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Dynamic Modeling of Visual Search

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Abstract

In 1998/1999 three participants trained for up to 74 hour long sessions to find a target in visual displays of 1, 2, or 4 objects. There were four targets and four foils that never changed. Displays occurred simultaneously, or the objects occurred successively, or the features of each object occurred successively. When successive, the SOAs were short (17, 33, or 50 ms) so the displays appeared simultaneous, making it likely that the search strategy was the same in all conditions. A 2004 publication examined only the simultaneous condition and found evidence for serial search as well as some small amount of automatic attention to targets, and occasional early or late search termination. A 2021 publication examined only the displays with single objects, obtaining evidence for dynamic perception of features. Building on these results we present a simple dynamic model that explains the main processes operating in all the experimental conditions.

Keywords: visual search; serial search; mathematical modeling

Introduction

An enormous literature has examined the processes of visual search (e.g. to pick a few examples from thousands: Eriksen & Hoffman, 1972; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977; Treisman & Gelade, 1980; Wolfe, 1994; Geisler, Perry & Najemnik 2006; Huang, Theeuwes, & Donk, 2021). Many of the studies have used static displays with binary decisions about target presence or absence: A target object is defined, and a display of N objects is presented, usually half the time containing the target and half the time not (in which case the display has all 'foils'). A binary response is made and its accuracy and response time are measured. The studies have identified a large number of factors that determine how search proceeds. Often, search is serial in nature, each object being assessed one at a time in turn, usually when search is difficult (for example when a conjunction of features is required to determine whether an object is a target or foil; e.g. Schneider & Shiffrin, 1977; Wolfe, Cave & Franzel, 1989). Sometimes, search is parallel, usually when search is easy (e.g. Shiffrin & Gardner, 1972; Treisman & Gelade, 1980), or when sufficient consistent training allows attention to be drawn automatically to a target (Shiffrin & Schneider, 1977; Shiffrin, 1988), or when abrupt onset of a stimulus draws attention (Yantis & Jonides, 1996). Occasionally, possibly always, search is a mixture of serial and parallel processes (e.g. Shiffrin & Czerwinski, 1988; Wolfe, 1998). Evidence from these various publications notwithstanding, it is notoriously difficult to establish whether search is fundamentally serial or parallel (Townsend & Nozawa, 1995.).

In an effort to explore the temporal aspects of search, two of the present authors carried out in 1998/1999 a visual search study with dynamic displays. The eight stimuli, four of which were targets and four foils, were initially novel and had four features each (see Figure 1). The stimuli and target-foil assignments never changed during training sessions (up to 74 one-hour sessions). The objects and features of the objects appeared in three types of conditions, each with display sizes of 1, 2, and 4: 1) simultaneous displays (the usual method); 2) displays in which the objects appear in sequence; 3) displays in which the objects appear simultaneously, but the features of the objects appear in sequence.

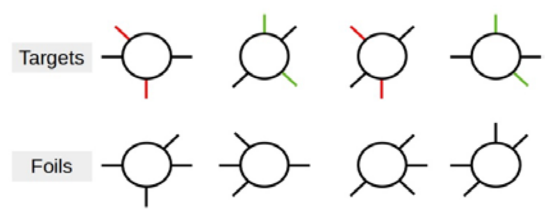

Figure 1. Experimental stimuli.

The stimuli were initially novel, so the search results would be minimally influenced by prior life experience. Extensive training was used so that the objects and their features would become extremely well learned, analogous to alphabet characters. Thus the aim was to understand search when the stimuli in the visual displays were well learned. In this report we analyze and model the results from two participants who completed seventy-four hour-long sessions, and one who completed 55 hour-long sessions. The stimuli are shown in Figure 1. Each consisted of a circle with four spokes extending in various directions. The four features defining targets and foils were chosen so that no single feature would discriminate targets from foils. Instead each target was defined by a conjunction of two features, the same two features for two of the targets and a different two features for the other two targets. These perfectly diagnostic features are highlighted in red and green in Figure 1, but were not color-highlighted in the actual study. When a single salient

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feature discriminates targets from foils, search is often described best by 'pop out' with search time and accuracy largely independent of display size, even for untrained stimuli (e.g. Treisman & Gelade, 1980). When targets and foils are discriminated by a conjunction of features, search tends to be strongly dependent on display size, with time approximately linearly increasing, albeit extensive training can produce occasional automatic attention to targets, short-cutting serial search (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977; Shiffrin, 1988; Wolfe, et al., 1989).

Cousineau and Shiffrin (2004) published an initial analysis of the 1998/1999 data based only on the simultaneous conditions, an analysis focusing particularly on the distributions of response times. The distributions for target responses had multiple modes when display sizes were 2 or 4, strongly suggesting serial search (the modes corresponding to a target being assessed in the first, second, or later serial position). More subtle aspects of the distributions suggested that two of the three participants on some trials had their attention attracted automatically to the target (so the target would be compared early, with a higher than random probability). Additional analyses suggested that the participants sometimes terminated search early on trials without a target, suggesting a small amount of fast guesses (Eriksen, 1988; Gondan & Heckel, 2008).

Harding, Cousineau, and Shiffrin (2021) examined and modeled the 1998/1999 conditions *in which only one object appeared*, but features appeared either simultaneously or one at a time. Again, using both accuracy and response time distributions, they obtained evidence that the features of the displayed object were perceived individually as time passed, rather than together as a group. Thus different features were perceived at different times. Their model assumed that each feature was independently perceived at an exponentially distributed time after the moment of presentation (the exponential assumption was made for convenience). Evidence was obtained that this dynamic perception took place even when the features arrived simultaneously (i.e. different features were perceived at different times). These stimuli were trained for a huge number of sessions, likely causing them to be learned holistically. If so it could be surprising that the features were perceived at different times. However, Harding et al. (2021) did obtain evidence for holistic/configural processing, but only after a sufficient number of features had been perceived. Thus processing occurred in stages, starting with individual features perceived separately and then, for well learned stimuli, coalescing into configural wholes (see also Cox & Shiffrin, 2017).

The evidence obtained by Cousineau and Shiffrin (2004) and Harding et al. (2021) was strong but based on subtle aspects of the response time distributions. We present a rather simple dynamic model in this article that is able to predict the main effects of accuracy and median response time for all the conditions of this study, without incorporating the subtle effects inferred from these two prior reports from the response time distributions. We believe that this demonstration is valuable because the processes of this simple model implement the main processes at work and explain most of the variance in the results. The demonstration that this model predicts the data quite well suggests that the medians of the response time distributions are a decent 'stand-in' for the entire distribution. If we did produce a model that included the various processes inferred from the analyses of the response time distributions, the model would be sure to fit well, but would be extremely complex. Such a model would make it difficult to ascertain the main processes at work: It would be difficult to see the forest for the trees.

Thus we present in this article a simplified model. It assumes that serial search is performed in a random order in all conditions except those in which the objects occur sequentially. In those conditions the model assumes that there is a tendency to start the search with the first object presented, the probability of doing so rising with longer SOA. Whatever object is chosen for the first comparison, the model for that comparison is based on the one presented in Harding et al. (2021). That should be appropriate because that model was applied to the conditions with a single object presented.

Method

The data we model in this paper is part of a large study exploring the dynamic aspects of visual search. The data were collected in 1998 and 1999 by Denis Cousineau and Richard Shiffrin. The number of objects presented on a trial was 1, 2, or 4. Half the trials contained one target and otherwise foils, and half contained no targets and all foils. The four targets and four foils never changed as the participants carried out visual search for a very large number of hour-long sessions. These eight stimuli were initially novel but were quickly learned.

Stimuli

Figure 1 shows the four targets and four foils. Each stimulus consisted of an empty circle with four spokes (the features) coming out of the circle at different angles. The four spokes could be placed in eight different positions on any given circle. The four features defining targets and foils were chosen so that no single feature would discriminate targets from foils.

Participants

Six participants participated in the experiment, but only three of them completed a sufficient number of trials to be included in the present analysis and modeling. Participants were instructed to respond as quickly as possible without exceeding 5% error rate. Participants A and D were women. Participant C is the second author. All three were right-handed. Participants A and D were uninformed of the sequential presentation manipulations. That the stimuli were well learned was shown when Participant C demonstrated practically perfect transfer of search ability after a 22 year delay (Maxcey, Shiffrin, Cousineau & Atkinson, 2021).

Procedure

Each trial included one, two or four displayed items. Half of the trials included a target object, and half only foils, the probability of each being 0.5. Targets and foils were selected randomly from their respective sets of four, and in positions that varied randomly from trial to trial. The objects were presented in four positions occupying the corners of an imaginary square with a central fixation point. After a 500 ms. signal that the next trial is starting, empty circles were presented for 500 ms. in the positions in which that trial's objects were going to appear. Then the objects, or the features of objects first appeared. Participants were instructed to give a binary decision to indicate whether a target object was displayed or not using the keys “1” and “2” of the numeric keypad of a regular keyboard.

Sessions with simultaneous presentations were randomly interleaved with sessions with sequential presentations. In the sequential sessions analyzed and modeled in this article, trials were randomly selected to be one of two types: The objects occur sequentially or the objects occur simultaneously but with features that occurred sequentially. When objects or features occur sequentially the SOA was either 17, 33, or 50 ms.; these SOAs were permuted randomly to occur with equal probability. In the sequential object conditions the target could be first or last; in the sequential feature conditions the two diagnostic features could be first or last, these conditions also being randomly ordered. Figure 2 shows an example for a foil trial with simultaneous objects but sequential feature presentations.

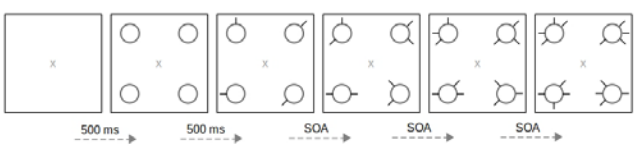

Figure 2. Example of a sequential feature presentation trial

The sessions containing the data analyzed and reported here were sessions 33 to 74 for Participants A and C, and sessions 33 to 55 for D, in addition to the odd-numbered sessions between 1 and 32 for all participants. Even-numbered sessions prior to session 32 included a different detection task that is out of this report scope.

The three SOA values were short enough that all the sequential displays would appear simultaneous, making it likely that the search strategies would remain invariant across the various simultaneous and sequential conditions. Subjective reports by the participants indicated the perception of simultaneity remained even at the end of very many sessions of training (one naive participant noticed that the display occasionally felt blurry).

Results

Figures 3 to 6 show median response times and average accuracy values for target and foil tests, for set sizes of 1, 2, and 4, for simultaneous conditions, object sequential presentation conditions with three SOAs (with target presented first or last) and feature sequential presentation conditions with three SOAs (with target features presented first or last). Median response times are reported and modeled because some conditions had insufficient data to justify detailed distributional analysis and modeling. On the other hand, the large number of training sessions contained enough data for each of the three participants to make the accuracy and median RT results we mention in this section highly statistically significant. With respect to this issue we emphasize that our goal is a model that captures the major processes at work in this study, a model that will match the qualitative patterns observed, not a model that will predict the results precisely.

Figures 3 (simultaneous conditions) and 4 (sequential object conditions) show the results for accuracy (probability of correct response) and median response time. In both the simultaneous and sequential conditions, targets had lower accuracy than foils. This could reflect a bias to respond ‘foil’ when early comparisons do not find a target. In addition, targets had faster response times than foils, a result that in part could reflect the bias in the prior paragraph, but the more important cause of this result would be search that is serial and terminates when a target is found: On a target trial comparisons stop when a target is found; on a foil trial comparisons continue through all the objects.

Strong evidence for serial search was reported by Cousineau and Shiffrin (2004) when they showed multiple modes of the RT distributions for targets, presumably reflecting termination at different comparisons. Here serial search is seen in the large increase in response times as set size rises from 1 to 4.

These figures illustrate differences among the three participants. Participant A exhibits uniformly higher accuracy and slower response times than C and D. Most striking, in the sequential object conditions, the results for participants C and D exhibited higher accuracy and faster responses when targets were presented first, and this result increased with SOA. In the modeling it is assumed that there is a tendency for these participants to start serial comparisons with the first presented object, a tendency that rises with SOA. In contrast, Participant A did not show much tendency if any to respond better and faster when targets arrived first. It may be that A was motivated to maintain accuracy at all costs, and in order to do so, decided to compare in an invariant chosen order on all trials. If so, that suggests that the tendency to start comparisons with the first arriving object, i.e. search governed by onset, is not a completely automatic process, and can be controlled by a participant.

Figures 5 and 6 present the data from the sequential feature conditions. In these conditions features appear sequentially but on all objects simultaneously: e.g. the first feature appears on all objects simultaneously (see Figure 2), and the same for subsequent features. Thus order of comparisons should be treated as random for all three participants. The median RT results are straightforward: They rise with set size and SOA, targets are faster if target features arrive first, and foils are faster if foil diagnostic features arrive first. Such results are natural because increases in SOA will delay the average arrival time of diagnostic features, and more so when those features are last to appear.

Participant A maintains high accuracy, as always, with a slight tendency to be less accurate when the target features arrive last. It appears that for the most part participant A waits to perceive most (or all) of the features in order to decide. The accuracy results are more complex and more variable for Participants C and D. Generally accuracy drops with set size. Averaging across the variable results, accuracy varies with SOA in a way that reflects the RT results, though inversely: Targets are more accurate when target features arrive first; foils are more accurate when foil features arrive first. It is best to interpret the results with the help of the modeling.

Modeling

As warranted by the data described earlier, and as is usually the case in visual search studies when target identification requires a conjunction of two or more features, we assume serial terminating search (e.g. Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1997): The visual objects are compared one at a time, with a decision to stop and report when a target is identified; when no targets are found a foil report is made. When set size is greater than one, it is assumed that the order of comparison is random, with one exception: when objects occur sequentially, there is a tendency to compare first the object that arrives first. This tendency is represented by a probability that rises with SOA is more evident in subjects C and D, and is estimated separately for each participant and each of the three SOAs. There are thus three onset parameters to be estimated.

Whatever object is first compared, the model for that comparison is the one published by Harding et al. (2021): That model is quite complicated because their evidence showed that features arrive dynamically at probabilistically determined times, even when the features are presented simultaneously. In addition the model has to take into account the diagnosticity of the features as they appear, the possibility of error, and all of the calculations are different at each SOA when features are presented sequentially. Incorporating that model into the present one would have made the model extraordinarily complex, making it difficult to understand the main processes at work. Thus we decided to simplify by using that model for the first comparison for the three participants, for every trial, and for every condition.

However, there was one complication in doing so. The Harding et al., model was fit to the response time distributions, and the present modeling only predicts median response times. It turns out that the 2021 model systematically overestimated the median response times, because the assumption (made for simplicity) that feature arrivals were exponential produced a predicted RT distribution that did not precisely match the observed distribution. Consequently, we decided it would be best to use the 2021 model, but re-estimate the parameter values based on a match to the median RTs rather than a match to the distributions. We then used these parameter estimates to produce predictions for every first comparison in the present modeling. The result was an excellent account of the data. It is that version of the model reported here. We attempted another model where response times and accuracy values of first comparisons were fitted, not borrowed from Harding et al. predictions. This model produced predictions that were qualitatively similar to those for the model reported here, but were somewhat less accurate quantitatively. The predictions of that model can be found on this archived version: *https://doi.org/10.23668/psycharchives.12560.*

The second assumption is that the time needed by a participant to finish the first comparison and make a decision is long enough that all objects and their features have been fully perceived by the time the second comparison takes place. For each participant, each comparison after the first is assumed to have an accuracy PT+ and PF+ for a comparison of a target and foil, and a median response time of T+ and F+ for correct responses. (We do not predict error response times because there were too few errors). Thus seven parameters were estimated for each participant.

To predict the accuracy and median response times for the various conditions it is necessary to consider all orders of comparison, all differences in order of presentation, all differences in diagnosticity of features at each stage, and all possibilities of errors for a comparison. For example, in the sequential object conditions, the first object may or may not be compared first, and in either case the results will differ depending on whether the target appears first or last; in addition, the possibility of error in comparison means that some target comparisons will be missed and some foil comparisons will be seen as targets, ending search.

Table 1: Estimated parameter values

		Participant		
	Parameter	A	C	D
p1	onset prob. for SOA 17	0.14	0.21	0.42
p2	onset prob. for SOA 33	0.14	0.35	0.63
p3	onset prob. for SOA 50	0.17	0.51	0.66
For comparisons after the first:				
T+	median RT for target	296	202	238
F+	median RT for foil	195	114	138
pT+	mean target accuracy	0.98	0.89	0.91
pF+	mean foil accuracy	1.00	0.98	1.00
Response time SSE		51	104	75
Accuracy SSE		55	227	443.5
Objective value (z)		106	331	518.5

To predict response times and accuracies jointly, we set the objective function to be the sum of squared differences between observed and predicted response times and observed and predicted accuracy values. The sum of squared differences was standardized for response times and weighted for accuracies to maintain comparable scales for both measures. The optimization program was constrained to ensure that the onset probabilities for participants C and D increased with SOA. Parameter values were estimated for each subject separately using a nonlinear optimizer "Ipopt" that was available through the Julia programming language (Bezanson et al., 2017). The parameter values that produced the best fit by this criterion are given in Table 1.

Model Assessment and discussion The predictions of the model (Figures 3-6) are qualitatively excellent, matching all the trends in the data, save for some variability that produces non-monotonic trends in a few conditions (these would be hard to predict for any model). Most of the predictions are pretty close quantitatively as well, though the task of the modeling was eased by fitting only median response times rather the entire distributions.

The present model is quite simple because most of the complex and interesting aspects of the visual search and decision processes occur during the first comparison, and the first comparison predictions were borrowed from Harding et al. (2021). That publication should be accessed for complete details and discussion, but we mention here just a few key aspects of the processes operating in the first comparison. The features of the first object compared are not perceived at once, but rather are perceived sequentially as time passes, so that different features are perceived at different times. At each moment the evidence for the object being a target or foil is determined by the current set of features perceived. That evidence will therefore depend on which features with what diagnosticity are perceived at different times (which will vary in accord with sequential conditions and timing). When enough features are perceived, they merge and operate configurally as a whole. Evidence accumulates until one of two decision criteria is reached. When there is only one object in the display a response is given in accord with that decision. Note that the decision criteria reached is not always the correct one. Thus for any display size the response made is usually but not always correct.

To use the Harding et al. model in the present modeling one needs to know which object is first compared. This is a random choice except in the object sequential conditions: In that case there is a probability of starting with the first object presented, a probability that rises with the SOA particularly for subjects C and D.

Although most of the model complexity lies in the first comparison, most of the variance in accuracy and response time lies in the set size effects and the order of comparison (and the way order interacts with target presented first or last in the object sequential condition). The first comparison predictions for the Harding et al. (2021) model show very little variation in accuracy and limited differences in response time: Most of the RT differences across conditions are quite small except for the feature sequential conditions when SOA is 33 and especially 50 ms. This latter result is unsurprising given that an accurate decision requires waiting until sufficient features are perceived. In this article we were interested in using a simplified model to capture the major processes that produce the largest effects, and these are due mostly to the choice of object for a first comparison (for participants C and D specifically) and the large effects of successive comparisons for sets sizes 2 and 4.

After the first comparison, matters become extremely simple, at least to a good approximation. We assume that by the time the first comparison is complete, all the objects and features of the current trial are fully perceived. This is a reasonable assumption because even the shorter comparison times after the first take more than 200 ms (see Table 1), and even the largest SOA only adds at most 150 ms to the first comparison. Thus after the first comparison we assume simple serial terminating search takes place, with some probability of correct comparison for targets and foils, and some time for a correct response for targets and foils. Thus all three participants have these four estimated parameter values.

A look at the estimated parameter values reveals some interesting results. The probability of a correct comparison is very high, as expected for stimuli and a task trained this extensively. Nonetheless there seems to be a bias for responding 'foil' because the probability correct for comparisons after the first is lower for a target trial than a foil trial. This hypothesis is strongly reinforced by the estimated time to respond correctly: This time is almost twice as high for responding to a target than a foil. Note that this difference is inconsistent and mostly missing for the first comparison, as shown by the predictions from Harding et al. (2021). A bias to respond 'foil' quickly after the first comparison would be natural for serial terminating search: As each comparison fails to find a target, the evidence mounts that the trial is a foil trial. For simplicity, the model estimates equal correct response times for all comparisons after the first. However, it would not be surprising if the bias to give fast foil responses rises as successive comparisons result in no target. We could have estimated different values of accuracy and response time for each successive comparison at the cost of four extra parameters per participant but this would have been a pointless exercise given the rather good predictions shown in Figures 3 to 6.

The probability of starting comparisons with the first object presented clearly rises as SOA increases. Such a result was expected, and is quite reasonable. The surprise was participant A who did not seem to respond strongly to onset and might have stuck with a predetermined order of processing.

For participants C and D, in the feature sequential conditions, there are strong effects of target features first or last (there is some indication this holds for participant A as well, for accuracy, but the high levels of accuracy for A make it hard to see such effects). The model of Harding et al. (2021) explains such effects due to the assumption of dynamic search: The momentary evidence is based on the features currently perceived. Thus target features first will produce evidence favoring target decisions. Target features last will do the opposite.

For the object sequential conditions there are strong effects of order for participants C and D—accuracy is higher and response time lower when a target appears first, and these effects are magnified as SOA increases. The model predicts such results because these participants are assumed to have a higher tendency to start comparisons with the first object that appears, a tendency that rises with the SOA.

Particularly for sets sizes of 2 and 4 the data exhibit a bias to respond more accurately and much faster for foil trials than target trials. The model predicts these effects for comparisons after the first with appropriate parameter values: Foil comparisons have higher estimated accuracy and much lower estimated response times. As mentioned earlier this bias is natural given that every successive comparison judged to be a foil increases the probability that the current trial is a foil.

In sum, it seems clear that this simple model, serial terminating search with a tendency for two participants to start search with an object that appears first, and with the first comparison predictions borrowed from Harding et al. (2021), captures the main findings from all the conditions of the 1998/1999 study. It does ignore certain processes that are evidenced by careful analysis of the distributions of response times, such as those reported by Cousineau and Shiffrin (2004) for the simultaneous conditions, such as a tendency for some participants to start comparisons with a target, and a tendency for some participants to terminate search early with a foil response. These effects may be valid but are very small in the larger picture. A more complex model with many more parameters to represent these processes could be fit to the data including the full distributions of response times. However the predictions would be hard to improve significantly.

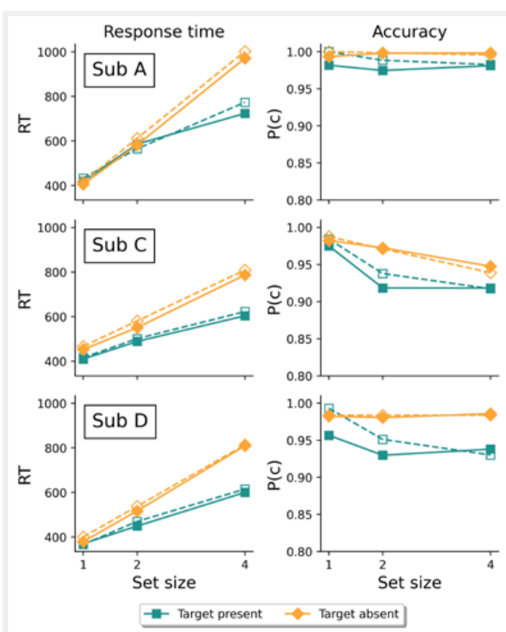

Figure 3. Predictions (dashed) and observations (solid) for simultaneous presentation conditions.

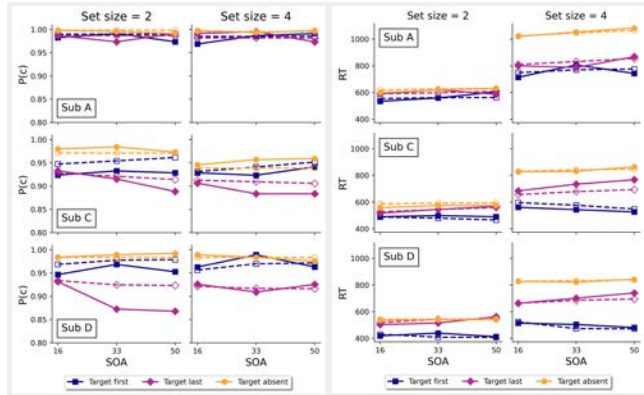

Figure 4. Predictions (dashed) and observations for the sequential object conditions.

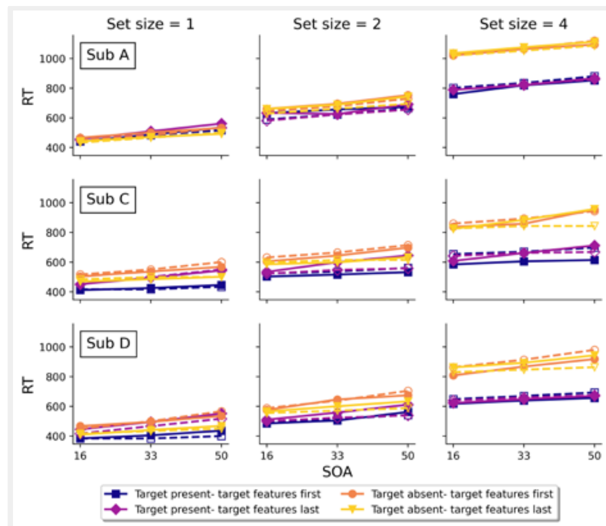

Figure 5. Predictions (dashed) and observations (solid) for response times, sequential feature presentation conditions.

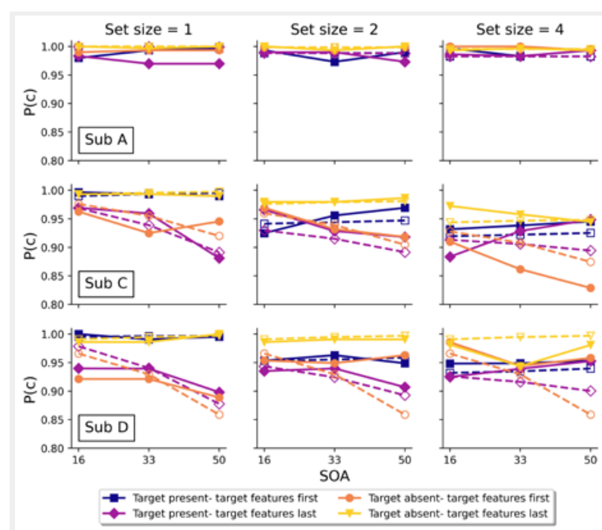

Figure 6. Predictions (dashed) and observations (solid) for accuracy, sequential feature presentation conditions.

References

Atkinson, R. C., Holmgren, J. E., & Juola, J. F. (1969). Processing time as influenced by the number of elements in a visual display. *Attention, Perception, & Psychophysics*, 6, 321-326.

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: a failed theoretical dichotomy. *Trends in Cognitive Sciences*, 16(8), 437-443. https://doi.org/10.1016/j.tics. 2012.06.010

Bezanson, J., Edelman, A., Karpinski, S., & Shah, V. B. (2017). Julia: A fresh approach to numerical computing. *SIAM Review*, *59*(1), 65–98. https://doi.org/10.1137/141000671

Cousineau, D., Donkin, C., & Dumesnil, É. (2015). Unitization of features following extended training in a visual search task. In *Cognitive modeling in perception and memory* (pp. 13-25). Psychology Press.

Cousineau, D., & Shiffrin, R. M. (2004). Termination of a visual search with large display size effects. *Spatial Vision,* 17, 327-352.

Cox, G. E., & Shiffrin, R. M. (2017). A dynamic approach to recognition memory. *Psychological Review*, *124*(6), 795–860. https://doi.org/10.1037/rev0000076

Egeth, H. E., Virzi, R. A., & Garbart, H. (1984). Searching for conjunctively defined targets. *Journal of Experimental Psychology*: Human Perception and Performance, 10, 32-39.

Eriksen, C. W. (1988). A source of error in attempts to distinguish coactivation from separate activation in the perception of redundant targets. *Perception & Psychophysics*, *44*(2), 191–193. https://doi.org/10.3758/bf03208712

Eriksen C. W., & Collins, J. F. (1969). Temporal course of selective attention. *Journal of Experimental Psychology*, 80, 254–261.

Eriksen, C. W., & Hoffman, J. E. (1972). Temporal and spatial characteristics of selective encoding from visual displays. *Perception & Psychophysics*, *12*(2), 201–204. https://doi.org/10.3758/bf03212870

Geisler, W. S., Perry, J. S., & Najemnik, J. (2006). Visual search: The role of peripheral information measured using gaze-contingent displays. *Journal of Vision*, *6*(9), 1. https://doi.org/10.1167/6.9.1

Gondan, M., & Heckel, A. (2008). Testing the race inequality: A simple correction procedure for fast guesses. *Journal of Mathematical Psychology*, *52*(5), 322–325. https://doi.org/10.1016/j.jmp.2008.08.002

Harding, S.M., Cousineau, D., & Shiffrin, R, M. (2021). Dynamic perception of well-learned perceptual objects. *Computational Brain and Behavior*, 4 (4), 497-518.

Huang, C., Vilotijević, A., Theeuwes, J., & Donk, M. (2021). Proactive distractor suppression elicited by statistical regularities in visual search. *Psychonomic Bulletin & Review*, *28*(3), 918–927. https://doi.org/10.3758/s13423-021-01891-3

Jonides, J. & Yantis, S, (1988). Uniqueness of abrupt visual onset in capturing attention. *Perception & Psychophysics*, 43, 346–354.

Kahneman, D., & Treisman, A. (1984). Changing views of attention and automaticity. In R. Parasuraman & D. R. Davies (Eds.), *Varieties of attention* (pp. 29–57). New York: Academic Press.

Maxcey, A. M., Shiffrin, R. M., Cousineau, D., & Atkinson, R. C. (2021). Two case studies of very long-term retention. *Psychonomic Bulletin & Review*, *29*(2), 563–567. https://doi.org/10.3758/s13423-021-02002-y

Najemnik, J. & Geisler W.S. (2009) Simple summation rule for optimal fixation selection in visual search. *Vision Research*, 49, 1286-1294.

Palmer, E. M., Van Wert, M. J., Horowitz, T. S., & Wolfe, J. M. (2019). Measuring the Time Course of Selection During Visual Search. *Attention, Perception & Psychophysics*, 81(1), 47-60. https://doi.org/10.3758/ s13414-018-1596-6

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological Review*, *84*, 1-66.

Shiffrin, R. M. (1988). Attention. In Atkinson, R. C., Herrnstein, R. J., Lindzey, G., & Luce, R. D. (Eds.), *Stevens' Handbook of Experimental Psychology, 2nd Edition*, 739-811. New York: Wiley.

Shiffrin, R. M., & Czerwinski, M. P. (1988). A model of automatic attention attraction when mapping is partially consistent. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *14*, 562-569.

Shiffrin, R. M., & Gardner, G. T. (1972). Visual processing capacity and attentional control. *Journal of Experimental Psychology*, *93*, 72-82.

Shiffrin, R. M., & Lightfoot, N. (1997). Perceptual learning of alphanumeric‐like characters. In R. L. Goldstone, P.G. Schyns, & D. L. Medin (Eds.) *The Psychology of Learning and Motivation, Volume 36*, pp. 45-82. San Diego: Academic Press.

Shiffrin, R. M., & Schneider, W. (1977). Controlled and automatic human information processing: II. Perceptual learning, automatic attending, and a general theory. *Psychological Review*, *84*, 127-190.

Townsend, J. T., & Nozawa, G. (1995). Spatio-temporal properties of elementary perception: An investigation of parallel, serial, and coactive theories. *Journal of Mathematical Psychology*, *39*(4), 321–359. https://doi.org/10.1006/jmps.1995.1033

Townsend, J. T.,Yang, H.& Burns, D. M. (2011). Experimental discrimination of the world's simplest and most antipodal models: The parallel-serial issue. In Hans Colonius and Ehtibar Dzhafarov (Ed.s), *Descriptive and Normative Approaches to Human Behavior in the Advanced Series on Mathematical Psychology*. Singapore: World Scientific

Treisman, A., & Gelade, G. (1980) A feature integration theory of attention. *Cognitive Psychology*, 12, 97–136.

Wolfe, J. M. (1994). Guided search 2.0 a revised model of visual search. *Psychonomic Bulletin & Review*, *1*(2), 202–238. https://doi.org/10.3758/bf03200774

Wolfe, J. M. (1998). What can 1 million trials tell us about visual search? *Psychological Science*, *9*(1), 33–39. https://doi.org/10.1111/1467-9280.00006

Wolfe, J.M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic & Bulletin Review*, 28, 1060–1092. https://doi.org/10.3758/s13423-020-01859-9.

Wolfe, J. M., Cave, K. R., & Franzel, S. L. (1989). Guided search: An alternative to the feature integration model for visual search. *Journal of Experimental Psychology: Human Perception and Performance*, *15*(3), 419–433. https://doi.org/10.1037/0096-1523.15.3.419

Yantis, S. & Jonides, J. (1990). Abrupt visual onsets and selective attention: Voluntary versus automatic allocation.*Journal of Experimental Psychology: Human Perception & Performance*, 5, 121–134