Title: Attentional guidance and match decisions rely on different template information during visual search

Xinger Yu^{*1,2}, Timothy D. Hanks^{3,4} and Joy J. Geng^{*1,2}

¹Center for Mind and Brain, University of California, Davis
267 Cousteau Pl., Davis, CA 95618 USA

²Department of Psychology, University of California, Davis
One Shields Ave, Davis, CA 95616 USA

³Center for Neuroscience, University of California, Davis
1544 Newton Ct, Davis, CA 95618 USA

⁴Department of Neurology, University of California, Davis
4860 Y St #3700, Sacramento, CA 95817 USA

*address correspondence to

Xinger Yu, xeyu@ucdavis.edu

Joy J. Geng, jgeng@ucdavis.edu

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Abstract

When searching for a target object, we engage in a continuous “look-identify” cycle in which we use known features to guide attention towards potential targets and then to decide if it is indeed the target. Target information in memory (the target or attentional template) is typically characterized as having a single, fixed, source. However, this notion is challenged by a recent debate over whether flexibility in the target template is “relational” (Becker, 2010) or “optimal” (Navalpakkam & Itti, 2007). Based on evidence from two studies in college students ($N=30$ Experiment 1; $N=70$ Experiment 2), we propose a resolution to this debate by proposing that the initial guidance of attention uses a coarse “relational” code, but subsequent decisions use an “optimal” code. Our results offer a novel perspective that template information differs in precision when guiding sensory selection and when making identity decisions during visual search (Wolfe, 2021).

Statement of Relevance

The objects that we look for are often hard to find because they are “hidden” amongst countless other objects in complex scenes (e.g., searching for keys in a cluttered kitchen). Theories of attention hypothesize that we accomplish the task by holding a veridical copy of the target, akin to a photograph of the target object, in memory and then moving attention and the eyes to template-matching objects (e.g., shiny metal). However, in two studies, we provide evidence that the target information used to perform visual search is dynamic and may even differ based on the stage of processing. Our results show that the target representation is shaped by the distractor context and moreover, that the information used to guide the initial attention is coarse and “relational”, but subsequent decisions about identity of the object (i.e., yes those are my keys or no those are not what I’m looking for) use a precise and “optimal” code.

Introduction

Imagine you are doing a field survey in India and the guide reminds you to be cautious of a tiger hiding in the grasslands. As you look around, the environment might be flooded with different types of animals, but there is a limit on how much information can be processed in any given moment. Therefore, we must hold a memory representation of the tiger, known as the “target” or “attentional” template, in mind while recursively locating and then inspecting candidate creatures within the same context until the target tiger is found (Malcolm & Henderson, 2010; Wolfe, 2021). Although the concept of a target template has been a staple of attention research for decades (Duncan & Humphreys, 1989; Eriksen, 1953; Green & Anderson, 1956), it has been largely assumed to contain a single, static, and veridical representation of what we are looking for. Recent studies have begun to challenge this notion by showing that template representations are dynamic and shift “off-veridical” when doing so increases the target-to-distractor distinctiveness (Geng & Witkowski, 2019). The goal of these studies is to go further and test the hypothesis that two versions of the search template are used at the guidance and decision stages of the “look-identify” cycle (Wolfe, 2021). While both can be off-veridical, we hypothesize that guidance operates on a more relational template whereas target decisions rely on a more optimal code.

Standard models of feature-based attention posit that the optimal template for a target contains highly specific information about the veridical features of the target (Treue & Trujillo, 1999), but studies in which the search target appears predictably amongst linearly separable distractors find that the target representation shifts “off-veridical” away from distractors (Bauer et al., 1996; Hodsoll & Humphreys, 2001; Scolari et al., 2012). For example, search for an orange tiger amongst yellow grasslands results in an attentional bias towards color values that are “redder” than the actual orange of the tiger. Becker and colleagues (Becker, 2010; Martin & Becker, 2018) propose that this effect is due to observers using a “relational” rule to guide attention and first

saccades towards the “reddest” object in the visual environment. In contrast, others argue that the bias is due to an “optimal shift” in the central tendency of the target tuning curve to more effectively discriminate the target from distractors (Geng et al., 2017; Navalpakkam & Itti, 2007; Scolari et al., 2012; Yu & Geng, 2019).

Even though the two positions may seem similar, they make very different predictions that have implications for understanding how target information is encoded and flexibly used during visual search. In particular, the two theories differ in predictions for how inclusive the template is of feature values that are opposite to the experienced distractors (i.e., the “negative” color values in Figure 1). The relational account predicts very broad inclusion of negative feature values because they all share the relational feature that defines the target from expected distractors (i.e., the “reddest”) (Figure 1A). There must be a boundary to relational inclusiveness, but this has not been established empirically. The optimal gain model instead predicts a shift in the central tendency towards a more negative value (i.e., being “slightly redder” than the orange target) but inclusion within the template of both negative and positive color values are scaled by distance from the shifted central value (Figure 1B). These differences can be visualized as the width of a response filter (Figure 1, left panel) or more generally as similarity matrices that capture the second-order pattern of expected responses (Figure 1, right panel).

Figure 1. Simulated responses to colored stimuli in an experimental context in which the target color is depicted at 0° (e.g., orange) and expected distractors are positive rotations from the target (e.g., “yellower” hues). “Response” refers to any of several possible dependent variables, including the probability of a first saccade to an object or a decision that object is the target. Similarity matrix generated from the same data computed as the absolute difference between responses to each pair of stimuli. Similarity analyses are a particularly useful method to directly compare patterns of data across modalities with different units of measurement (e.g., manual responses, eye metrics, and model estimates) (Kriegeskorte et al., 2008). A) The relational account predicts higher attentional priority, and therefore a greater proportion of behavioral responses, to all features that fit the relational rule that distinguishes targets from distractors such as being the “reddest” object. This results in high similarity in expected responses to all stimuli with negative values, as illustrated by the dissimilarity matrix. C) The optimal gain model predicts a shift in the central tendency of the target representation with all other features are scaled by distance from the center value. This results in scaled similarity for both negative and positive feature values. See Methods (statistical analysis) for a detailed description of how simulated data points were estimated.

One possible explanation for why there appears to be evidence for two theories that ostensibly refer to the same “target template,” is that they derive from studies using different methods. Some use RT or first saccade destinations as the metric of the template (Martin & Becker,

2018), while others use a separate probe task to measure the learned target feature (Navalpakkam & Itti, 2007; Scolari & Serences, 2009; Yu & Geng, 2019). We hypothesize that these differences may tap into different stages of the look-identify cycle: the first saccade reflects early guidance of attention to the best match whereas the probe task requires binary decisions regarding target identity. This leads to an important question of whether attentional guidance and match decisions use the same or different template information during visual search. We hypothesize that guidance might rely on a coarser version of the template and match decisions require a more precise representation (Bravo & Farid, 2014; Martin & Becker, 2018; Rajsic & Woodman, 2020; Wolfe, 2021; Wu et al., 2013).

The template has long been hypothesized to guide attention and eye-movements to potential targets by modulating sensory gain (Desimone & Duncan, 1995; Reynolds & Heeger, 2009; Treisman & Gelade, 1980), but only more recently has it been explicitly postulated to operate on decision processes about the target match as well (Bravo & Farid, 2014; Geng & Witkowski, 2019; Wolfe, 2012). For example, Hout & Goldinger (2015) hypothesized that the target template serves a dual-function to guide attention to potentially relevant items and to compare visual inputs to the memory template for target verification or rejection (see also Rajsic & Woodman, 2020). While such studies have used eye metrics to measure the effect of the template at two time-points within the “look-identify” cycle, few have considered whether the information used during guidance and decisions is the same or different. One exception to this is a proposal by Wolfe (2021) that argues the search template can (and should) be divided into two: a “guiding” template in working memory that is used to direct attention to items that might be the target; and a “target” template in long term memory that is used to determine if a candidate object is, in fact, the target. The idea that there may be two active templates, one for guidance and one for target

decisions is consistent with evidence that it is possible to hold one active template in working memory (to guide search) while holding one or more other target representations in a latent state within working memory or in long-term memory (Olivers et al., 2011; Woodman et al., 2013).

The aim of the current experiments is to test if attentional guidance and target match decisions rely on different information during visual search. Although we frame our hypothesis in terms of a single search template that has two informational formats during guidance versus decisions, the concept is compatible with Wolfe's (2021) characterization of separate templates for guidance and the target memory. Using a visual search task for a target amongst linearly separable distractors, we test the hypothesis that early attentional guidance will be based on relational information (e.g., prioritizing the “reddest” object irrespective of its exact hue) whereas subsequent match decisions will be made against an “optimal” off-target feature (e.g., the slightly redder version of the orange target). If true, this would suggest that attentional guidance operates on a coarser code to weight sensory information and target match decisions use a more precise representation to determine identity. Our findings offer a novel perspective on how template information operates to guide attention and make identity decisions during visual search.

Experiment 1

The purpose of this experiment was to use eye-tracking to investigate whether distinct template information is used during the guidance and decision making stages of the “look-identify” visual search cycle. We use eye data as our main dependent measure of interest to test the hypothesis that guidance (first saccades) will be driven by the *relative* target feature (Figure 1A) but that match decisions (fixation dwell times) will be determined by *optimal* off-target feature tuning (Figure 1B).

Method

Participants. To determine the appropriate sample size for Experiment 1, we first conducted a pilot study with 7 subjects (data were not included in Experiment 1) using the similar methods and procedures. The smallest effect size of the two dependent measures of interest (in this case fixation dwell times, $r = .55$) was entered into G*power calculation (<http://www.gpower.hhu.de/>). The results estimated that $N = 30$ was necessary to detect significant effects ($p = .05$, two-tailed) with a power .9. Therefore, thirty subjects (10 males, 1 left-handed, ages from 18-23) from University of California, Davis participated in Experiment 1 in partial fulfillment of a course requirement. Each participant was provided written informed consent in accordance with the local ethics clearance as approved by the National Institutes of Health. Each participant's color vision was assessed by self-report and an online color blindness test (<https://colormax.org/color-blind-test>). All participants had normal or corrected-to-normal vision and all had typical color vision.

Apparatus. Participants were seated in a sound attenuated room 60cm away from a ASUS MG279Q monitor with a spatial resolution of 1920×1200 pixels and a refresh rate of 60hz. The operating system was Windows 7, and Matlab Psychtoolbox (Brainard, 1997; Pelli, 1997) was used to create all stimuli. Eye movements were tracked using a video based eye-tracking system (Eyelink 1000, SR Research, Ontario, Canada) sampling from the right eye at 500 Hz.

Stimuli. All stimuli were presented against a gray background (luminance = 37.0 cd/m^2). The target (194°) and distractor colors were selected from a color wheel defined in CIELAB color space (a, b coordinates = 0, 0; luminance = 70; from Bae et al., 2015). We used a green-blue border color

as the target color to control for the potential color category effects on responses (Bae et al., 2015). Experiment 1 included three types of trials: 1) *standard* visual search trials to set up expectations for the distractor colors; 2) *critical* search trials to assess how target templates are used during guidance and decision making stages of visual search; and 3) template *probe* trials to measure the template contents independent of simultaneous distractor competition.

Standard visual search trials (Figure 2) were composed of a target and five distractor circles ($3^\circ \times 3^\circ$), located equidistantly along an imaginary circle (diameters: $12^\circ \times 12^\circ$). The locations of all six stimuli were randomly rotated 10 degrees clockwise or counterclockwise along the imaginary circle on every trial in order to prevent fixed expectations of where each stimulus would be located. The color of the five distractors were either all negatively or positively rotated 10 degrees from the target color. The rotational direction (positive or negative) was counterbalanced across subjects, so that each subject only saw one set of distractors (Yu & Geng, 2019). Because the directionality of the distractor colors did not affect performance ($ps > .15$, $BF_{01} > 1.30$), this factor was not included in subsequent analyses to maximize power. For descriptive simplicity, the distractors from the standard search trials (i.e., “trained” distractor colors) will always be referred to as positive rotations from the target. Each object contained either a left or right oriented line (1° of visual angle; black). Participants were asked to report the tilt of the line within the target circle.

Critical search displays (Figure 2) were identical to the standard search displays with only one exception: one of the regular circle distractors was replaced with a dodecagon shape (henceforth referred to as the “critical distractor”) (Martin & Becker, 2018). We used a different shape for the critical distractor because we wished to use the true target color as a critical distractor in order to test how observers responded to it when the template shifts off-veridical. A different shape was used to avoid the presence of two target objects on a single trial. The critical distractor

color was selected from a range of -60° to 60° from the target color, in steps of 15° . This resulted in a total of 9 possible critical distractor colors. Among the 9 colors, the -45° and 45° distractors were focal colors within the green and blue color categories, respectively. Thus, the $\pm 60^\circ$ distractors were beyond the blue-green color category boundary (Bae et al., 2015) and served to interrogate the boundary conditions of the relational and optimal theories.

Probe trials contained a color wheel (12° of visual angle radius; 2.1° of visual angle thickness) defined by the same LAB space coordinates was displayed (Figure 2). The inner colored circle presented at the center of the screen was an enlarged version of where the mouse was pointing at on the wheel. The color wheel was randomly rotated on each presentation.

Figure 2. Example of *standard* and *critical* visual search trials and template *probe* trials in Experiment 1. *Standard* and *critical* visual search trials: Participants were instructed to locate the target color circle and report the line orientation within. A high tone (600 hz) was given for correct responses, and a low tone (200 hz) for incorrect responses. The dashed white squares illustrate the target and the red square illustrates the critical distractor, but were not visible to the participants. Template *probe* trials: participants were instructed to report the target color on the wheel by clicking on its location. The central dot illustrated the color over which the mouse dot hovered. No feedback was provided in the probe task.

Design. Participants completed 20 practice trials before the experiment started. The main experiment was composed of 324 standard visual search trials, 324 critical search trials and 60 template probe trials. Trials were presented in six blocks. The three types of trials were randomly interleaved within each block, with the constraint that there were no consecutive template probe

trials. The locations of the target and distractors were randomly selected on each visual search trial. The target and critical distractor were equally likely to appear at all six possible locations, but the target and critical distractor were never adjacent to each other within a trial. Each search display contained an equal number of left or right oriented lines within the objects. The lines within the target and critical distractor were equally likely to be oriented to the left or right.

Procedure. The target color was presented to the participant before the experiment started. Participants were encouraged to make a fast and precise eye movement, and take their time to make the button press to ensure high accuracy of the manual response. A 9-point calibration was performed at the beginning of the experiment. To ensure that the eyes were fixated on the central square ($.3^\circ \times .3^\circ$, black) at the onset of each search display, each trial began only after gaze was detected within a $1.5^\circ \times 1.5^\circ$ box around the fixation square for 200ms. Upon presentation of the display, participants searched for the predefined target-color circle and reported the line orientation inside by pressing the left or right mouse button with their right hand. The search display was presented until the manual response or up to 10s. Auditory feedback was provided immediately following the responses (600hz tone for correct; 200hz tone for incorrect).

In the probe trials, the color wheel remained on screen until the manual response or up to 10s. Participants were instructed to report the target color on the color wheel by clicking on its location with a mouse. No feedback was provided in the probe trials. A central fixation square was presented for 800-1000ms between trials.

Statistical analysis. The *standard* visual search trials were mainly used to establish expectations for the distractor colors. Overall search performance was high (accuracy: $M = .97$, $SD = .02$; RT:

$M = 1158\text{ms}$, $SD = 309\text{ms}$) indicating that participants had a target representation that could be successfully distinguished from distractors. The data of primary interest therefore included only the *critical* search and *probe* trials; only data from these trials are described in subsequent analyses.

Trials with errors were excluded from the analyses; these included trials in which participants incorrectly identified the orientation of the line within the target color, or the total trial duration exceeded 3 standard deviations of that participant's mean reaction time. This resulted, in a loss of 4.8% of data (see Supplemental materials for full description of error rates and RT data). Furthermore, when the first saccade could not be assigned to a stimulus or when the eye movement never left the fixation region, the respective trials were excluded from the analyses, which led to a further loss of 5.2% data. Trials where the first saccade started more than 1000ms after the trial began were also removed, which accounted for .16% data.

The goal of Experiment 1 was to use eye data to directly compare the relational and optimal models of template shifting during visual search. Although sharing some similarities, the two models make qualitatively different predictions for how *critical distractors*, particularly those from the “negative” (i.e., untrained) direction of the target will be processed. The predictions from the two models, illustrated in Figure 1, were applied to both the proportion of first saccades on the critical distractors as well as fixation dwell times to decide that the stimulus is *not* the target. Specifically, if attention was tuned to the *relative* target feature, first saccades should be captured by all negative critical distractors more than the positive ones (Figure 1A). In contrast, the optimal gain theory predicts that first saccades should follow a Gaussian tuning curve with a peak over an *optimal* off-veridical feature (Figure 1B). We chose the following values for our simulation parameters based on the findings from our previous study (Yu & Geng, 2019): $\sigma = 6$ (width of the gaussian tuning curves), and $\mu = -4$ (mean of the gaussian tuning curves).

In order to statistically compare our results against the theoretical models, we chose to convert each dependent measure of interest (first saccades and fixation dwell times) into a normalized space based on response similarity. Representational similarity analysis (RSA) is commonly used in brain imaging studies to convert data from very different units including brain, behavior, and computational models into a common space for comparison (Kriegeskorte et al., 2008; Nili et al., 2014). Using RSA in this study has several advantages: first, all dependent measures can be compared against both theoretical models without unit conversion or adjustments based on model specific parameters; second, the overall pattern of the data can be established without the need to directly compare single data points (e.g., using a series of t-tests); and third, similarity matrices are “parameter free” and the fit of the data to the theoretical models is determined by a simple correlation between the two patterns.

The primary analysis consisted of converting first saccade and dwell time data from critical search trials into representational dissimilarity matrices (RDM). The value in each cell of the RDM indicates the dissimilarity (inverse of similarity) of the dependent measures between a pair of stimulus conditions (Figure 3B and 3D). For example, if the proportion of first saccades to the -15° critical distractor was about the same as the -30° distractor, similarity would be high irrespective of the actual proportion of first saccades to the -15° and -30° distractors. The diagonal entries are dissimilarity values between identical conditions and are 0, by definition. Once similarity matrices were computed for the first saccades and fixation dwell times, the primary analysis involved correlating each eye data RDM with each of the two theoretical RDMs to determine which of the two models better describe the data. The two theoretical RDMs were not significantly correlated ($r = -0.1, p = .56$). Thus, any correlation between the eye data RDMs and each theoretical matrix cannot be explained by partial correlations with the other.

The significance of correlations between the eye data and theoretical RDMs was evaluated by permutation tests. The null distribution for the correlation was estimated by randomly rearranging the stimulus labels of one of the two RDMs of interests for each participant. Then, we correlated this randomized similarity matrix with another RDM of interest, and computed the spearman correlations between those two RDMs. This step was repeated 10,000 times for each set of data and used to create a null distribution of permuted correlations. The p value of the true correlation was calculated as the rank order of the true correlation in the permuted null distribution. For example, if the real correlation is larger than any of the permuted values within the null distribution, then the p value is estimated as $p < .0001$. We rejected the null hypothesis if the real correlation was larger than the top 500th permuted correlation ($p < .05$).

Results

Analysis of the first saccades that went to the critical distractors. The proportion of first saccades to each critical distractor (Figure 3A) were converted to a representational dissimilarity matrix (RDM) (Figure 3B) for comparison against the relational (Figure 1A) and optimal model matrices (Figure 1B) using a permutation test by randomizing stimulus labels (see Methods). The first saccade RDM had a significantly positive correlation with the relational RDM ($r_{\text{rel}} = .71$, $p_{\text{rel}} = .0001$), but not the optimal RDM ($r_{\text{opt}} = .003$, $p_{\text{opt}} = .44$). In addition, the r values from these correlations were compared against each other using a permutation test and found to be significantly different, $p(r_{\text{rel}} > r_{\text{opt}}) = .0001$, confirming that the first saccade RDM was more strongly correlated with the relational RDM than with the optimal RDM. These results strongly support the hypothesis that early attentional guidance, indexed by the first saccade, was tuned to the *relative* feature of the target, in replication of Becker and colleagues (Becker, 2010; Martin &

Becker, 2018). However, while all negative critical distractors had a high likelihood of capturing attention, the proportion of first saccades to negative distractors did gradually decrease as color similarity decreased, suggesting the strength of capture was weakly modified by color similarity (Figure 3A).

Figure 3. A) The proportion of first saccades to the critical distractors. B) The first saccade RDM averaged across participants. C) The fixation dwell times on the critical distractors. D) The fixation dwell time RDM averaged across participants. All error bars are the 95% confidence intervals.

Analysis of the fixation dwell times on the critical distractors. We next compared the RDM (Figure 3D) converted from the mean fixation dwell times (Figure 3C) against each of the two theoretical model RDMs. The dwell time RDM was significantly correlated with the optimal RDM ($r_{\text{opt}} = .67$, $p_{\text{opt}} = .004$), but not with the relational RDM ($r_{\text{rel}} = .04$, $p_{\text{rel}} = .28$). Additionally, the correlation between the dwell time RDM and the optimal RDM was stronger than between the dwell time

RDM and the relational RDM, $p(r_{\text{opt}} > r_{\text{rel}}) = .0001$. These results demonstrate that the target match decisions, occurring once an object was fixated, followed the optimal tuning mode (Navalpakkam & Itti, 2007; Yu & Geng, 2019). These results were replicated in a second experiment that used a finer grained measurement for near target ($\pm 5^\circ$) critical distractors (see Supplemental materials Experiment 1b). It should be noted that the modulation of color similarity on the fixation dwell times, as presented in Figure 3C, was asymmetrical between the positive and negative directions. The negative distractors appeared to be more difficult to reject as non-targets than the corresponding positive ones, suggesting that the match decisions were more difficult overall in the negative direction, hinting at a contribution from the relational model.

Analysis of the probe performance. The probe task measured the contents of the target template, which are presumed to be held in memory (Giesbrecht et al., 2013; Woodman et al., 2013), uncontaminated by many processes involved in concurrent visual search, such as those necessary for resolving target selection and distractor suppression. The relative click distance from the true target color was divided into 5° bins (Figure 4A) and then converted to an RDM (Figure 4B). As expected, there was a significantly positive correlation between the probe RDM and the optimal RDM ($r_{\text{opt}} = .80$, $p_{\text{opt}} = .004$), but a non-significant correlation between the probe RDM and the relational RDM ($r_{\text{rel}} = -.05$, $p_{\text{rel}} = .48$). The comparison between the r values confirmed that the probe RDM was more strongly correlated with the optimal RDM than with the relational RDM, $p(r_{\text{opt}} > r_{\text{rel}}) = .0001$. This replicated previous findings (Geng et al., 2017; Navalpakkam & Itti, 2007; Scolari & Serences, 2009; Yu & Geng, 2019) that the target representation was shifted away from distractors to enhance optimal off-target features to increase the template-to-distractors distinctiveness (Geng & Witkowski, 2019).

Figure 4. A) Group averages of relative click distance from the veridical target color in the template probe task. Raw data were divided into 5° bins. All error bars are the 95% confidence intervals. B) The probe RDM averaged across participants.

Experiment 2

We concluded from Experiment 1 that attentional guidance and target match decisions rely on a relational and an optimal code, respectively. However, dwell times, which were used to infer decision processes may not have been a pure measurement of target decisions since they were terminated based on a final “non-target” decision that could also rely on shape information. Furthermore, while first saccades are routinely considered reflection of guiding templates, fixation dwell times are a less standard measurement of decision processes. To address this in Experiment 2, we applied the drift diffusion model (DDM) to visual search performance to characterize how accurately and quickly the target was discriminated from distractors. To do this, we modified the search paradigm to include only one target and one distractor, which were always the same shape. Additionally, in order to test the relationship between long-term memory representations of the target and the drift rates, we again included the independent continuous memory probe task. Finding a correlation between the long-term memory of the target color and the target match decision (drift rates) would suggest that the target template held in long-term memory is used to generate target match decisions (Wolfe, 2021).

Method

Participants. To determine the sample size for Experiment 2, we first conducted a pilot study with 25 subjects (data were not included in Experiment 2) using the similar methods and procedures. The effect size for the correlation between drift rates and probe responses ($r = .377$) was entered into G*power calculation and estimated that $N = 69$ necessary to detect significant effects ($p = .05$, two-tailed) with a power .9. We opted for a sample size of 70 to allow counterbalancing of the distractor colors in the standard visual search trials. Data were collected online until we obtained a sample of 70 participants after exclusion criteria (accuracy in the standard search was below 75%) were applied. 40 participants were excluded from data analysis. A large number of outliers was expected due to the fact that the experiment was conducted online and we did not provide any feedback (see Procedures for detailed information). 70 participants (16 males, 6 left-handed, ages from 18 - 31) from University of California, Davis participated online in Experiment 2 in partial fulfillment of a course requirement. Each participant was provided written informed consent in accordance with the local ethics clearance as approved by the National Institutes of Health. Each participant's color vision was assessed by self-report. All participants had normal or corrected-to-normal vision and all had normal color vision.

Stimuli. The experiment was conducted entirely online through Testable (<https://www.testable.org/>). All stimuli were created in Illustrator, saved as PNG files and uploaded to Testable.org. Although we expected colors to vary when viewed on different monitors, the relationship between the target and distractors was expected to present across participants. Variability was expected to disadvantage our ability to detect the hypothesized optimal pattern in

the data since the optimal pattern requires greater precision in distinguishing colors. All stimuli were presented against a gray background (color hue = ‘#808080’). The target and distractor color (10°) in the *standard* visual search trials were identical to Experiment 1. Each search trial (Figure 5) consisted of two bilaterally presented target and distractor circles (radius: 135 pixels) at the center of the screen (distance between the centers of the two circles: 400 pixels). The two directions of distractors were again counterbalanced between subjects and because there were no spurious differences ($ps > .45$, $BF_{01} > 3.2$), the data were collapsed in all subsequent analyses. The *critical* distractor set was constructed in steps of 5° from the target color to 60° positive or negative rotations from the target color, resulting in a total of 24 distractor colors.

The color wheel in the *probe* trials (Figure 5) was divided into 72 bins (5° per bin) and each bin had a number attached. Participants reported the number of the color wedge that best matched the target color in memory. There was a total of six possible rotations of the color wheel.

Figure 5. Example of *standard* and *critical* visual search trials, and template *probe* trials in Experiment 2. Participants were instructed to locate the target color circle and press the respective mouse button. On probe trials, participants typed the number corresponding to the estimated target color bin. There was no feedback given on any of the trials.

Design. Participants completed 20 practice standard visual search trials with feedback before the main experiment started. The main experiment was composed of 144 standard visual search trials, 144 critical search trials and 12 template probe trials. The three types of trials were presented in 12 blocks and randomly interleaved within each block, with the limitations that the probe trials only appeared after the standard search trials, and that there were no consecutive probe trials.

Procedure. An example of the target color was presented prior to the beginning of the experiment. On search trials, participants were instructed to indicate whether the target color appeared at the left side by pressing the left mouse button or at the right side by pressing the right mouse button. The stimuli appeared on the screen for 500ms and participants had up to 5s to make their responses. On probe trials, participants were required to type the number of the color wedge that best matched the target color in memory in a response box at the bottom of the screen. The color wheel would remain on the screen until response. Because Experiment 2 used a 2AFC design to measure the decision process through the pattern of choices and response times, we did not provide any feedback in the critical search trials to keep the responses unbiased from feedback. In order to equate the absence of feedback, no feedback was given in the other two types of trials as well. After responses, a central fixation cross was presented for 800-1200ms before the next trial started. Participants were instructed to fixate on the center cross when no stimuli were presented on the screen.

Statistical analysis. Consistent with Experiment 1, the goal of the standard search trials was to set up expectations for the distractor colors. Overall performance was significantly higher than chance (accuracy: $M = .89$, $SD = .07$; RT: $M = 583\text{ms}$, $SD = 106\text{ms}$), suggesting that these participants held an effective target representation. Trials were excluded when search RTs were below 200 or above 2500ms, or when the responses in the probe task were outside of the blue-green color range, which accounted for a total of 2% of the data.

The main analysis consisted of modeling visual search performance (error rates and RT; Figure 6) from the critical trials using a drift diffusion model (DDM). The separation between the two decision boundaries (a) and the non-decision time (t) were estimated as fitted free parameters that were the same across color distractor values for each subject while the drift rate (v) was estimated as a free parameter per distractor condition. There was no theoretical reason to believe the decision boundary and non-decision time should vary between critical distractors (see Supplemental materials). Instead, we were interested in how the drift rate (v), which characterizes the accumulation of noisy evidence over time until one of two decision boundaries is reached, differed across conditions (Ratcliff & McKoon, 2008). Drift rates in this experiment represent how easily the target can be distinguished from the distractor: Higher drift rates indicate stronger evidence, whereas lower drift rates suggest weaker evidence.

All parameters were estimated using a hierarchical Bayesian parameter estimation method. The hierarchical approach is particularly useful for this study given the small number of choices and RT values measured per subject (due to constraints in online experimentation) because it captures commonalities across individuals and at the same time estimates each individual's parameter values (Ratcliff & Childers, 2015). To perform hierarchical DDM, we used the Python-based toolbox, HDDM (Wiecki et al., 2013). The HDDM model was fit to accuracy-coded data

(i.e., the upper and lower boundaries correspond to correct and incorrect responses, and the starting point was fixed at 0.5).

For each participant's data, we used Markov chain Monte Carlo (MCMC) sampling methods to estimate the posterior distribution of each parameter. Each chain was run with 10000 samples, with the first 5000 warm-up samples discarded as burn-in. A total of 5 chains were run. Convergence was assessed by computing the Gelman-Rubin $\hat{R}$ statistic for each parameter. If the samples of the different chains converged, the $\hat{R}$ statistic should be close to 1. The range of $\hat{R}$ values across all group parameter estimates was between 0.99-1.10, suggesting satisfactory convergence. Goodness of fit was visually inspected with the posterior predictive check method (Figure 6).

Figure 6. Error rates and RTs from the critical visual search trials. The black dashed lines represent the "fitted curves" for error rates and RT from the DDM for the best fit DDM parameters. The model fits illustrate the fact that the DDM captured the pattern of RT and accuracy well, rendering interpretation of the drift rates reasonable. All error bars are the 95% confidence intervals.

Results

Analysis of the drift rates. Figure 7A shows the group mean posterior estimates of the drift rates for each search condition. Following the analysis strategy from Experiment 1, each subject's drift rates were converted to a dissimilarity matrix (Figure 7B) for comparison against the relational

and optimal model matrices (Figure 1) using a permutation test by randomizing stimulus labels. The theoretical RDMs were upsampled to match the number of conditions in the drift rate RDM. The two theoretical RDMs were only weakly correlated ($r = .12, p = .05$). The drift rate RDM was significantly correlated with both theoretical RDMs (optimal: $r_{\text{opt}} = .77, p_{\text{opt}} = .0001$; relational: $r_{\text{rel}} = .22, p_{\text{rel}} = .005$), but the correlation with the optimal RDM was significantly greater than the relational RDM ($p(r_{\text{opt}} > r_{\text{rel}}) = .0001$). As shown in Figure 7A, the drift rates for positive critical distractors were larger than that for negative distractors overall but there was a monotonic increase in drift rates for both negative and positive distractors as they became more dissimilar from the target. Interestingly, the nadir was at the -5° distractor and the drift rate was negative. This indicates that the accumulation of evidence was slow and the “wrong” decision was made more often than not. These results support the conclusion that the target match decisions were strongly modulated by the similarity to the optimal off-target feature centered over -5° , but there was also an overall directional bias. The blend of both models in these data are not unexpected given the dependent variable here involves accuracy and RT data, which would include combined effects of covert attentional guidance and decision processes, but it is noteworthy that the optimal model explained significantly more variance in the results.

Figure 7. A) The drift rates for different critical search conditions. All the error bars are the 95% confidence intervals. B) The drift rate RDM averaged across participants.

Analysis of the probe task. The color wheel was composed of 72 color wedges sampling color hue in steps of 5° . Therefore, the relative click distance from the veridical target color was divided into 5° bins (Figure 8A) and then converted to an RDM (Figure 8B). The probe RDM was significantly correlated with both theoretical model matrices, $r_{\text{opt}} = .56$, $p_{\text{opt}} = .0001$, $r_{\text{rel}} = .11$, $p_{\text{rel}} = .001$. The comparison between the r values from these correlations confirmed that the probe RDM was more strongly correlated with the optimal RDM than with the relational RDM, $p(r_{\text{opt}} > r_{\text{rel}}) = .0001$. These results converged with Experiment 1, suggesting that the target representation was shifted away from distractors to enhance optimal off-target features.

Figure 8. A) Group averages of relative click distance from the veridical target color in color wheel probe task. All error bars are the 95% confidence intervals. B) The probe RDM averaged across participants.

Correlation between performance on the memory probe and search tasks. Next, we conducted a correlation analysis on individual differences between how well the probe data match the optimal RDM and drift rates. A positive correlation between these two metrics would suggest that individuals whose responses on the probe task were closer to the optimal model also made faster and more accurate decisions about which of the two objects was the target during visual search. First, the correlation between each subject's probe matrix and the optimal RDM from above was

used as a measurement of how well their target templates fit the optimally tuned template. Second, new drift rate parameters were estimated for each subject with data collapsed across color directions (negative, positive) in order to reduce the feature space (cf. a drift rate parameter per distractor color). The resulting correlation values were then correlated with their drift rate parameter from visual search. We found that participants who had more optimally tuned templates showed faster drift rates, reflecting an easier discrimination of target from distractors, with both negative and positive distractors (negative: $r = .28, p = .02, BF_{10} = 3.50$; positive: $r = .35, p = .003, BF_{10} = 14.70$). These results highlight the underlying relationship between the target decision processes and the target color held in long-term memory over time.

Figure 9. The relationship between the goodness of fit of each participant's template to the optimally tuned template and the drift rates during visual search.

General Discussion

The purpose of these experiments was to test hypotheses of how template information is used during guidance and decision stages of visual search. Using a visual search task for a target amongst linearly separable distractors, the results demonstrate that early attentional guidance was a coarse process mainly based on “relational” sensory information, whereas subsequent match decisions were compared against a more precisely tuned template centered on an “optimal” off-

target feature. Although previous studies have found evidence for coarse guidance (Kerzel, 2019; Martin & Becker, 2018) and precise decisions (Rajsic & Woodman, 2020) separately, our experiments provide direct evidence that the informational content of a single target object is used differently on these two subprocesses of visual search.

There is a long history of work showing that the contents of the template can bias the deployment of attention and saccades towards potential targets (Chelazzi et al., 1998; Olivers et al., 2011; Soto et al., 2008). Recent research has shown that the template may not be precisely centered over the specific target feature, as previously assumed, but instead be shifted to increase the distinctiveness of the target from distractors (Hodsoll & Humphreys, 2001; Navalpakkam & Itti, 2007; Scolari & Serences, 2009). In line with Becker and colleagues' relational account (Becker, 2010; Martin & Becker, 2018), the eye data in Experiment 1 showed that all negative critical distractors that were relational matches captured attention and first saccades more strongly than positive distractors. Thus, attention appears to be initially guided by the relative feature of the target, not specific feature values. This coarse representation of the target might be well suited for rapid stimulus prioritization under noisy sensory conditions, e.g., when many stimuli are in peripheral vision where color and spatial acuity are poor (Hulleman, 2010; Hulleman & Olivers, 2017; Rosenholtz, 2017).

Once one item is selected, however, a decision must be made regarding the exact identity of the stimulus as a match or non-match to the target. Unlike attentional guidance, the importance of this decision process on visual search has only been explored more recently (Hout & Goldinger, 2015; Malcolm & Henderson, 2010; Rajsic & Woodman, 2020). In the current study, we used fixation dwell times (Experiment 1) and the DDM drift rates (Experiment 2) as measurements of target-match decisions. The optimal model fit both dwell times and drift rates, indicating that the

decision process operates on an optimally shifted and precisely tuned template. The precision appears necessary for accurate decisions to be made and the shift increases the target-to-distractor discriminability to speed decisions.

It should be pointed out that although the first saccades were better described by the relational model and the dwell times and drift rates were better described by the optimal model, both sets of data showed hints of the other pattern. Therefore, it is possible that guidance and decision are influenced by both relational and optimal tuning, but the relative bias towards one or the other is weighted by the pressure to perform fast guidance or precise decisions. These results raise an open question about whether guidance and decisions during the visual search cycle operate using two discrete representations or a single, flexible template that is weighted by the exact computation required at each stage of visual search.

Both ideas, that of separate templates and that of flexible weighting of a single template source are present in the literature. For example, Wolfe and colleagues suggest that there is a “guiding” template in working memory and a separate “target” template in long term memory to guide search when there is a large (>100) number of potential targets (Cunningham & Wolfe, 2014; Wolfe, 2021). Our results are compatible with this framework, and further suggest that the target template in long-term memory serves as the template on which match decisions are made. Participants who established more optimally tuned target templates in long-term memory had higher drift rates, suggesting that decisions during visual search are directly related to the off-veridical target representation in memory (Geng & Witkowski, 2019; Lleras et al., 2020). This finding is consistent with the characterization of target templates held in long-term memory in Guided Search 6.0 (Wolfe, 2021), in which a potential target in working memory selected by the

guiding template is compared against a target template held in long-term memory through a drift diffusion process.

Our findings also recall the literature surrounding questions about how active representations are used in working and long-term memory to guide attention during visual search. Our results are consistent with the finding that stable search targets are stored in long-term memory, and that this information can be used for target match decisions (Carlisle et al., 2011; Woodman et al., 2013). We do not have a position at this time on whether relational guidance is based on an active working memory template that is separate from the optimal memory representation of the target, or whether relational guidance reflects a coarser manifestation of the same target template in memory. The former is a possibility given that one target representation can be held in active working memory while the other is held as an accessory or latent item in working or long-term memory (Olivers et al., 2011; Woodman et al., 2013). The latter is also a possibility given findings that there are versions of a single target representation in multiple brain regions, with the exact computation done on the target information being dependent on the stage of processing (Lee et al., 2013; Long & Kuhl, 2018). Another possibility is that participants simply set different criteria on a single template for each stage of processing: a liberal criterion to broadly capture all potential targets in the visual field (possibly also accounting for acuity degradations in peripheral vision), and then a more conservative criterion for more precise decisions. Future work is necessary to determine the exact mechanisms by which guidance and decisions operate on different information patterns. Finally, the current findings were based on the special case of search for a target amongst linearly separable distractors. Real-world search targets, however, are infrequently linearly separable from distractors. The generalizability of our findings

should be further investigated under more typical conditions to determine if the differences in the precision of guidance and decision are a general property of visual search.

Taken together, our findings suggest that the target template operates distinctively during guidance and decision stages of visual search. Early attentional guidance is a coarse process to weight sensory information, but later match decisions depend on a more precise representation of the target to efficiently determine identity. To return to our example of searching for a tiger in the grasslands, our results suggest that out in the field, guidance is coarse and will select anything that might be a tiger. In contrast, once attention has selected an object, an optimal target template is more useful for deciding if the object is indeed a tiger, or not. Although we are not able to fully address whether the information source for the two stages of processing is identical or separate with only the current behavioral data, the results offer a resolution to the debate in the literature over how template information is shifted in response to expected distractor features.

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