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Hysteresis in Visual Search

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Hysteresis in Visual Search

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Abstract

People perform complex visual tasks. Airplane pilots land planes safely on the ground and baseball players swing bats at speeding fastballs. Drivers weave through traffic and sports fans skillfully track the movements of their favorite team. These are examples of visual search, the process of looking for something. Classic experiments have provided much information about characteristics affecting search efficiency (i.e., efficiency =display size/speed; Treisman & Gelade, 1980), but visual search literature is split on the underlying mechanisms involved in visual search. Visual search may be random (Wolfe, 2007), memory-driven (Zelinsky, 2008), or self-similar over time (Aks, Zelinsky, & Sprott, 2002). These standpoints assign memory at least some role in determining search behavior—the current work explores this possibility by looking for evidence of nonlinearity in visual search response times. Participants performed 250 visual search trials in one of three conditions, ascending-first, descending-first, or random. Ascending-first participants performed 125 searches increasing in difficulty, then 125 searches decreasing in difficulty. Descending-first participants completed 125 searches decreasing in difficulty, then 125 searches increasing in difficulty. Random participants completed 250 searches pseudo-randomly varying in difficulty. We constructed hysteresis plots for each condition and nonlinearity emerged in the data that does not fit traditional concepts of memory, practice, and fatigue. The findings suggest that the term *memory* may not be a useful concept for describing the visual search process. Hysteresis in visual behavior indicates history-dependence—we suggest the term *history* as a replacement for *memory*.

Hysteresis in Eye Movement Patterns

People perform complex visual tasks. Pilots guide aircraft to the ground, coordinating complex visual cues with motor behavior. Drivers navigate through traffic, avoiding other motorists, pedestrians, and unforeseen road construction. Athletes rely on vision for many tasks, gauging the distance to a goal, "reading" golf greens, and swinging bats at 95 mph fastballs. Often visual behavior is less extreme, but equivalently complex. Friends recognize one another across a crowded room; storm watchers detect subtleties in cloud formations; and pub-crawlers find differences between complex visual scenes while sitting on a bar stool. These are all examples of visual search—the process of looking for something—and imply that visual behavior is flexible and adaptive. This description has recently faced critique as some contend visual behavior exhibits task-independent structure (e.g., Over, Hooge, Vlaskamp, & Erkelens, 2007). Task-independent structure is inconsistent with the view that memory steers search behavior. The current work explores the possibility that visual behavior may also be context-dependent—visual behavior may exhibit nonlinear fluctuation according to photometric scene characteristics and specific task demands. Nonlinear fluctuation may indicate history-dependence (i.e., hysteresis). Hysteresis in visual search questions current assumptions regarding the part memory plays in directing search, while providing an possible explanation for seeming task-independence.

Visual search means looking for something. The visual search literature often calls that something a *target* and anything else a distractor. The same literature distinguishes between types of visual search—feature, conjunction, and natural (or real-world) search (e.g., Biederman, Glass, & Stacy, 1973; Brockmole & Henderson, 2006; Henderson, 2003). Feature search tasks involve looking for simple targets such as upright blue rectangles amidst many rotated from 90 degrees blue rectangles (e.g., Treisman & Gelade, 1980; Wolfe, 1998). Conjunction searches involve detecting targets along more than one dimension such as rotated violet rectangles amidst rotated pink and blue rectangles. Finally, natural search is generalized conjunction search because natural scenes (e.g., fields of wildflowers) present many complex conjunctions, and the distinction between target and distractor is blurry at best (Wolfe, Horowitz, Palmer, Michod, & Van Wert, 2010). Natural search is easy to understand because people do this when they search for car keys, the remote, or a runaway earring back. These perspectives have provided visual science with valuable information.

Visual search studies typically focus on search efficiency, a broad term referencing some speed by area measurement (e.g., Duncan & Humphreys, 1989). Researchers plot push-button response times against display size or area (e.g., number of distracters; Duncan & Humphreys, 1989; Treisman & Gelade, 1980; Treisman, 1991; Wolfe, 1998). Without density measurements, display size only loosely relates to area—one could have 25 1-cm^2 search items on a 25-cm^2 display or the same search items on a 100-cm^2 display. Feature searches often result in flat efficiency curves—increasing display size does not affect search efficiency, providing putative support for parallel processing of visual stimuli (Müller, Heller, & Ziegler, 1995; Thornton & Gilden, 2007; Treisman & Gelade, 1995). However, increasing display size during conjunction searches results in efficiency curves often interpreted as linearly increasing, supposed evidence of serial processing of visual stimuli. The idea is that the increased distractor quantity and processing speed explain the linear increase observed for conjunction searches.

Parallel processing expedites feature searches by allowing observers to scrutinize an entire scene at once, a relatively fast process (about 400 ms); whereas, serial processing slows visual search by forcing observers to examine each distractor one by one (response times are sometimes as high as 2400 ms; Treisman and Gelade, 1980). The argument is compelling—conjunction search appears dependent on display size because increasing the number of to-be-searched items increases search times linearly, but feature search appears independent of display size because increasing display size fails to precipitate increased response times. Explicit in Treisman and Gelade (1980) and Wolfe (2008) is the idea that processing speed and storage limitations prevent observers from accruing information about search scenes—visual search is amnesic or random.

Some researchers interpret characteristic efficiency curves as evidence that visual search is random (Horowitz & Wolfe, 1998; Horowitz & Wolfe, 2003; Wolfe, 1998). This interpretation is understandable. If visual search has a universal structure, then one might expect display size commensurate increases in search times for the simple and sufficient reason that a larger display requires more time to search. However, this interpretation follows from the assumption that response times are linear. Is this an accurate representation of efficiency curves? The fractal (i.e., nonlinear) dynamics in response times have long been established (e.g., Thornton & Gilden, 2005; Van Orden, Holden, & Turvey, 2003) and researchers have begun to recognize that efficiency curves are not as linear as once thought (Wolfe et al., 2010). For example, a striking non-linearity appears in response time curves—linear predictions extending from small display sizes to large display sizes quickly increase in error as efficiency curves follow a curvilinear trajectory. Such non-linear trends often indicate complex dynamics.

Tools and concepts from dynamical systems theory may help explain non-linearities in visual search and response time data and may reveal that experience is fundamental to visual search (Aks, Zelinsky, & Sprott, 2002). One such method involves examining visual behavior for history dependence (i.e., hysteresis). The following illustration explains the concept of hysteresis. Imagine a mountain climber scaling an alpine summit—one could easily trace her path from the pitons left in the rock face as she makes her ascent. However, tracing the descent might reveal a different trajectory. The mountain climber is not the same when beginning her ascent as when beginning here descent, and for that matter, neither is the mountain. The mountain climber's perspective has changed—seeing above a sheer drop is different than seeing beneath one. The rock face has also changed—the eventual scree that falls from beneath the climber's feet creates subtle changes in the rock formation that prevents precise backtracking. These changes in perspective and form force the climber to alter her path from the peak relative to her path from the base. Thus, the measurement of the climber's path depends on the direction of measurement, and this property, this history-dependence is hysteresis.

The study of hysteresis originated in ferromagnetic material research (e.g., Ewing, 1900), but since then the cognitive-perceptual domain and others have also applied the concept (e.g., Farrell, 1999; Holden, 1998). For example, when researchers incrementally vary a simulated object's motion path on a computer screen, people experience a perceptual flip from horizontal to vertical motion when the aspect ratio between horizontal and vertical motion length reaches a certain threshold (e.g., Hock, Bukowski, Nichols, Huisman, & Rivera, 2005). One example is a motion quartet, a grid-like structure containing four dots configured dark, light, dark, light. Participants view the configuration as the dots blink between light and dark. If the motion paths—the distance between successive dots— are equivalent in the horizontal and vertical direction, an observer perceives this as directional motion. Diners have been motioning people into their booths like this for years. If researchers slowly change the horizontal/vertical aspect ratio, observers report perceptual change in motion direction at a critical point, like the point at which water transitions to ice. Hysteresis occurs when researchers incrementally reverse the aspect ratio—perceptual flips occur at different aspect ratios when experienced in ascending versus descending order. Thus, hysteresis occurs in more-or-less pure visual perception.

Hysteresis also occurs in object wielding—people transition between holding an object with one hand and holding an object with two hands at different times depending on which action occurs first (e.g., Frank, Richardson, Lopresti-Goodman, &Turvey, 2009). Wielders may start to grasp an object with one hand but if researchers increase object size (i.e., length, mass, or density) to some critical point, then wielders switch to two-hand grasping. Hysteresis occurs when wielders begin with a two-hand grasp because the critical size at which they switch to a one-hand grasp is different than the point at which they switched from a one-hand to a two-hand grasp. Thus, hysteresis is also present in more-or-less pure motor behavior. Given that hysteresis occurs in almost pure perceptual experience and motor behavior, it makes sense to examine visual behavior for hysteresis because perceptual and motor processes (i.e., eye movements and response times) comprise visual search. However, this stance challenges conventional thoughts on the role memory plays in visual search.

Visual short-term memory is a hypothetical mental storage center for temporary stimulus representations (e.g., search images)—this storage serves to guide future search (e.g., Guided Search 4.0; Wolfe, 2007). Suppose someone asked you to find an upright

"T" amidst an array of rotated "Ts". Your eyes would make an initial random sweep across the array collecting information (i.e., item representations). What you may not know is this storage is quite small—capacity only spans about four items (Wolfe, et al., 2010). Therefore, one may have access to only about four "Ts" at any one time from visual short-term memory, but if you do not find the upright "T", then the visual system guides you to another possible location and updates the storage center with new information. You also might not be aware that you must transfer items from short-term to long-term memory if you want to use this information later. This means you must constantly monitor visual short-term memory for relevant information and then send it to long-term memory, but this process is also taxing because there is a perceptual bottleneck—little information makes its way from the retina to long-term memory (e.g., Van Essen, Anderson & Felleman, 1992). These supposed limitations to the visual system create challenges in understanding how memory guides visual search.

Hysteresis provides an alternative lens for understanding visual behavior. Perspectives on memory's prevalence in visual search span a wide continuum (cf. Aks, et al., 2002; Wolfe, 2007; Zelinsky, 2008). One end of this continuum maintains that visual search is random (e.g., Horowitz & Wolfe, 1998), while the other end promotes memory as fundamental to visual search (e.g., Zelinksy, 2008). The intermediate position simply posits a relationship between visual behaviors across time (e.g., Aks, et al., 2002). Trial randomization in visual experiments expresses a tacit knowledge that visual search is not random—behavior experienced at one point time influences later behavior (i.e., practice effects). However, the inability to improve search efficiency even when re-searching the same display for the same object (e.g., Kunar, Flusberg, & Wolfe, 2008) contradicts the viewpoint that memory plays a primary role in guiding visual search. What then is visual behavior's temporal relationship? If neither memory nor randomness is adequate to describe visual behavior, then hysteresis argues against randomness as an explanation and suggests a reason for memory-like effects. The described here tests the hypothesis that visual behavior exhibits hysteresis.

Method

Participants

Eighty-three students volunteered for the experiment. Students participated in exchange for course credit. All participants reported normal or corrected-to-normal vision without color-blindness. We discarded 28 participants' data because of a minor task modification early in data collection. We also discarded data from 25 participants because of failures in the calibration procedure and equipment malfunctions. Our final sample was 30 participants (Female = 22). The mean age of participants was 20.53 (*SD* = 0.45). Four participants reported wearing glasses, seven participants reported wearing contact lenses, and three participants reported having had corrective eye surgery. Twenty-five participants reported being right-handed and twenty-three participants reported English as their first language. Five participants reported their ethnicity as African American, four reported being Asian, fourteen reported being Caucasian, two reported being Hispanic, three reported being Native American, and two reported being Middle Eastern. Participants were randomly assigned to experimental conditions such that 10 participants experienced each condition.

Materials

The researcher constructed 245 original stimulus slides comprised of satellite imagery superimposed by golf balls (Figure 1). The background satellite image remained constant across all 245 stimulus slides; however, golf ball images varied with respect to opacity. Target opacity varied with respect to stimulus background, ranging from 20 to 100 percent, with 5 levels (20, 40, 60, 80, and 100 percent). Stimulus slides were constructed such that 49 slides contained each level of opacity and were taken from a larger stimulus set. The original stimulus set (1225 slides) varied opacity and size but preliminary analyses revealed no effect of size on difficulty rating. Graduate students (six) and faculty (one) rated all 245 slides for difficulty using a method similar to S. S. Stevens (1957) magnitude estimation (see Appendix A). Cluster analysis identified five distinct categories, interpreted as difficulty levels. We assigned scores to each slide based on the cluster analysis and then selected 25 slides at random from each difficulty level to use in the experiment. The final number of 25 slides per level was chosen so that participant engagement remained under thirty minutes. This limitation ruled out expired vigilance as a possible confound.

Figure 1. Example stimulus slide at 40 percent opacity. Target is located in the lower-left quadrant.

Apparatus

An ASL series 5000 (Model 504) eye tracker captured eye movement behavior. This system (sampling rate = 60 Hz) uses near infrared corneal and pupil reflection to track participant gaze position relative to screen/scene location. Participants performed searches on an 81.28 cm Elo Touchsystems LCD touch-screen monitor (refresh rate = 60 Hz, resolution = 1024×768) from a distance of approximately 104 cm, subtending a visual angle of about 16.31° vertical and 21.32° horizontal, left and right of center. GazeTracker® software from Eye Response running on a Dell Optiplex® computer presented stimuli. The laboratory was kept dark except for the ambient lighting produced by monitors and the eye-tracking equipment. Participants used a mouse to advance trials and indicate when they located targets.

Procedure

Upon entering the laboratory, each participant read an informed consent form explaining the procedure and any potential risks. After reading the informed consent form, each participant printed and signed their name to indicate agreement with participation in the procedure. The researcher then switched off the overhead light and began the calibration procedure. Each participant followed the researcher's instruction and looked at nine equally spaced points (i.e., three rows by three columns) in sequence. The background for the calibration points was solid blue-green, and each point was an off-white color superimposed by black numerals (1-9). The eye-tracker recorded the focal point from each participant's left eye as they looked at each point. Once participants viewed all nine points, the researcher directed the participants' attention to the calibration points again to ensure fixations were within 0.5 degrees, corresponding to the perimeter of each calibration point. If any monitored fixation did not meet this criterion, the researcher repeated the calibration until measurement error reached tolerance.

Each participant then read the instructions and completed 250 visual search trials, each separated by a 1000 ms interstimulus interval where they observed a slide of white noise constructed with Adobe Photoshop CS4 (see Appendix B for instructions). Participants in the *ascending-first* condition performed 125 visual searches that increased in difficulty from 1 to 5 and then 125 visual searches that decreased in difficulty from 5 to 1. Participants in the *descending-first* condition performed 125 visual searches that decreased in difficulty from 5 to 1 and then 125 visual searches that increased in difficulty from 1 to 5. Participants in the *random* condition performed 250 visual searches that pseudo-randomly varied in difficulty ranging between 1 and 5. Participants in all conditions viewed the same slides in block one as in block two such that the experimental conditions blocks were identical except for being in reverse order. At the conclusion of the experiment, the researcher asked all participants if they were aware that the two blocks were identical. This question probed whether explicit memory explained differential response time slopes between blocks one and two.

Design

The design was a 2_W (block) × 3_B (direction) × 5_W (difficulty) mixed design. The first independent variable was *block,* with block one corresponding to first half trials and block two corresponding to second half trials. The second independent variable is *direction* with three levels, ascending-first, descending-first, and random. The third independent variable was difficulty and ranged between 1 and 5 according to the rating procedure discussed in the materials section. The dependent variable was response time, where the time difference between the beginning of a trial and a key-press response indicating that a participant had located.

Results

Eye Movement Data

Technical issues prevented the analysis of eye movement data. The intention was to analyze *acquisition time*, the time difference between the beginning of a trial and the time participants fixated a target. This measure relies on defining an area of interest, the area that contains each target. However, participants often pressed the left mouse button to advance the trials before their gaze reached the target, preventing reliable calculation of acquisition time. A solution to this problem in future research would be to use a gaze contingent display. This would allow participants to control stimulus presentation with their eyes and provide an accurate measure of when and if participants located the target.

Response Time Data

We tested the hypothesis that visual behavior collected during visual search would exhibit hysteresis. Participants exhibited individual variability in response times so we standardized each participant's response times by converting them to *z*-scores. Then we performed a $2_{\text{W-block}} \times 3_{\text{B-direction}} \times 5_{\text{W-difficulty}}$ mixed analysis of variance. Mauchly's test for spehericity was significant so we used a Greenhouse-Geisser correction to adjust degrees of freedom. The analysis revealed a three-way interaction, $F(2.63, 35.54) = 4.762$, $p = .009$, partial eta squared = .261, observed power = .833. The three-way interaction confounds the main effects of block and difficulty, as well as two-way interactions, so we omit reporting or interpreting these statistics.

Nested within group variables create a challenge in interpreting the three-way interaction (Figure 2a and 2b). We addressed this difficulty by computing change scores such that change was the difference between block two and block one. There is some concern about taking change scores because members from different groups may start at different values (e.g., Meltzoff, 1999). A common treatment for this concern is converting raw data to delta scores, which take into consideration the correlation between initial and final values. However, converting raw data to *z*-scores provides an equivalent solution because *z*-scores and delta scores are linearly related (Nunally & Bernstein, 1994). We converted raw data to *z*-scores for statistical tests, but used raw data to generate figures to aid interpretation (Figure 2c). Negative change scores indicate quicker response times during block two compared to block one, whereas positive change scores reflect slower response times during block two compared to block one. We followed up by performing a two-way $3_{\text{B-direction}} \times 5_{\text{W-difficulty}}$ mixed analysis of variance. Again, Mauchly's test of sphericity was significant so we adjusted degrees of freedom with a Greenhouse-Geisser correction. The analysis revealed a significant two-way interaction, F (2.64, 35.65) = 4.75, p = .009, partial eta squared = .260, observed power = .832.

Paired-sample *t*-tests with Bonferroni correction (α = .01) clarified the interaction. Descending-first participants located targets more slowly at difficulty level four during block two (M = 2,931.10 ms, SD = 1,479.49 ms) than during block one (M = 1,279.50 ms, SD = 431.81 ms) resulting in an average approximate difference of 1,650.00 ms (SD = 1,781.15 ms), $t(9)$ = 2.93, p = .008 (Figure 3b). However, descending-first participants found targets more quickly at difficulty level five during block two (M = 7,807.10 ms, SD = 4,096.75 ms) than during block one (M = 13,518.60 ms, SD = 6,643.68 ms), resulting in an average approximate difference of -5,711.50 ms (SD = 5,415.43 ms), $t(9)$ = 3.34, p = .004 (Figure 3b). Ascending-first participants located targets more quickly at difficulty

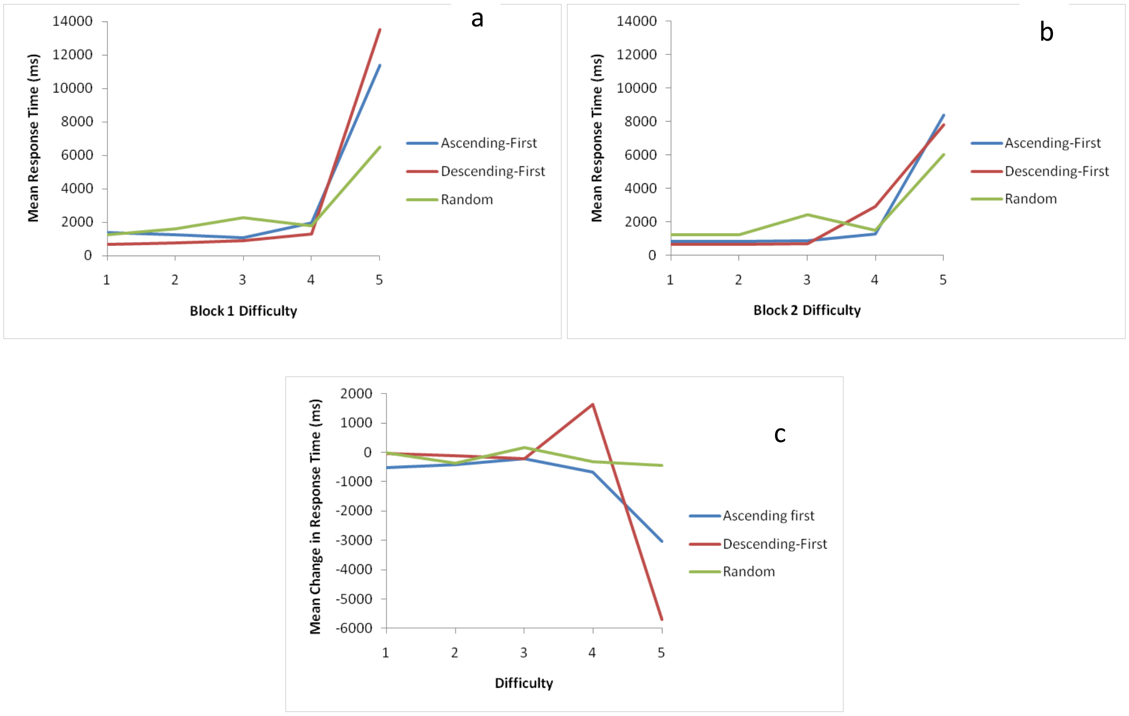

Figure 2. Plots of response times by difficulty in (a) block one and (b) block two. Plot shows the response time differences (c) between blocks for each level of difficulty. Lines represent between group levels. Negative values indicate faster response times during block two compared to block one.

level five during block two (M = 8,367.20 ms, SD = 2,672.64 ms) than during block one (M = 11,396.30 ms, SD = 3,953.95 ms), resulting in an average approximate difference of -3029.10 ms, $t(9) = 8.52$, $p = .000$ (Figure 3a). Figure 3c indicates no differences in response times for the random condition between blocks one and two.

Independent sample t-tests with Bonferroni correction (alpha = .01) assuming unequal variance helped decipher the three-way interaction. Descending-first participants showed a larger change in performance at difficulty level four than ascending first participants, $t(9) = 3.68$, $p = .001$. Descending-first participants also showed a larger change in performance at difficulty level five than ascending-first participants, $t(9) = 3.32$, $p = .005$. Descending-first and ascending-first participants had larger changes in

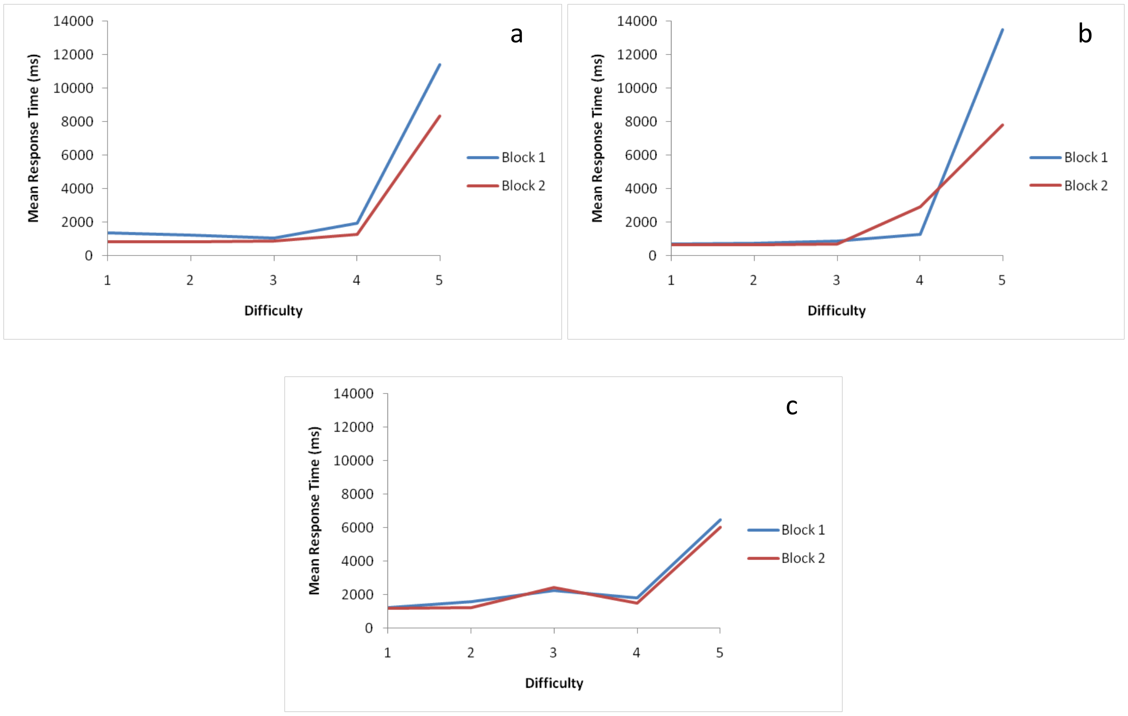

Figure 2. Hysteresis plots of response times in the (a) ascending first condition, (b) the descending-first condition, and (c) the random condition.

performance than the random group (*M* = -437.00 ms, *SD* = 3,494.08 ms) at difficulty level five, $t(9) = 3.69$, $p = .001$, and $t(9) = 2.78$, $p = .008$, respectively. Finally, descending-first participants showed a greater change in performance than the random group (*M* = -310.00 ms, *SD* = 1,795.61 ms) at difficulty level four, $t(9) = 2.45$, $p = .01$. All participants reported being naïve to the identical slides in blocks one and two.

Discussion

The current work explored the possibility that visual behavior exhibits hysteresis. Hysteresis can be inferred based on nonlinear patterning of response times at nested levels of block and difficulty. That is, response times that differ at the same difficulty level at different points in time may express a nonlinearity called hysteresis. The current results suggest several ways that visual search response times exhibit a history-dependent quality. First, the ascending-first and the descending-first conditions, when compared to the random group, produced faster response times at block two with respect to block one at the highest levels of difficulty (i.e., four and five; Figure 2a and b). This finding implies that order of difficulty plays a role in search performance. Second, the average benefit for the ascending-first group between blocks one and two at difficulty level five was about 3,000 ms; whereas, the descending group showed an even greater benefit at around 5,700 ms. This disparity between ascending-first and descending-first conditions indicates that performance benefit may depend on experienced difficulty direction. Third, the descending-first condition experienced a cost of about 1600 ms at difficulty level four, a nonlinearity that seems contradictory to standard models of visual memory. Thus, there are at least three ways the current findings support our hypothesis that visual behavior exhibits hysteresis.

The appearance of hysteresis gives evidence of nonlinear visual behavior, but this interpretation invites alternative explanations. One possibility is that the observed difference in the descending-first group at difficulty level four is owing to fatigue. Descending-first participants may have responded slower during block two trials because they were tired, but this is a weak argument because the ascending-first and random conditions failed to demonstrate the same fatigue effect—the comparable time interval for the ascending-first condition gave the opposite trend. Ascending-first participants performed faster at difficulty level two during block two than at the same level during block one. If fatigue was the culprit behind the descending-first nonlinearity at difficulty level four, one would expect a similar trend in the ascending-first condition but improved block two performance by the ascending-first group opposes this interpretation and necessitates a separate account.

So-called practice effects may explain improved performance by the ascending-first and descending-first groups during block two at difficulty level five—participants may have increased their search efficiency according to increased familiarity with the task constraints. This interpretation is plausible but fails to address the observed findings for at least two reasons. First, relegating performance to practice contradicts the interpretation that the nonlinearity observed in the descending-first group stemmed from fatigue. If practice effects are sufficient to obscure fatigue trends in the ascending-first group, it follows that practice effects would have the same effect on the descending-first group—this was not the case as performance by the descending-first group slowed during block two at difficulty level four. Second, participants in the random condition did not generate a patent improvement during block two at all levels of difficulty. The same logic applied when exploring differences between the experimental groups applies here—there is no why fatigue should overcome practice effects in the random group but not the ascending-first group. Thus, practice effects and fatigue seem mutually exclusive in explaining the current findings. If observed patterns come from practice effects alone, then the fatigue explanation for the descending-first group cost at difficulty level four falters. If observed patterns stems from fatigue, then practice effect explanation for the ascending-first group benefits at difficulty levels four and five becomes indefensible.

If fatigue and practice effects are inappropriate for explaining differences between experimental groups, then perhaps explicit (or declarative) memory may account for observed ascending-first improvement. After all, participants viewed the same images in block one and block two, providing the opportunity to encode, store and retrieve each target location. Again, there are at least two reasons why this interpretation is ineffective. First, we asked experimental group participants if they noticed that block one and block two trials were identical—all participants reported being naïve to this fact. Expectation effects might explain participant reported naïvety and we might make this concession were it not for the second reason an explicit memory interpretation is untenable. Expectation effects and explicit memory accounts fail to explain the performance cost observed for descending-first participants during block two at difficulty level four. If participants relied on explicit memory stores to guide block two searches, we would have observed a consonant improvement in all three conditions (cf. the fatigue – practice argument above), but the descending-first nonlinearity muddies a clear relation to explicit memory.

Failure to explain observed trends through explicit memory does not rule out implicit (also procedural) memory as the mechanism underlying ascending-first participants' improvement during block two. It is possible that participants accumulated a map of the unvarying background image, facilitating block two performance; however, this only makes sense when considering the ascending-first condition because random and descending-first participants showed decrements in performance during block two (Figure 3b and c). In fact, implicit memory could only benefit search if participants had background image specific knowledge. If any relation exists between theorized implicit memory stores and the observed within condition variability, then one might reason that interplay among implicit memory, explicit memory and whatever memory form is responsible for practice effects impaired its detection. If this is the case, our experimental procedure lacks sufficient constraints to tease apart this relationship. However, we argue that this is not the case because performance by the random group supports our interpretation. Perhaps the difficulty in decoding memory's contribution rests in the assumption that memory stores play a role in visual search (cf. Horowitz & Wolfe, 1998).

Contemporary visual search theories suggest that visual-short term memory can hold only about four objects at one time—such a visual system would be taxed to encode and store 125 unique target locations simultaneous to encoding and storing even a coarse background image map (Wolfe, et al., 2010; Rao, Hayhoe, Zelinksy & Ballard, 2002). At least three reasons hint why this may be so in the current work. First, natural terrain comprised the unvarying background image—natural imagery is often complex and provides a near infinite number of potential distractors. Encoding and storing a natural scene would require vast processing and storage abilities—this seems inconsistent with a four-item visual short-term memory capacity, not to mention the perceptual bottleneck connecting short- to long-term memory. Second, we introduced a stimulus mask between trials—a noise mask should overwrite visual-short term memory stores. The mask then reduces the likelihood that the visual system would transfer information from visual short-term memory to permanent memory stores, implicit, explicit, or otherwise. Third, we varied target opacity relative to background image, blurring the distinction between target and distractor—any background image map would include erroneous information because the presence of targets would render variable the unvarying background image map. We hesitate to call a fluctuating map a map, at least in the traditional sense of a first order isomorphism. It seems even approaches that assign memory only a limited role in visual search may not be suitable to address the current findings.

Our interpretation of the current results with traditional memory concepts has fallen short in explaining the nonlinearities in our data. Descending-first participants performed worse at difficulty level four during block two than during block one—if observers relied on memory to guide search during block two, then they should have experienced a marked benefit compared to block one. They did not. This is a clear contradiction to memory-based models because participants performed the same searches in each block and there was no clear evidence of fatigue. Also, descending-first participants showed greater benefit than either ascending-first or random participants at the most challenging searches—if experienced direction were trivial, then we should have observed equal benefit across experimental conditions from block one to block two. We did not. Furthermore, the fact that any differences exist between the random condition and the experimental conditions is remarkable—if simple practice conferred benefit to the experimental conditions, it should have conferred similar benefit to the random condition. It did not. Thus, we argue that hysteresis provides a more robust explanation for the nonlinearities that emerged from the current data.

If one compares the concepts of memory and history-dependence (i.e., hysteresis), both terms impart the importance previous experience plays in shaping now and future behavior—organisms do change from interaction with their environments, as do the environments. This idea is similar to the mountain climber example from earlier—the climber and the rock face changed from their interaction and this interaction made identical ascending and descending trajectories improbable if not impossible. Memory models make specific—and so error prone—predictions about these trajectories but history-dependence makes no specific prediction about behavioral variability. Hysteresis is by definition nonlinear and so is suited to describing the current findings. Does this mean that visual search behavior is unpredictable? Perhaps—hysteresis comes from the study of dynamical systems wherein long-term unpredictability is the norm rather than the exception (Sprott, 2003). Does this also mean visual behavior lacks structure? Not necessarily—many dynamical systems have complex structure that is not apparent (e.g., fractals). The current findings support this perspective because traditional concepts failed to predict response time variability, but consistent patterns emerged within each condition.

The current findings provide support for hypothesis that visual behavior exhibits hysteresis. Perhaps three methodological considerations are necessary for studying visual behavior. First, the results indicate the need to study visual behavior over time—accurate characterization of visual behavior may only be possible through protracted observational windows. Though the current work moved in this direction, response times may not be the ideal dependent variable because they include motor processes that occur after the search. In addition, response time data is less reliable without a reliable without an indicator of target acquisition. Eye movement data may provide a clearer description because eye-trackers have high sampling rates (60-1000 hz) and so may capture subtleties not apparent in response time data. However, eye movements are correlated with response times (e.g., Zelinsky & Sheinberg, 1997), suggesting that eye movement data may generate similar patterns. Second, visual researchers may consider revisiting well-known experiments with new methodological and analytical approaches. Technological advances in computing and motion tracking may reveal new information from classic experiments. Advances in dynamical systems research stems from powerful computing, complex data modeling, and simulations—these tools may likewise benefit the study of visual behavior. Third, the current results question the role memory plays in visual search and suggests that the term *history* may better reflect the visual process. Future work will also address other cognitive tasks (e.g., word naming) for hysteresis. History as a replacement term for memory may be a difficult concept to grasp. We conclude by explaining how powerful history or persistent change can be.

J. J. Gibson's (1986) theory of direct visual perception suggests that everything needed to perceive exists within the light emanating from objects, surfaces, and mediums. This is because of *affordances*, features that offer something to an observer. For example, the undulating pattern light makes as it reflects from a stream is unmistakable and water affords people hydration, cleanliness, and food. Environmental features, as conceived by Gibson, do not possess invariant affordances, but affordances emerge from the interaction of an organism with its environment (Chemero, 2009; Gibson, 1986). A packet of sugar is great in tea, but it also balances a wobbly table—table steadying is not an invariant quality of sugar packets but in right context an observer detects and exploits this affordance.

Affordances make possible direct perception and explicit in Gibson's (1986) theory is the idea that if animals directly perceive their environments, then there is no need to store memories of objects. This does not mean that organisms do not learn—Gibson suggested that perceptual systems attune to affordances. This, in turn, does not mean representations are stored, but that perceptual apparatus flexibly adapt to environmental context. Positing internal representations (i.e., memory) does not improve explanation or prediction despite the ability of representational systems to mimic behavior (e.g., computers, Chemero, 2009). Memory is inextricably linked to a computer metaphor, one of input and output, a metaphor that obfuscates the role of intentional agents in fluctuating environments. The current findings question the role of memory in visual search—perhaps visual search operates from history instead of memory.

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Appendix A

Raters read the following instructions:

> Welcome to the experiment!
>
> Following the instructions, you will be shown a series of pictures. Within each picture, the researchers have hidden a round object similar to a golf ball. The hidden object will vary in size, and camouflage. Thus, some searches will be very easy and some searches will be very difficult. You will have two tasks. Your first task is to find the golf ball, and press the spacebar. After you have found the golf ball, you will be given the opportunity to rate the difficulty of each search. Press the spacebar to continue the instructions.
>
> The rating procedure you will use is different than others you may have performed. You will be shown examples of the search task along with ratings others have given them. You may use the examples to develop your *own* rating scale. The only requirements are that you rate each picture, and that each rating must be equal to or greater than zero. A zero rating represents your easiest searches. Let's look at a few examples now. Press the spacebar to continue.

Participants then saw three consecutive examples of to-be-conducted searches. Each example explained that another participant had given the search a specific rating. Raters viewed the examples and then read these additional instructions:

> The first 50 searches will be for you to practice developing your rating scale. This will give you an idea of the range of difficulty the researchers will present. Use the examples you were shown and your own ratings as a reference to rate other searches. For example, you might think, "That last one was a 15, but this one was only a little more challenging, so I will give it a 25." One more note of caution

> before you begin. It is easy to think that a search is easy once you have found the object. Try to avoid using this logic as you create your scale. Let's practice. You will be notified when the practice session has ended. Press the spacebar to continue.

After completing the practice session, participants read these final instructions:

> You are now ready to begin. If you DO NOT understand what you are supposed to do, ask the researcher for clarification. If you DO understand, press the spacebar to begin rating the pictures. There are a large number of searches and you will be given breaks periodically throughout the experiment.

Breaks were administered approximately every 300 trials to prevent participant fatigue. Because each participant generated their own magnitude estimation scale, we converted participant ratings to *z*-scores. After obtaining *z*-scores, we used cluster analysis (Ward's method) to separate participant ratings into levels of difficulty. Cluster analysis revealed five distinct clusters, treated here as five levels of difficulty. Researchers then randomly selected 25 slides from each difficulty level to serve as the stimuli for the main experiment.

Appendix B

Upon completing a successful calibration, the researcher started the experiment and instructed the participant to read the following instructions as he read them aloud:

> Welcome to the Experiment!
>
> The researcher will now show a series of pictures. Within each picture, the researchers have hidden another picture of a green golf ball. Your task is to find the golf ball as quickly as possible. When you have located the golf ball, press the left mouse button. Some searches will be easy and some will be difficult, so it is important that you try your best every time. Also, once you locate the golf ball, keep looking at it until the screen goes turns black. When you have finished reading these instructions, say, "I'm finished."

After the participants said, "I'm finished," the researcher asked if they understood the task and if they were ready to begin. The researcher answered any questions, and instructed participants to begin by pressing the left mouse button.