demonstrates that there is considerable degree of object identification that takes place prior to fixating an object (Deubel & Schneider, 1996; Godwin et al., 2013; Reingold & Glaholt, 2014), and, here, the presence of lag-2 revisits is consistent with object identification continuing after moving the eyes from an object. Indeed, it appears that, at any one moment, the search system is not only identifying the currently-fixated object, but may also be processing a previously-fixated object and/or beginning to identify objects that have not yet been fixated. A situation of this type would be entirely in line with classic accounts of search that have argued that visual search involves the limited-capacity parallel processing of a number of objects simultaneously (e.g., Townsend, 1990).

Overall, in the present study, we have shown that lag-2 revisits offer valuable and novel insights into the push-pull relationship between the need to spend time examining fixated objects and the need to make plan and initiate saccades to new locations. Our EVS model is the first such model to encapsulate this dynamic relationship and we plan to use it in future studies to further tease apart the manner in which the expectation that any object fixated will be the target influences visual search and eye movement behavior.

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**Figure Captions**

*Figure 1*. Example of a lag-2 revisit. The participant is searching for a blue *T-*shape and the example shows a sequence of fixations (red circles) and saccades (arrows) beginning at the center of the display and progressing to an initial target fixation, a fixation on an intervening distractor, and then terminating with a second target fixation (i.e., a lag-2 revisit). Note that, for illustration purposes, the objects are not to scale with regard to the stimuli used in our study.

*Figure 2.* Observed and simulated means for probabilities of lag-2 revisits for distractors (upper row) and targets (lower row), shown as a function of the number of distractors (i.e., many vs. few). Data from three different simulations are presented, one per column of panels, each corresponding to the number of different permissible best-fitting values of the *ε* parameter used in the simulation (i.e., 0, 1, or 2). Error bars represent SD. Note the differences in scale for the target and distractor panels, adopted to make the difference between the few/many conditions visible for distractors.

*Figure 3*. Mean observed and simulated fixation durations (ms) on distractors, the distractors intervening between the first and second target fixations, and the first target fixations. The simulated results from three different simulations are presented (i.e., 0-, 1-, and 2-*ε*). Error bars represent SD. (Note that mean values for conditions in which too few data were generated by a given model are not plotted.)

*Figure 4*. Mean observed and simulated number of fixations per trial. The simulated results from three different simulations are presented (i.e., 0-, 1-, and 2-*ε*). Error bars represent SD.

*Figure 5*. Mean observed and simulated trial accuracy. The simulated results from three different simulations are presented (i.e., 0-, 1-, and 2-*ε* models). Error bars represent SD.

1. It is important to distinguish lag-2 revisits from *inhibition of saccadic return* (ISR). In ISR, the fixations preceding the movement of the eyes back to an already-fixated location are elongated in duration (Hooge, Over, van Wezel, & Frens, 2005). It is interesting that, during lag-2 revisits, ISR is not active, lending further support to the claim that the former are due to online cognitive processing (e.g., a willful return to an objects) rather than being some type of artefact of oculomotor control (e.g., saccadic error). [↑](#footnote-ref-1)
2. It is important to note that the actual lag-2 fixations on the targets coincided with button-press responses. As a consequence, these fixations were of elongated duration and thus cannot be directly compared to other fixations. [↑](#footnote-ref-2)
3. The observed fixation numbers were high for participants. The stimuli were small (0.3 degrees), thereby eliminating search guidance by shape and forcing fixation for identification. In this study, a target was present on every trial. One might therefore expect that, on average, approximately half of the target-similar distractors would be fixated, as would be expected in a typical target-present versus target-absent search experiment. However, given that a target was always present, participants were aware to continue search until a target had been found (the target-absent response is not available), and therefore numbers of fixations would be boosted by prolonged search, possibly due to refixations of stimuli once the previous fixation of them had been forgotten. [↑](#footnote-ref-3)
4. Note that, as would be expected for a simple task of this nature, response accuracy was high for both conditions. and there were no differences in response accuracy between the two [*t*(15) = 1.68, *p* = 0.11]. [↑](#footnote-ref-4)