

PARALLEL PROCESSING OF EFFICIENT, HETEROGENEOUS VISUAL SEARCH WITH
REAL-WORLD OBJECTS

BY

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THESIS

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ABSTRACT

Previous work in our lab has demonstrated that efficient visual search has a reaction time by set size function that is best characterized by logarithmic curves, and the steepness of these logarithmic curves is determined by the similarity between target and distractor items (Buetti et al., in press). This thesis presents a theoretical account of these phenomena, emphasizing that a parallel, unlimited capacity, exhaustive processing system must be underlying such data. Two experiments were conducted to expand our findings to a set of real-world stimuli, in both homogeneous and heterogeneous search displays. Based on our current theory and numerical simulations, we were able to very accurately predict RT performance in heterogeneous search using parameters from homogeneous search tasks of a different group of subjects. By examining the systematic deviation of our predictions from observed data, we concluded that early visual processing for individual items were not independent. Instead, items in homogeneous displays seemed to facilitate each other's processing by a multiplicative factor. These results challenge previous accounts of heterogeneity effects in visual search, and demonstrate the explanatory and predictive power of our current theory of visual search.

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Chapter 1: Introduction

Part 1: Parallel processing in visual search

Starting from the retina, early stages of the human visual system are organized in a massively parallel architecture, so that low-level information are extracted and represented for a wide view of the world (Breitmeyer, 1992). On the other hand, there are several central bottlenecks limiting the amount of information that the mind can actively maintain, process and respond to. Such bottlenecks include the capacity of visual working memory (Sperling, 1960; Luck & Vogel, 1997; Awh, Barton & Vogel, 2007), the psychological refractory period (Pashler, 1992; Sigman & Dehaene, 2008), and the attentional blink phenomenon (Shapiro, Raymond & Arnell, 1997; Vogel, Luck & Shapiro, 1998). The needs to both have parallel access to basic visual information around us and to focus high-level processing power selectively underlies the problem of visual attention. Because the mind is almost always motivated for a specific goal, understanding of goal-directed visual processing is thus essential to understand visual attention. By presenting one or multiple target objects among various distracting or task-irrelevant items, visual search provides a convenient method to capture the goal-directed selection process of attention, and has been widely used and studied in visual attention research.

Notably, much of the effort in the visual search literature has been devoted to unveil how visual attention serially processes items in the display, from which strong inferences can be drawn about the limited nature of visual attention. Plenty of empirical research has thus focused on the dependent variable of search slope—how much longer on average it takes for the visual system to process an additional item, and tried to establish a relationship between different task setting variables and changes in search slopes. These variables include how many features define the target (Treisman & Gelade, 1980), whether target is defined by definite features (Bravo & Nakayama, 1992), similarity between target and distractors (Duncan & Humphreys, 1989), or what specific features are used to differentiate target and distractors (Wolfe & Horowitz, 2004). When this kind of relationship is successfully mapped out, inferences can be drawn about the nature or function of focal attention. For example, a key question in the history of visual search research had been under what conditions search slope becomes non-zero, which was thought to

reflect the limit of the power of parallel processing in the visual system. The fact that conjunction search produced non-zero search slopes while feature search didn't led to the suggestion that focused attention is necessary for the binding of different features onto an object file (Treisman & Gelade, 1980). Obviously, this approach is based on a linear relationship between reaction time and number of items (or 'set size'), which is easily observed and well supported by the known limited capacity of high level processing. As a consequence, many prominent theories of visual search (and by extension, of visual attention) have been essentially accounts of the search slope given a specific search task (e.g., Duncan & Humphreys, 1989; Wolfe, 1994). Although alternative focus on the accuracy of responses has also generated important insights such as the signal detection theory of visual search (Verghese, 2001), the traditional approach of studying reaction time vs. set size function has become one of the most popular fields of attention research.

Perhaps partly because of this tradition, cognitive experimental research on visual search has become somewhat disinterested in understanding parallel processing in visual search. The specific reason for this disinterest is because of the assumed correspondence between parallel processing and 'flat' search functions. This correspondence is based on two conceptions: first, when linear regression of RT-set size data returned a slope coefficient that's close to zero, search function is typically assumed to be a flat straight line; second, parallel processing with unlimited capacity was thought to mean that no additional time cost is introduced by additional items. So when search slope is found to be near zero, the usual inference is that items are processed in parallel, there's no need for attentional selection, so the result is not informative for understanding attention. Yet in fact both ideas are misconceptions, the reasons of which we shall clarify in the following discussion. Nevertheless, this disinterest had led to major theories of visual search to assume that parallel visual processing produce no variability in reaction time at all. Guided Search (Wolfe, 1994) had used a fixed 400 ms for the time cost to process the search display and compute the 'priority map'. Bundesen's Theory of Visual Attention (1990) also had a mathematically explicit goal to make search time independent of set size in so-called pop-out searches, which were thought to depend entirely on parallel processing. Interestingly, even when non-slope changes (i.e. differences in intercepts) in reaction time – set size function were observed, the effect was attributed to changes in the processing efficiency of the later limited capacity stage (Wolfe, Oliva, Horowitz, Butcher & Bompas, 2002).

As a result, our knowledge about the parallel processing of a visual scene has largely come from a computationally-oriented approach to vision, in which the central goal is to predict the series of loci of attention or eye fixation given a specific scene or image with or without a target. By the success of these computational models of attention, one can argue that low level, parallel computations carried out by these models should be mimicking the parallel processing of human vision. For example, the work by Itti and Koch (2000; 2001) suggested that bottom-up, image-based control of attention can be formalized by the computation of a ‘saliency map’, or summed featural contrast at different spatial scales. Similarly, by comparing model-based predictions and experimental results on visual search, Rosenholtz, Huang and Ehinger (2012) provided a hypothesis for the nature of crowding, which influences the resolution limit of peripheral vision. While the models themselves are typically highly detailed and systematic, allowing for well-defined, testable predictions, many efforts with this approach tend to be limited by a trade-off between their ability to account for human behavior and the complexity/interpretability of their models. For example, the currently top 2 ranking saliency models on the MIT Saliency Benchmark (Bylinskii, Judd, Durand, Oliva, & Torralba, 2014) were both based on deep neural networks (Kruthiventi, Ayush, & Babu, 2015; Vig, Dorr, & Cox, 2014). This approach has an emphasis on learning hierarchical features represented by multiple layers of neurons, but there has been little effort to understand or demonstrate correspondence between these learned features and actual representations in the human visual system.

Consequently, important aspects of the influence of parallel processing in visual search have been largely uncharted. There are several reasons why understanding of this processing stage is important. *A priori*, selective attention evolved to address the need to optimally bridge the gap of processing capacity between early parallel visual processing and higher level processing, therefore understanding what information the parallel stage can process naturally provides an upper limit of what the attentive, limited capacity stage needs to do. More importantly, the usual assumption of constant time cost given parallel, unlimited capacity processing simply does not hold: Townsend and Ashby (1983) had given precise mathematical formulation of varieties of such processing models, many of which predict non-trivial RT by set size functions. The counter-intuitiveness of these results can be readily dispelled if one considers that unlimited capacity should not and does not equal infinite capacity, because the metabolism limitation of the finite brain means that devoting maximum amount of energy available to any

current cognitive process is highly cost-ineffective. Therefore early parallel processing can be very informative and interesting to attention research. Empirically, there are various experimental results indicating that the visual system can rapidly access quite substantial information without focused attention, such as scene gist (Potter & Levy, 1969; Potter, 1976; Schyns & Oliva, 1994; Oliva, 2005), statistical properties in a scene (e.g., Parkes, Lund, Angelucci, Solomon & Morgan, 2001; Chong & Treisman, 2005a, 2005b; Haberman & Whitney, 2009), and some basic categorical information of objects (Li, VanRullen, Koch, & Perona, 2002; Li, Iyer, Koch & Perona, 2007). Such processing power must be based on this parallel processing stage, about which relatively little has been learned. Additionally, current theories often fail to account for search performance variability in real world scenes (e.g. Itti & Koch, 2000; Wolfe, Alvarez, Rosenholtz, Kuzmova & Sherman, 2011), which could at least be partly due to their neglect of accounting for variability arising from the parallel processing stage.

Recent work in our lab has uncovered an important reaction time signature of the parallel processing stage in visual search (Buetti, Cronin, Madison, Wang & Lleras, in press). Our results showed that in addition to a linear increase in reaction time caused by distractor items highly similar to the target, other less similar items can produce a logarithmic reaction time cost. This logarithmic function can be easily overlooked if one does not sample the set size conditions appropriately and simply make a linear regression to the data. Figure 1 illustrates key aspects of our results. These two different signatures in reaction time lead us to propose the distinction of two types of distractors: candidates and lures. Candidates require focused spatial attention to be distinguished from the target because they share the same set of basic features (such as color, curvature, line intersection, orientation); lures are sufficiently different from the target in some of these basic visual features that they do not require close scrutiny. When candidates and lures are both present, they elicit dissociable linear and logarithmic RT increments (Figure 1A). Different types of lures produce logarithmic RT by setsize functions with different steepness according to their visual similarity to the target: lures more similar to the target produce steeper logarithmic curves (Figure 1B). Notably, if linear regressions were performed, most of these data will yield close to 0 linear slopes, and be deemed uninteresting. In other words, many efficient visual search tasks do not produce just a flat line even if their linear slope appears close to zero.

Given these results, we proposed that lure items are processed in the first parallel stage of vision to the degree that there is sufficient evidence to reject them as possible candidates of being the target. Naturally, candidates go through this parallel stage because they are similar enough to the target for this resolution-limited stage, and enter the limited capacity processing stage with focused spatial attention. Additionally, the relationship between lure similarity to the target and slope of the logarithmic function indicate that similarity determines the efficiency of processing for each individual lure item. Therefore, we developed the following set of hypotheses to construct a theoretical model of stage-one visual processing:

- (1) Stage-one processing has a parallel architecture and unlimited capacity. Hence all items in the display (i.e. both lures and candidates) are simultaneously processed with a rate that doesn't depend on set size. This is basically an adoption of the traditional assumption about the architecture and capacity of this stage (Treisman & Gelade, 1980; Wolfe, 1994).
- (2) The amount of processing required for each item is proportional to its similarity to the target. This follows from the idea that the more similar an item is to the target, more information is needed to reject that item from requiring further inspection. The target and candidates always need the maximum amount of processing, which is dictated by the resolution limit of this parallel stage.

In order to make explicit predictions with this theory, we specify the following assumption to model individual item processing:

- (3) Processing of individual items is modeled by noisy accumulators. The rate of information accumulation is drawn at each instant from a Gaussian distribution with a positive mean value. Processing is complete when accumulated information or evidence reaches a certain threshold, which we propose is proportional the item's similarity to the target. This process is thus mathematically equivalent to a Brownian motion with a constant drift rate towards a given threshold. Completion time t of this process follows the Inverse Gaussian distribution (Chhikara, 1988):

$$f(t|A, k, \sigma) = \frac{A}{\sqrt{2\pi\sigma^2 t^3}} e^{-\frac{(A-kt)^2}{2\sigma^2 t}}$$

Where A is the accumulator's threshold, k is the constant drift rate (or mean accumulation speed), and σ is the standard deviation of accumulated information at each instant.

These assumptions enabled us to numerically simulate different implementations of parallel, unlimited capacity processing system, and derive the expected time cost as a function of number of items to be processed, modulated by the similarity of items to the target. Specifically, following the pioneering work by Townsend and Ashby (1983), we implemented different termination rules (self-terminating vs. exhaustive) in systems with or without resource reallocation in the case of efficient search (see Buetti et al. (2016) for results and detailed methods of these simulations in Figure 3 and appendix A.). Our results indicated that only a system with exhaustive termination rule and no reallocation of resources produce series of logarithmic curves, and the steepness of these curves are modulated by similarity of lure items to the target just as observed in our experiments (see Figure 1B). In other words, we found evidence (based on empirical data and a set of reasonable assumptions) that stage one in visual search seems to be a parallel, unlimited capacity, exhaustive processing system. When there are no candidate items in the display (other than the target), this model can account for all the systematic reaction time variation caused by changes in the number of lure items. More interestingly, our simulation revealed that there is a clear linear relationship between the accumulation threshold (i.e., evidence require to classify an item as target or non-target) and the coefficient of the logarithmic term in the time cost (Buetti et al., in press, Appendix A). Together, these findings demonstrated how our main hypotheses led to the discovery of the appropriate model of stage one processing, and explained the results we observed.

Part 2: Predicting heterogeneous lure search

Given our current theory of stage one processing in visual search, one very intriguing application is search tasks where distractors are heterogeneous. Many laboratory experiments on visual search used highly homogeneous displays, i.e. the distractor items were either completely identical, or composed of groups that differ from each other in only one feature dimension. In the real world, however, an arbitrary scene often consists of mostly non-repeating objects. When a specific target is defined, it is also usually the case that most non-target objects are highly dissimilar to the target, so that very few of them need to be actually examined (Wolfe et al., 2011; Neider & Zelinsky, 2008). Thus, it seems that many visual search-like tasks performed in the real world will be best conceptualized as search for the target among a heterogeneous set of lure items.

Notice that many conclusions drawn from homogeneous search tasks cannot be extended to a heterogeneous search scenario simply. Duncan and Humphreys (1989) had already pointed out that distractor-distractor similarity or heterogeneity in the distractor set has an effect independent of target-distractor similarity. Guided Search theory (Wolfe, 1994) proposed that top-down attention could ‘guide’ parallel processing by prioritizing items with specific feature values of the target. Yet in the real world, objects are defined as conjunctions of many different feature dimensions so that groups of objects can share a few features, but each object is sufficiently dissimilar to every other one in many feature dimensions. Nordfang and Wolfe (2014) had found that in the case of high feature dimensionality, the effect of heterogeneity in visual search cannot be explained by a linear summation of the ‘guidance’ afforded by each feature dimension. Therefore the difference or relationship between homogeneous and heterogeneous search is still relatively unclear.

One prominent aspect of our current theory is that it emphasizes the role of visual similarity in the parallel stage of processing, and it makes a more specific formulation of the effect of target-distractor similarity in comparison to Duncan and Humphreys (1989). Clearly, the concept of visual similarity is abstract enough to be applied to both artificial and naturalistic stimuli alike. Hence, we expect our results to extend to tasks using natural images as search items. Specifically, efficient search should always be modulated by target-lure similarity, and should produce logarithmic RT – set size functions. For example, search for a teddy bear target

among an array of toy pandas and model cars should both produce logarithmic RT by set size functions because both toy pandas and model cars look sufficiently dissimilar to the target. And the function for toy panda lures should be steeper than the log curve produced by a search for a teddy bear among model cars, because a toy panda is arguably more similar than a model car to a teddy bear because of similarity in shape and texture.

More importantly, similarity between one distractor item and the target item should not depend on whether the distractor set is homogeneous or heterogeneous. Moreover, as mentioned above, our theory and results suggest that the ‘slope’ of the logarithmic function measured in homogeneous search can be a valid behavioral index of target-distractor similarity. Hence in principle, we could derive predictions for search times in lure-heterogeneous displays based on participant's performance on lure-homogeneous displays. This follows because our model describes a definitive correspondence between accumulation thresholds and log slope coefficients. If this exact correspondence is found, then we'd be able to derive accumulation thresholds for each lure type from observed log slopes of homogeneous search data. Then we can use these thresholds to predict search RT for novel, heterogeneous scenes. This fact alone illustrates the advantage of our theory being both generalized across different types of search displays and yet specific enough to make predictions to novel experimental scenarios. With these predictions in hand we can then gather experimental data on heterogeneous lure search and test whether predictions are verified or falsified.

However, there are two issues to be resolved before we can take on this approach. The first issue is that an analytical solution for stage one time cost based on our current theory and model is not available. Even though the individual accumulator's completion time is well understood, in the case of heterogeneous displays (where individual completion times are sampled from multiple groups of different Inverse Gaussian distributions), the maximum of all items' completion times (since our model assumes an exhaustive termination rule) requires an integral that seems to be unsolvable¹. Thus, the exact correspondence between accumulation

¹ With 2 types of items, for example, the essential integral to be solved takes the following form:

thresholds and log slopes cannot be established for now. To circumvent this issue, we took a computational simulation approach to find numerical mappings between thresholds and log slopes, which allowed for numerical predictions of heterogeneous search.

Another issue lies in the fact that our model assumed individual items' processing are independent of each other, and this assumption still lacked definitive evidence. Although Buetti et al. (in press) had rejected an alternative, resource-reallocating model, their method of model comparison cannot rule out the possibility of an interaction effect that's constant over the time course of stage one processing. This is because the various simulation results were qualitatively compared to the empirical finding of logarithmic RT by set size functions. That approach was able to reject resource reallocation models because reallocation of processing resources introduces an acceleration of processing over time. Obviously, if homogeneity or heterogeneity in the search scene introduced an additive or multiplicative change in the processing of items, the shape of RT functions would still be logarithmic, so this comparison cannot rule out these time-constant effects. Hence the model's predictions could be inaccurate up to a multiplicative or additive factor. For instance, we may expect that heterogeneity in the distractor set could slow down overall processing, or equivalently, homogeneity could facilitate processing via a mechanism like the 'spreading suppression' suggested by Duncan and Humphreys (1989).

In order to create some testable predictions for the case of heterogeneous search, we revert to our simulations as a source of numerical predictions of our model. Based on different assumptions about the processing of heterogeneous search scenes, we developed several hypothetical equations that aim to approximate time cost as a function of the number of each type of lures and their logarithmic slope coefficients measured in homogeneous search tasks.

$$\int \left(1 - \Phi \left(\sqrt{\frac{\lambda_1}{t}} \left(\frac{t}{\mu_1} - 1 \right) \right) - e^{2\lambda_1/\mu_1} \Phi \left(-\sqrt{\frac{\lambda_1}{t}} \left(\frac{t}{\mu_1} + 1 \right) \right) \right)^{n_1-1} \left(1 - \Phi \left(\sqrt{\frac{\lambda_2}{t}} \left(\frac{t}{\mu_2} - 1 \right) \right) - e^{2\lambda_2/\mu_2} \Phi \left(-\sqrt{\frac{\lambda_2}{t}} \left(\frac{t}{\mu_2} + 1 \right) \right) \right)^{n_2} \left(e^{-\frac{\lambda_1}{t} \left(\frac{t}{\mu_1} - 1 \right)^2} + e^{2\lambda_1/\mu_1} e^{-\frac{\lambda_1}{t} \left(\frac{t}{\mu_1} + 1 \right)^2} \right) t dt$$

where n_1, n_2 are the numbers of two types of items, and $\lambda_1, \mu_1, \lambda_2, \mu_2$ are corresponding parameters, $\Phi(x)$ is the CDF of standard normal distribution. We welcome any ideas or suggestions about how to mathematically solve this problem.

Then we used numerical simulations to validate the goodness of these approximations by the following procedure. First, we simulated homogeneous search tasks with different types of lures (i.e. different accumulation thresholds), and found the corresponding logarithmic slope coefficients (we will denote them as D values in the following discussion). With these D values, we computed predictions of stage one processing times of heterogeneous search tasks using the different approximating equations we developed. Then, using the same set of threshold values (which represent the same set of lure items) we ran simulations of heterogeneous search scenes, each with different compositions of multiple types of lures (i.e. accumulators with different thresholds). The achieved simulated time costs were then compared to the sets of predicted time costs from the different equations to evaluate which equation performed best. This best performing equation would be our optimal formulation of the relation between homogeneous and heterogeneous search, given the difficulty of a rigorous analytical solution. Hence, the effective prediction of our theory becomes a prediction of which equation best predicts reaction time in heterogeneous search experiments. The detailed methods and results of this simulation procedure will be presented in the Predictive Simulation section below.

Naturally, an empirical testing of this simulation-based prediction should follow, which would provide a rigorous method of testing our current theory of stage one processing. This can be achieved by simply replacing simulated homogeneous and heterogeneous search data with empirical data. More specifically, we needed two experiments with homogeneous (Experiment 1) and heterogeneous (Experiment 2) search displays consisting of the same set of stimuli. Within Experiment 1, best-fitting log slopes were estimated for each type of lure item, which were then used to predict search RT using different approximating equations. These predicted RTs were compared to a set of observed RT from heterogeneous search tasks in Experiment 2, to test whether the same equation favored by our theory-based simulation outperform all other alternative equations.

Assuming that such consistency exists between simulation and experiments, this best-performing equation can be used to further investigate whether individual item processing is independent or if there can be some form of temporally constant interaction. Because our simulation was conducted under the assumption of between-item independence, the predictions of this equation naturally carry that assumption along. Hence, any systematic deviation of

predicted stage-one processing times from observed heterogeneous search data can be interpreted as effects of homogeneity (or heterogeneity, depending on the viewpoint). Specifically, if we fit predicted stage-one processing times to observed data via linear regression, then the estimated slope coefficient would represent a multiplicative effect of homogeneity, whereas the intercept coefficient would correspond to an additive effect of homogeneity. This is because if there is truly no additive nor multiplicative effect (i.e. items are always processed independently), then observed and predicted stage-one time costs should line up perfectly along the $y = x$ line. If homogeneity causes an additive facilitation effect, the observed time costs would then be shifted below the $y = x$ line (which means a non-zero intercept); similarly if homogeneity leads to a multiplicative change in item processing, then the regression line would rotate (or ‘tilt’) accordingly, so that slope is no longer equal to 1.

As a summary, the current study consists of a predictive simulation and two experiments. The simulation will provide a best-approximating equation for predicting the completion times for stage one in heterogeneous visual search, using parameters obtained from homogeneous visual search displays. Next, we used a set of real-world object images to construct homogeneous search displays for Experiment 1 and heterogeneous search displays for Experiment 2. Experiment 1 served both as an extension of our previous ‘feature search’ results (as in Experiment 1 of Buetti et al., 2016) to real-world objects and as the data source for estimating log slope (D) coefficients for prediction of heterogeneous search RT. In Experiment 2 we collected behavioral data of visual search with heterogeneous lures. By comparing different equations’ predictions of RT to observed RT, we will be able to (1) test whether the ‘best-approximating’ equation from our theory-based simulation works best in reality, and (2) examine whether there is a multiplicative or additive effect of homogeneity facilitation, and potentially estimating the magnitude of this effect.

Chapter 2: Predictive Simulation

Methods

Approximating equations for heterogeneous search

We developed the following set of equations in the hope that some of them may be a good approximation of the exact analytical solution of stage one time cost in heterogeneous lure search. Each equation describes time cost of stage one processing, T , as a function of the D coefficients and numbers of each type of lure items (N), i.e. $T = f(\{D_i\}, \{N_i\})$. For each equation, its form in the case of 3 types of lures will be presented below (rather than the general form with arbitrary number of types of lures). D coefficients will have the ordering of $D_3 > D_2 > D_1 > 0$, i.e. we denote lure no.3 to have the highest similarity to the target and lure no.1 with lowest similarity.

Equation 1:

$$T = D_1 \ln(N_1 + N_2 + N_3 + 1) + (D_2 - D_1) \ln(N_2 + N_3 + 1) + (D_3 - D_2) \ln(N_3 + 1)$$

This equation was formulated to approximate the time cost assuming that all groups of lure items are processed in parallel, which is in strong accordance to our theory. Intuitively, the first term represents time cost for all 3 types of lure items to arrive at the threshold for lure type 1 (as represented by D_1), the second term represents the time cost for evidence about lure types 2 and 3 to continue accumulation from the threshold of lure type 1 (D_1) until they reach the threshold for type 2, D_2 , (hence the term $D_2 - D_1$), and so on. In other words, in this model we assume that (a) all lures are processed in parallel, and (b) that at each threshold, evidence stop accumulating at the locations where lures associated with that threshold are present, and (c) that evidence continue to accumulate at the same speed at locations where lures with higher thresholds are present.

Equation 2:

$$T = D_1 \ln(N_1 + 1) + D_2 \ln(N_2 + 1) + D_3 \ln(N_3 + 1)$$

Equation 2 above assumes that the groups of lures are processed in a serial and exhaustive fashion, while within each type of lure, individual items are processed in parallel. Imagine a display with blue, red and orange lures, this model would mean that first all blue lures are discarded, then the red ones and last the orange ones, assuming blue is the least similar lure, followed by red, followed by orange. We consider this possibility because many of our previous results are based on homogeneous search tasks, so that strictly speaking we do not have yet strong evidence for independence or parallel processing across different types of lures.

Equation 3:

$$T = \max\{D_1, D_2, D_3\} \ln(N_1 + N_2 + N_3 + 1) = a + D_3 \ln(N_1 + N_2 + N_3 + 1)$$

Equation 3 makes a strong but possible assumption, which is that while all items are being processed in parallel and exhaustively, the amount of information required to complete processing is determined by the lure with highest similarity to the target (i.e. lure type no.3). Thus this can be understood as a specific type of interaction between different types of lures. This is probably the best representation for theories that assume a single threshold of similarity or priority, where objects below threshold will not affect later stages of processing (e.g. Guided Search, Wolfe, 1994; TAM, Zelinsky, 2008).

Equation 4:

$$T = \frac{D_1 + D_2 + D_3}{3} \ln(N_1 + N_2 + N_3 + 1)$$

Equation 4 serves as an alternative to equation 3. Here the log slope is estimated by the mean of the 3 types of lures, while all items are still processed exhaustively in parallel.

We note here that the above 4 equations include variations in different aspects of processing across lure types. Equation 1 is the strongest extension of our theory since it assumes both parallel processing and independence across lure types. Equation 2 assumes independence but serial processing across lure types, whereas equations 3 and 4 assumes parallel processing but with interaction between different lure types.

Simulation & Analysis

The goal of this simulation is to find out which of the 4 equations above best accounts for simulated time costs of stage one processing of heterogeneous scenes. According to our theory, this time cost is equivalent to the maximum (exhaustive termination rule) of all the item's processing time, where each individual item's processing is modelled by a noisy accumulator whose threshold represents its similarity to the target (and regardless of whether the items are all identical to each other or not). Further, because of the system's unlimited capacity and independence between items, the rate of information accumulation will always be sampled from the same Gaussian distribution regardless of how many items are being processed. Therefore, the critical parameters are the threshold values for each type of item, whereas the drift rate k and noise range σ should remain constant for one simulation run.

We created two sets of parameters representing two different sets of stimuli. We then simulated stage one completion times using the same architecture for both sets of parameters. Choosing two different sets of parameters estimates allows us to be confident that our simulations and our equations are not overly dependent on any specific parameter, and that in fact, they generalize well across the parameter space. For both runs, three types of lure items were simulated to ensure a sufficient degree of heterogeneity without requiring too many conditions. Simulation no. 1 had a target item whose threshold was 20, and three types of lure items with thresholds of 15, 17, and 19. The drift rate k was fixed at 4 and noise range σ was also a constant 2. Simulation no. 2 had a target threshold of 62, three lure thresholds at 48, 53, and 58, with drift rate of 9 and noise range of 4.

Given a specific set of parameters, the simulation procedure and algorithm can be described as follows:

(1) For each type of lure item, we simulated homogeneous search time as a function of set size. At set size N , there were 1 target item and $N-1$ lure items. The target item's processing time was found by randomly sampling from an Inverse Gaussian distribution² defined by the target threshold A_t , the drift rate k and the noise range σ . Each of the $N-1$ lure items was similarly simulated by sampling from another Inverse Gaussian distribution with a lure threshold value A_l

² This can be accomplished by using MATLAB functions `makedist()` with the 'InverseGaussian' option and `random()`.

and the same k and σ . The overall processing time was simply the maximum of all individual items' processing times. Because of the randomness in the sampling procedure, we took the mean processing time cost of 2000 repetitions at each set size as the final output.

(2) For each type of lure, we computed a regression of $RT = \hat{D} \ln(N) + \hat{a}$ based on the simulated results from step (1). The estimated coefficients $\hat{D}$ and $\hat{a}$ were used for predicting heterogeneous search time cost.

(3) We simulated heterogeneous search time with a range of combinations of the 3 types of lures. Each type of lure was 'presented' 1, 3, 7 or 15 times in combination with one or two other lures, which yielded a total of 111 different combinations. Processing time costs were simulated in the same way as step (1), with 2000 repetitions per condition.

(4) For each of the 4 approximating equations, we computed the predicted completion times for each "display" condition simulated in (3) using the estimated $\hat{D}$ and $\hat{a}$ coefficients from (2). We then compared predicted completion times (T) against simulated T values by computing a linear regression for each equation to estimate the equation that best fits the simulated data. We used several diagnostics for goodness of fit including the R square, log likelihood, and the slope and intercept coefficients of the regression models.

Results

We plotted simulated T values for heterogeneous scenes against predicted T values for each equation along the $y=x$ line in Figure 2 for both simulation runs.

Table 1 summarizes regression model characteristics that measure how well predicted T values based on each equation match simulated processing time results. In both simulations, Equation 1 had the highest R squares, the estimated slope coefficient was closest to 1, and the estimated intercept was closest to 0. Predictions of Equation 1 also fell closest to the $y=x$ line in Figure 2 for both simulations. From these results we can conclude that Equation 1 most successfully accounts for stage one processing time of simulated heterogeneous scenes, given the knowledge about processing efficiency (D values) of each lure type in simulated homogeneous search tasks. Equation 1 is thus our best approximating equation for predicting heterogeneous lure search.

Chapter 3: Experiment 1

Experiment 1 serves not only as preparation for the subsequent experiment and analysis, but also as a confirmation and extension of our previous findings. Our previous results had been based on two groups of simple stimuli with relatively few distinguishing features (see Figure 4 in Buetti et al., 2016). In this experiment we aim to show that the same pattern of results as seen in Figure 1B can be obtained using images of real-world objects. In other words, when target and distractors differ from each other along more than a couple of key feature dimensions, we should still find logarithmic search RT functions to be modulated by similarity between target and lures.

Methods

Participants. 26 Participants were recruited through the Course Credit Subject Pool at University of Illinois, Urbana-Champaign. All participants were screened for normal color vision and had reported normal (or corrected-to-normal) visual acuity. We excluded 3 participants whose overall accuracy was below 90%. For the 23 participants included in analysis, their age ranged from 18 to 24 years, 14 are female, 21 were right-handed.

Apparatus and Stimuli. Stimuli are presented on a 20 inch CRT monitor at 85 Hz refresh rate and 1024*768 resolution. Participants sat in a dimly lit room at a viewing distance of 75 cm. The experiment was programmed with Psychtoolbox 3.0 (Kleiner et al., 2007) in the MATLAB environment, and run on 64 bit Windows 7 PCs.

Search objects were chosen from a collection of images studied by Alexander and Zelinsky (2011), which were originally sampled from Cockrill (2001) and the Hemera Photo-Objects collection. Combining visual similarity ratings based on computational models and human subjects' subjective rating of similarity (provided by Alexander & Zelinsky, 2011), we selected groups of images that were consistently rated as having high or medium similarity to the teddy bear category. In this study, search stimuli are images of a target teddy bear, a red humanoid 'carrot man', a white reindeer toy, and a grey model car (see Figure 3).

These images of objects were presented with sizes of approximately 1.3 degrees visual angle horizontal and 1.7 degrees visual angle vertical. All images had a small red dot overlaid on the left or right side, with a diameter of 0.2 degrees of visual angle. In each search display, there

was always only one target and at most one type of lure item. The items were randomly allocated onto the screen based on an invisible 6-by-6 square grid that spanned 20 degrees of visual angle horizontally and vertically. Each item's actual location was then randomly jittered within 1 degree horizontally and vertically. On average the minimal distances between two items (i.e. the distance between two adjacent grid points) was 3.5 degrees. The grid was populated with equal numbers of items in four quadrants of the screen. A white fixation cross was also presented at the center of the screen, spanning 0.6 degrees vertically and horizontally. All displays had a grey background with a color vector of [121, 121, 121].

Procedure. At the beginning of the experimental session, instructions were both shown on the screen and delivered verbally to participants. They were told to look for the target teddy bear (whose image was shown on the screen) and respond to whether the red dot appeared on the left or right side on the bear. They were asked to press the left arrow key with their left index finger when the red dot was on the left, and right arrow key with right index finger when the dot was on the right. Speed and accuracy of response were equally prioritized.

Trials started with a brief presentation of the central fixation cross, with a duration randomly selected from 350 to 550 ms. Then, the search scene was displayed for a maximum duration of 2.5 seconds, during which time the participant was required to make a response on the keyboard. As soon as a legitimate response was detected, the trial ended and the screen turned blank. When the response was erroneous, a warning tone (1000Hz sine wave lasting 250 ms) was played. The inter-trial interval was selected randomly between 1.4 to 1.6 seconds. Each experiment session started with a practice block of 32 trials.

Design. The two main independent variables, lure type and set size are both within-subjects factors and are fully crossed. There can be 1, 4, 9, 19, or 31 lures of the same identity on the display along with one target item (so that total set sizes are 2, 5, 10, 20, or 32); additionally, there is a target-only condition where only the target image appeared on the screen. Therefore there are a total of $3 \times 5 + 1 = 16$ experimental conditions. The location of the red dot on the target image was pseudo-randomized to ensure that it appears on the left or right equally often. Locations of red dots on lure images were randomized with 0.5 probability on the left or right. Each condition was repeated 50 times, so that there are 800 trials total in one experimental

session. All conditions are randomly intermixed. There were short break periods every 20 trials that lasted up to 20 seconds if participants did not resume the experiment sooner.

Results

First of all, the results show that the RT by set size functions found in this experiment seem to be best characterized by a series of logarithmic functions. We compared regression models based on logarithmic and linear RT by set size relationships using R square and log likelihood as measures of goodness of models. In order to test an alternative hypothesis that the results could be better described by a bi-linear model assuming a transition point at set size 2, we also compared the log and linear models using data without the target-only condition. These results are summarized in Table 2. When the target-only condition was included, logarithmic models clearly outperformed linear models, indicating that a logarithmic model is more accurate and plausible in describing the data than a simple linear model; without the target-only data point, logarithmic models still consistently had higher R squares and log likelihoods than corresponding linear models. In Figure 3 we plotted reaction time against set size, separating the three groups of data by lure type, along with the best-fitting logarithmic curves to each group of data. The estimated logarithmic slope coefficients for each type of lure are: $D_{\text{red carrotman}} = 66.278$, $D_{\text{white reindeer}} = 28.492$, $D_{\text{grey car}} = 26.581$.

It should be noted that the estimated ‘linear slopes’ were very small and would be categorized as ‘efficient’ or ‘pop-out’ search according to traditions in the literature. When the target-only condition was included, the estimated linear slope coefficients were 6.380 ms/item, 2.559 ms/item, and 2.446 ms/item for carrot man, reindeer and model car lures, respectively. Without the target-only condition, these changed to 4.531 ms/item, 1.727 ms/item, 1.503 ms/item.

A within-subjects ANOVA using lure type and set size as factors on correct RTs was also conducted to test for the pattern of results. Main effects were significant for both lure type, $F(2, 44) = 265.3739$, $p < 0.001$, Cohen’s $f = 3.4720$, and set size, $F(5, 110) = 217.6928$, $p < 0.001$, $f = 3.1454$. More importantly, the interaction between set size and lure type was significant, $F(10, 220) = 54.1342$, $p < 0.001$, $f = 1.5685$. These results indicate that the different levels of lure-target similarity lead to different magnitudes of set size effects, i.e. lure-target similarity modulated search processing efficiency. To further understand this difference, we computed

paired t-tests on individual subjects' logarithmic slope estimates, comparing each pair of lure types. Consistent with the visual pattern in Figure 3, we found that log slopes for the red carrot man lure was significantly larger than both the log slopes for the white reindeer lure, $t(22) = 15.853$, $p < 0.001$, Cohen's $d = 3.3056$, and for the grey model car, $t(22) = 15.535$, $p < 0.001$, $d = 3.2393$, while there was no significant difference between the log slopes for reindeer and model car, $t(22) = 1.423$, $p = 0.1688$.

Discussion

Overall our results provide evidence that a logarithmic function captured the relationship between efficient search reaction time and set size better than a linear model in a target discrimination visual search task. Importantly, this conclusion was not contingent upon whether the target-only condition was included in analysis. Additionally, the steepness of the logarithmic curves depended on the similarity between target and lures, the higher similarity, the steeper or more inefficient search functions. This pattern of results replicates our previous findings and corroborates the notion that visual similarity modulates early parallel visual processing, regardless of whether search objects differ from each other along one or multiple feature dimensions (Buetti et al., in press). We can also conclude that all the distractor objects used are sufficiently different from the target teddy bear, so that they can be efficiently processed in the first, parallel stage of visual processing, hence we can use these stimuli to study how this stage handles heterogeneous search scenes.

Chapter 4: Experiment 2

In Experiment 2, we used the same object images as in Experiment 1 to construct heterogeneous search displays, and then compared observed RT with predicted RT values from the 4 approximating equations. Our objectives were two-fold: first, to test whether Equation 1 outperformed other equations as the simulation analysis predicted; second, to examine what kind of systematic deviation existed between theory-based RT predictions and observed results. Because of the limited number of conditions we could afford within one experimental session (about 50 minutes), we designed several different sets of conditions of heterogeneous displays, characterized by different types of lure combinations (described below). We then analyzed data from each subset separately as well as combined, in order to explore whether different ways of mixing the lures produce different patterns of results. This experiment, along with the predicted RT equations was pre-registered on the Open Science Framework: <https://osf.io/2wa8f/>.

Methods

Participants. Using effect size of the two-way interaction effect in Experiment 1, we estimated that in order to achieve power of 0.8, we needed 19 good subjects (effect size $f = 1.5685$, numerator $df = 10$, denominator $df = 7$, actual achieved power = 0.815, computed with G Power, Faul, Erdfelder, Lang & Buchner, 2007). In anticipation of need to replace some subjects, we collected data on 26 subjects recruited from the Course Credit Subject Pool at the University of Illinois at Urbana-Champaign. No participants in this experiment participated in Experiment 1. Two participants were excluded from analysis because overall accuracy was lower than 90%. For the 24 subjects included in the analysis, their age ranged from 18 to 22 years and had a mean of 19 years, 12 were female, and 22 were right-handed.

Stimuli and Apparatus. In contrast to Experiment 1 where only one type of lure is present in each search display, displays in Experiment 2 contain 2 or 3 types of lures. These lure items are randomly intermixed across all possible spatial configurations under the constraint that each quadrant of the screen contained the same number of items. All other aspects of the stimuli and apparatus were the same for Experiments 1 and 2.

Instruction and Procedure. The experiment procedure and instructions were the same for both Experiments 1 and 2, with the exception that the practice session at the beginning of Experiment 2 had 27 trials.

Design. There were 21 total conditions in this experiment, where each condition is specified by the number of carrot men, of reindeers, and of model cars. They can be sorted into 5 different subsets, each exhibiting a specific kind of variation in number of lure items, which are detailed in Table 3. Each condition was repeated 38 times, so that there were 798 total trials. Location of the red dot on the target image was pseudo-randomized with equal probability of left or right, while for lure images they were randomized with 0.5 probability.

Notice that in both Experiments 1 and 2 we had included a target-only condition where the only item in the display is the target. We consider reaction time in this condition to be an important baseline where there is effectively no stage-one processing time cost. This is because in both experiments, participants were told that there will always be one target in the display, so they can immediately learn that whenever there's only one item on the screen, that item is the target they need to discriminate. Mean RT in this condition therefore represents all the RT components that do not depend on set size, e.g. time for visual information to arrive at cortex, motor response time, etc. In the case of efficient search for targets among lures, the only component depending on set size should be the stage-one processing time, which can be computed by subtracting target-only RT from RT values in each condition.

Data analysis. According to the hypotheses laid out in the introduction, the key analysis for this experiment should be based on a linear regression of predicted RT data to observed RT data in each condition. In Experiment 1, we estimated log slope coefficients for each type of lure. These values were applied to each of the 4 equations we created. Then, we computed predictions of stage-one processing times in each condition by plugging numbers of each type of lures as listed in Table 3 into the equations. Predicted RT for each condition can be found by adding the mean RT in target-only condition to the predicted stage-one time costs. Linear regression models could thus be constructed for each equation, and for all conditions together as well as each subset of conditions. To compare the performance or 'goodness of fit' across these models, we computed the R square and the Akaike Information Criterion (AIC; Akaike, 1974) values for

each model. These computations were carried out using the `fitlm()` function, the `Rsquared` and the `ModelCriterion` methods of the `Linear Model` class in Matlab.

To estimate the effect of heterogeneity/homogeneity, we performed regressions on stage-one time cost (i.e. without the added target-only RT) based on the best performing equation, and examined the estimated regression coefficients for each group. This way, the estimated intercept coefficients become a useful indicator of the additive effect of interaction between lure items in homogeneous search. If this interaction does not cause an additive RT difference, then the estimated intercept should be equal to the actual observed target-only RT, assuming that our best performing equation provides a truthful prediction. Hence, any substantial difference between the estimated intercept and observed target-only RT becomes a measure of the magnitude of this additive effect. By the same logic, deviation of the estimated slope coefficient from 1 represents any potential multiplicative effect of between-lure interaction in homogeneous search displays.

Results

Mean RTs across subjects are plotted for each condition separated by subsets in Figure 4. Visual observation indicates that instead of being relatively evenly spaced, the 4 subsets with the red carrot man lure tend to form a cluster of data points whereas subset 1 without the red carrot man lure was singularly shallow. This pattern was also apparent when we applied simple logarithmic regression to each subset of data, whose results were summarized in Table 4. The Log slope of subset 1 was very close to the homogeneous slope estimates of white reindeer ($D_{\text{white reindeer}} = 28.492$) and of the grey car ($D_{\text{grey car}} = 26.581$), while slopes for subsets 2 to 5 were all greater than the homogeneous slope estimate of the red carrot man ($D_{\text{red carrotman}} = 66.278$), even though each of these subsets include at least one type of lower-similarity lures. Also notice that all regressions had very large R squares, indicating that for each of these subsets, the underlying processing was still similar with the homogeneous case and consistent with the parallel, exhaustive nature of stage one proposed by our theory.

To test the prediction that Equation 1 should predict heterogeneous search reaction time most accurately, 4 sets of predicted RTs were computed and regressed to observed mean RTs. The linear fitting R squares, AIC values (corrected for small sample sizes) and root mean square errors (RMSE) are summarized in Table 5. All three measures indicated that predictions given by

Equation 1 were most accurate and likely. Specifically, the corrected AIC values indicate that the model based on Equation 1 was 166 times more likely than the second best model (Equation 3)³. Also the R square value for Equation 1 (0.9681) is roughly the same as the R squares obtained when Equation 1 was used to predict simulated heterogeneous search data (see Table 1 in Predictive Simulation section). The RMSE for Equation 1 was 14.520 ms which can be interpreted as the average amount of error in prediction, and this was comparable to the minimum of standard errors of mean RTs at 14.181 ms (in the condition where there were 13 carrot men, 4 reindeers and 14 grey cars). The accuracy of Equation 1's predictions is further highlighted by the fact that the predictions for these novel search displays were based on estimated parameters from Experiment 1 with a different group of participants. Therefore we can conclude that the empirical data from Experiments 1 and 2 exhibit the same relationship as was obtained from our simulations, which was best characterized by Equation 1. To investigate any potential effect of homogeneity facilitation between identical lure items, observed RT were first transformed to observed stage-one processing time by subtracting out the target-only RT, and then fitted to predictions of stage one processing time based on Equation 1 since it's the best predicting equation we have found. Regression was computed for all conditions combined as well as for separate subsets, and the resulting coefficients are listed in Table 6 along with standard error of estimates. To better evaluate the additive effect, we also reported p values of t tests for estimated intercept coefficients against 0 (for the regression with data from all conditions, df = 19; for the regressions with one subset of conditions, df = 3). All intercept estimates did not differ significantly from the observed target-only RT, indicating that there was no meaningful additive deviation when we predict heterogeneous search time using efficiency parameters (D values) from homogeneous search data.

Similarly, estimated slope coefficients were tested against 1. Notably, these slope coefficients were significantly different from 1 for all subsets of data combined, as well as 3 out of 5 subsets of conditions. This means our best predicting equation systematically under-predicted stage one processing time in heterogeneous search tasks by a multiplicative factor. This multiplicative

³ The relative likelihood ratio between two linear models can be computed using AIC values by the formula $\exp((AIC_1 - AIC_2)/2)$. Thus Equation 1 based model was $\exp\left(\frac{194.392-174.533}{2}\right) = 20527.07$ times more likely than the Equation 2 based model, $\exp\left(\frac{184.757-174.533}{2}\right) = 166.00$ times more likely than the Equation 3 based model, and $\exp\left(\frac{195.003-174.533}{2}\right) = 27861.47$ times more likely than the Equation 4 based model.

factor seems to be approximately 1.3 for this particular set of search stimuli. Recall that when making predictions using Equation 1, the log slope parameters for each lure type were estimated from homogeneous search data, and that Equation 1 assumed processing independence between individual items. The most straightforward explanation of this multiplicative deviation, then, is that in Experiment 1 when adjacent lures were identical, processing of individual lure items sped up by a multiplicative factor of about 1.3. So the estimated D parameters from Experiment 1 were in fact under-estimating the true ‘standalone’ processing efficiency of each individual lure item. In heterogeneous search, adjacent items are no longer identical and thus could not facilitate processing of each other. Thus when using D parameters from homogeneous scenes to predict heterogeneous search RT, predictions are multiplicatively lower than actual RT. **Discussion**

As our theory-based simulation predicted, Equation 1 provided the best predictions of heterogeneous search reaction time using log slope values estimated from homogeneous search data. Thus the predictive power of our theory was confirmed by empirical data, and we have found a successful formula that predicts heterogeneous search RT, accounting for 96.81% of variance for a total of 21 different experimental conditions. Since our simulation on both homogeneous and heterogeneous search assumed independence between each individual item’s processing, this assumption is also inherent in Equation 1’s predictions. We found a systematic difference between the predicted and observed stage one processing times, suggesting that in homogeneous displays, identical items do interact in a facilitative fashion and are not truly independent. However, this facilitation effect can be characterized by a constant multiplicative factor that does not depend on set size. Because the general formula to describe RT – set size functions in efficient visual search take the form of $RT = a + D \ln(N)$, where N is set size, we can infer that the facilitation effect resulted in an underestimation of the D coefficients in our Experiment 1. And since D coefficients were found to be directly related to the thresholds of accumulators, we propose that the facilitation was a result of a multiplicative lowering of the thresholds between adjacent, identical items. We discuss this finding further in the General Discussion.

It should be noted, however, that regression analysis on stage one processing times for two subsets of conditions did not produce slope estimates that’s significantly different from 1. Specifically, estimated slope of the regression model for subset 1 (estimate = 0.9554, standard error = 0.0938) was very close to 1. On the other hand, the insignificant statistics for the slope

coefficient in subset 3 seemed to have mainly come from the large standard error (estimate = 1.2063, standard error = 0.1179) due to relatively lower goodness of fit. Thus an open question remains here: why did this multiplicative effect of homogeneity disappear in some groups of conditions? Knowing that subset 1 (whose results most strongly indicated an absence of the multiplicative difference between homogeneous and heterogeneous search) was based on displays with mixtures of reindeers and model cars, both being relatively low similarity lures and having very close D coefficients in homogeneous search, we propose that either (1) homogeneity facilitation disappear for low similarity lures, or (2) when two types of lures are equally similar to the target, they can mutually facilitate each other when mixed. More data is needed to answer this question.

Chapter 5: General Discussion

Early parallel visual processing has important influences on visual search performance that the visual search literature has largely overlooked. We proposed a theory of stage one processing in vision based on the concept of visual similarity that successfully accounted for the logarithmic RT – set size functions and the similarity modulation of these functions. In this article we exploited the versatility and specificity of our theory to derive predictions on efficient, heterogeneous visual search tasks. These predictions were empirically tested and verified with Experiments 1 and 2, further demonstrating the explanatory power of our theory and model. Using data from homogeneous search tasks with real-world objects, we were able to predict heterogeneous search RT at an accuracy of 0.9681 R squared and 14.520 ms RMSE for the same set of objects. Notice that this prediction was based on an entirely new set of participants that had never participated in one of these search experiments. And further, the only shared condition across the two experiments was the target-only condition. In other words, the two sets of subjects viewed entirely different displays. Given the precision of these predictions, we further examined the facilitative effect when search displays had multiple identical lure items, by comparing predicted and observed stage one processing times. We found evidence that this facilitation seemed to result in a multiplicative overestimation of processing efficiency in homogeneous search, although this effect was not consistent across all groups of conditions.

Implications

The methodology and results demonstrate that our current theory of early parallel processing in vision is both very versatile (insofar as it can predict RTs to novel scenarios) and at the same time highly specific. The fact that RT by set size functions in both experiments were best characterized as logarithmic functions implies that the same parallel, exhaustive processing underlies a wide range of abstract as well as naturalistic stimuli, irrespective of whether they were presented in homogeneous scenes or not. Moreover, similarity between target and distractors was found to be the key modulator of processing efficiency for these stimuli. Our model also provided specific implementations of all key components of the theory, including a new way of understanding how similarity impact early visual processing: by modulating the threshold of noisy accumulators. This enabled us to carry out numerical simulations for any

arbitrary configurations of search displays, which led to very specific predictions of the relationship between homogeneous and heterogeneous search processing.

The fact that an exhaustive termination rule underlies the logarithmic RT by set size function suggests all items in a scene were processed to some degree. More importantly, the extent to which they are processed depended on their identity (see Experiment 1), the task goal, and the target template (Buetti et al., in press, Experiment 1). These findings indicate stage one processing is highly adaptive and responsive to top-down control. So it seems that early visual processing is not as passive as many used to assume, rather it could be utilized to compute different information depending on the task demand (Buetti et al., in press).

Also notice that the nature of the unlimited capacity of stage one implies that the visual system can recruit or afford as much resource as needed to process the entirety of the visual scene in the parallel stage. But at the same time, it also remains frugal in the sense that no more resource is spent than what would be enough to make processing of each item equally efficient (as in having the same information accumulation speed). This view is in contrast with some popular conception of ‘unlimited capacity’, where one might assume that the system always devote all the resource available so that when fewer items are present, each of them would be processed faster. Notice, however, that the notion of ‘all resource available’ seems to be already in contradiction with ‘unlimited capacity’. Moreover, we argue that such a strategy may not be optimal in terms of cost-benefit: because early parallel processing is exhaustive, the largest reduction in processing time under this strategy should occur at the smallest set sizes. But in the real world, scenes with small set sizes are very rare, so that the benefit would be rarely significant while the expense is high. Additionally this strategy also may not be viable because, borrowing from a computer science analogy, the machinery for this information accumulation process could be mostly hardware-based, and thus not re-allocatable.

In addition to testing and verifying our theory in the case of heterogeneous search, our analysis also estimated the effect of homogeneity facilitation and found it to be a constant multiplicative factor. In other words, processing of each lure item was facilitated by a multiplicative factor when lures in the display were identical (homogeneous), compared to when they were intermixed with other types of lures (heterogeneous).

The idea that degree of heterogeneity (or homogeneity) influences visual search processing efficiency is not new. Duncan & Humphreys (1989) referred to it as the nontarget-nontarget similarity effect. However, their claim that nontarget-nontarget similarity increases processing efficiency was mainly based on their experiments 3 and 4. In both experiments, search slopes for homogeneous displays were collapsed across different distractors and compared to heterogeneous search slopes, which were also collapsed across easy and difficult conditions in experiment 4. More importantly, there was not a direct manipulation of the degree of heterogeneity in these experiments, because there was always nearly equal numbers of two types of distractors in the heterogeneous conditions. Therefore, the essential evidence found was for the binary difference between homogeneous and heterogeneous displays. Yet, Duncan and Humphreys made the proposition that search slope should increase continuously as degree of nontarget-nontarget similarity decrease (Figure 3, Duncan & Humphreys, 1989). In comparison, here we have developed and carried out a systematic evaluation of this effect, and provided a numerical measure of its strength for a particular set of stimuli. We experimented with varying degrees of heterogeneity, and analyzed homogeneous search separately for three different types of lures. These design characteristics enabled us to understand the effect of heterogeneity to a much finer degree. Importantly, while Duncan and Humphreys suggested increasing linear search slopes with increasing degree of heterogeneity, we found that different mixtures (e.g. mixing two or three types of lure items) can be accounted for by a single constant factor. Therefore, the effect of heterogeneity seemed to not depend on the degree of heterogeneity, which do not lend support to the spreading suppression account of heterogeneity effect.

At the theoretical level, according to Duncan & Humphreys, items were given different attentional weights or different amounts of resources from a limited pool, based on their match with a search template. Homogeneous distractors group with each other, because their weights covary to the extent that they are similar to each other, so that when one item is given low attentional weight, the other's weight automatically decreases. This so-called 'spreading suppression' account was thought to be an advance further from the traditional 'perceptual grouping' accounts (Bundesen & Pedersen, 1983; Farmer & Taylor, 1980). In contrast, our current model and results require an alternative mechanism for the increase in processing efficiency of homogeneous scenes. This is because our theoretical framework differ from Duncan and Humphreys', in that processing capacity is unlimited, and items are assumed to

receive equal amounts of resources. We propose that instead of grouping similar search items, decisions are still made for each individual item, but adjacent identical distractor items facilitate each other by reducing the amount of information needed (i.e. threshold of accumulators) to reach a decision of rejection. This lowering of the thresholds could be due to the knowledge that only a single target exists in the display, which implies that for two adjacent similar items, either would be less likely to be the target. Notably, in Duncan & Humphreys (1989), facilitation effect was based on covariance of the attentional weights, which were assigned after the template matching process; whereas in our view, the lowering of accumulator thresholds must be no later than the parallel information accumulation process itself (which is most comparable to the template matching process). Finally, it is difficult to imagine how Duncan & Humphreys' theory would be able to account for the basic finding of logarithmic RT – set size functions. Hence current data present a challenge to traditional views of the distractor heterogeneity effects, and suggest that a different view on the mechanism of the homogeneity facilitation effect should receive further consideration.

Limitations

It is important to note that the visual search task used in this study was a target discrimination task, where there is always a target present in the display, and the participants had to locate it in order to make a decision about its details (where the red dot appears). This is different from the target detection task more common in the literature, where only the presence or absence of a target is to be reported (e.g. Jonides & Gleitman, 1972; Treisman & Gelade, 1980). It is possible that the task used here partially explains the difference between our logarithmic RT functions and the often-observed linear ones. However, there are reasons to believe the phenomenon is not accidental and the nature of stage one processing is fully revealed in this target discrimination search task. First of all, the two tasks very likely induce different processing strategy, especially in the case of efficient visual search. In a target discrimination task, the need to extract details from the target compels participants to fixate or at least focus spatial attention to the target (Bravo & Nakayama, 1992), even when all distractors can be efficiently rejected or filtered out. In a target detection task, there is no such demand, and when target and distractors are highly dissimilar, the presence or absence of the target could create a strong difference in the global pattern or topology of the search scene. Hence the whole search

scene could be processed as a single ‘structural unit’ (Duncan & Humphreys, 1989) or ‘object file’ (Kahneman, Treisman & Gibbs, 1992). As soon as a global topological feature is detected, a response decision can be made, and there is no need to find out the exact location of the target. In real-world scenarios, many search tasks involve not only detecting but also locating the target, because most often the end goal of search is to interact with the target object, whether it’s searching for a specific key on the key chain, or searching for a specific book on the bookshelf. Therefore the target discrimination task is at least as ecologically meaningful as the target detection task. Finally, there are indications in the literature (Treisman & Gelade, 1980; Palmer, Ames & Lindsey, 1993) as well as our own unpublished data showing that even in a target detection task, logarithmic functions can be observed.

We will also point out that the estimation of homogeneity facilitation effect is reliable to the extent that Equation 1 truthfully represent the prediction of stage one processing time assuming independence between individual items. As our simulation analysis indicated, Equation 1 was not a perfect prediction but came very close. The imperfection in R squares and estimated coefficients in Table 1 most likely arose from randomness in the simulations, and was small enough to not affect the conclusion about the homogeneity facilitation effect. That being said, the obvious (but seemingly inevitable) limitation of this approach is the unavailability of an exact mathematical solution for stage one processing time in the case of multiple different types of items. Without this solution, there’s always possibility that a better equation than Equation 1 could be found to describe the relationship between homogeneous and heterogeneous lure searches.

Future directions

One natural venue of future research is to apply the same experimental procedure on different sets of search stimuli, in order to explore whether different stimuli exhibit different relationship between homogeneous and heterogeneous search performance. Such possibility is already hinted by the absence of the multiplicative facilitation factor for the analysis on subset 1 of Experiment 2. We consider this to be indication that in this subset of conditions, mutual facilitation happened across two different types of lures. There are at least two possible reasons for this to have happened. First, it could be because the two types of lures involved, the white reindeer toy and the grey car model, were both highly dissimilar to the target, as evidenced by

the very low logarithmic slope coefficients estimated in Experiment 1. Another possibility is such across-identity facilitation could take place between lures who are equally similar to the target—in the current study, slope coefficients for the reindeer and the car were nearly equal, representing nearly equal similarity to the target teddy bear. By testing multiple sets of stimuli, we may be able to distinguish these possibilities. Also it would be interesting to see whether Equation 1 still maintain strong performance in predicting heterogeneous search reaction times for other types of stimuli, under greater degrees of heterogeneity, and with different ways of intermixing distractors.

Another interesting scenario to examine is when different types of lures are separated into homogeneous regions in the scene, so that within each region, adjacent items are identical. According to our suggestion, the between-item facilitation effect was thought to be based on the spatial adjacency of identical items. Therefore, in this type of displays, within each homogeneous region, processing of individual items should facilitate each other similar to when the entire display consisted of identical lures. Notably, if log slope coefficients estimated from homogeneous search scenes are used to predict search RT in this type of display, we would expect the prediction to be close to perfect. This is because in both scenarios (homogeneous search scenes and scenes consisting of several homogeneous regions) there should be roughly the same amount of between-item facilitation effect. Therefore the D coefficients from homogeneous search results no longer need any correction for the absence of facilitation effect, unlike Experiment 2 where adjacent items are often different. In other words, for this type of display, Equation 1 should provide almost perfect prediction when using D coefficients estimated from homogeneous search data.

Conclusion

A series of novel data highlighting logarithmic RT – set size function led us to propose a new theory of early visual processing—that the system processes all items in a parallel, unlimited capacity, exhaustive mode. Under this conceptualization, meaningful relationship between heterogeneous and homogeneous search was predicted by simulation and confirmed by experiments with a novel methodology. Instead of being completely independent, individual items seemed to facilitate each other's processing when they appear in the context of other identical items. This facilitation effect can be characterized by a multiplicative factor in

logarithmic space that did not change with set size. This result presents a challenge for traditional accounts of distractor heterogeneity effects. These findings extend the application of our theory to real-world objects and heterogeneous search tasks, and demonstrate the specificity and accuracy of our current model of stage one processing. Parallel processing in visual search is therefore non-trivial, because it systematically contributes to reaction time, plays an important role in achieving the search goal, and can be mechanistically understood.

Chapter 6: Figures and Tables

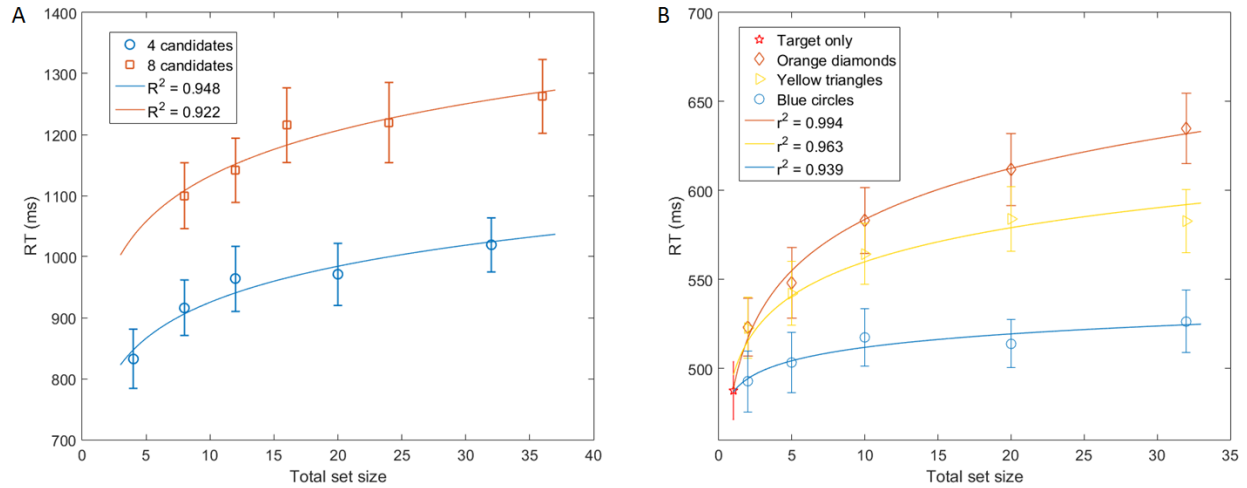


Figure 1. Key findings demonstrating logarithmic RT by set size functions from Buetti et al. (2016). A. Data from Experiment 3A of Buetti et al. (2016). Reaction times to find a ‘T’ target among ‘L’ candidates and thick orange cross lures are best described as a logarithmic function of total set size when the number of candidates is held constant. B. Data from Experiment 1A of Buetti et al. (2016). Reaction times to find a red triangle target among different types of lures are logarithmic functions, whose steepness or ‘slopes’ are modulated by the similarity between lure and target.

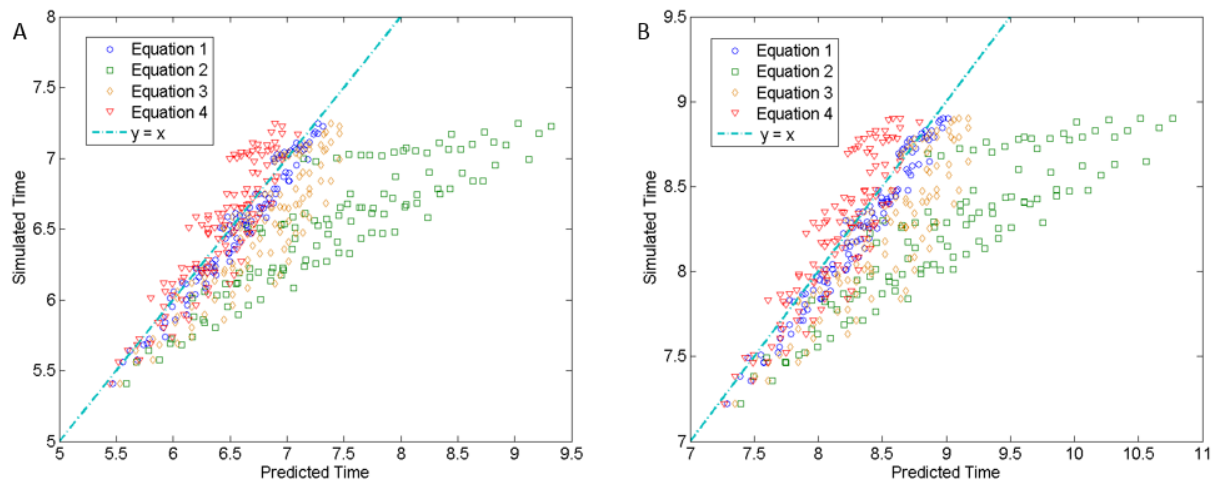


Figure 2. Predicted processing time according to 4 approximating equations for heterogeneous search plotted with simulated processing time. Panels A and B present results from two different simulation runs using different sets of parameters (see text for more details).

Table 1. Model characteristics of regressions of predicted to simulated processing times

	Simulation 1				Simulation 2			
	R ²	Log likelihood	Slope (Standard Error)	Intercept (Standard Error)	R ²	Log likelihood	Slope (Standard Error)	Intercept (Standard Error)
Eq 1	0.9615	114.031	1.005 (0.019)	-0.109 (0.127)	0.9637	124.179	1.008 (0.018)	-0.152 (0.156)
Eq 2	0.8045	23.816	0.463 (0.021)	3.075 (0.163)	0.8095	32.107	0.482 (0.022)	3.871 (0.203)
Eq 3	0.7934	20.758	0.877 (0.043)	0.570 (0.291)	0.7709	21.878	0.861 (0.045)	0.905 (0.383)
Eq 4	0.8049	23.953	1.112 (0.052)	-0.652 (0.338)	0.7852	25.452	1.137 (0.057)	-1.058 (0.466)

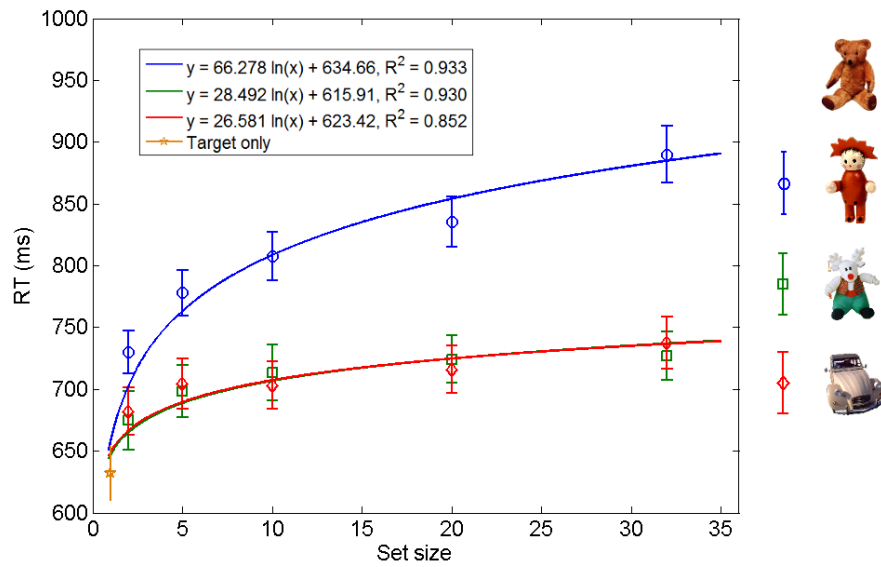


Figure 3. Reaction times for Experiment 1 plotted as a function of set size, separated by 3 types of lures. Curves indicate best-fitting logarithmic functions. Error bars indicate standard errors of mean. Images of search stimuli and the corresponding data symbols are presented on the right.

Table 2. Logarithmic vs. linear regression results of RT by set size functions in Experiment 1

	With target-only condition				Without target-only condition			
	Logarithmic		Linear		Logarithmic		Linear	
	R square	Log Likelihood	R square	Log Likelihood	R square	Log Likelihood	R square	Log Likelihood
Red carrot man	0.933	-27.178	0.713	-31.558	0.965	-18.718	0.924	-20.650
White reindeer	0.930	-22.251	0.619	-27.351	0.951	-15.365	0.711	-19.827
Grey model car	0.852	-24.354	0.595	-27.380	0.938	-14.636	0.919	-15.300

Table 3.

Subset	Number of red carrot man	Number of white reindeer	Number of grey model car	Notes
Subset 1	0	1	2	Comparable numbers of white reindeers and grey cars
	0	3	4	
	0	7	8	
	0	15	16	
Subset 2	1	0	2	Roughly equal numbers of red carrot man and white reindeers
	3	0	4	
	7	0	8	
	15	0	16	
Subset 3	1	6	0	Fixed 6 reindeers, varying number of carrot man
	5	6	0	
	9	6	0	
	21	6	0	
Subset 4	1	1	1	Roughly equal numbers of all 3 types of lures
	2	2	3	
	5	5	5	
	10	11	10	
Subset 5	1	4	2	Fixed 4 reindeers, comparable numbers of carrot men and cars
	3	4	4	
	7	4	8	
	13	4	14	
Included in all subsets	0	0	0	Target only condition

Table 4. Logarithmic regression results of search RT for each subset of conditions

Subset	Log Slope (D)	Intercept	R squared
1	26.881	663.97	0.9722
2	79.59	649.38	0.9811
3	75.183	650.16	0.9307
4	70.196	654.85	0.9801
5	71.974	649.76	0.9573

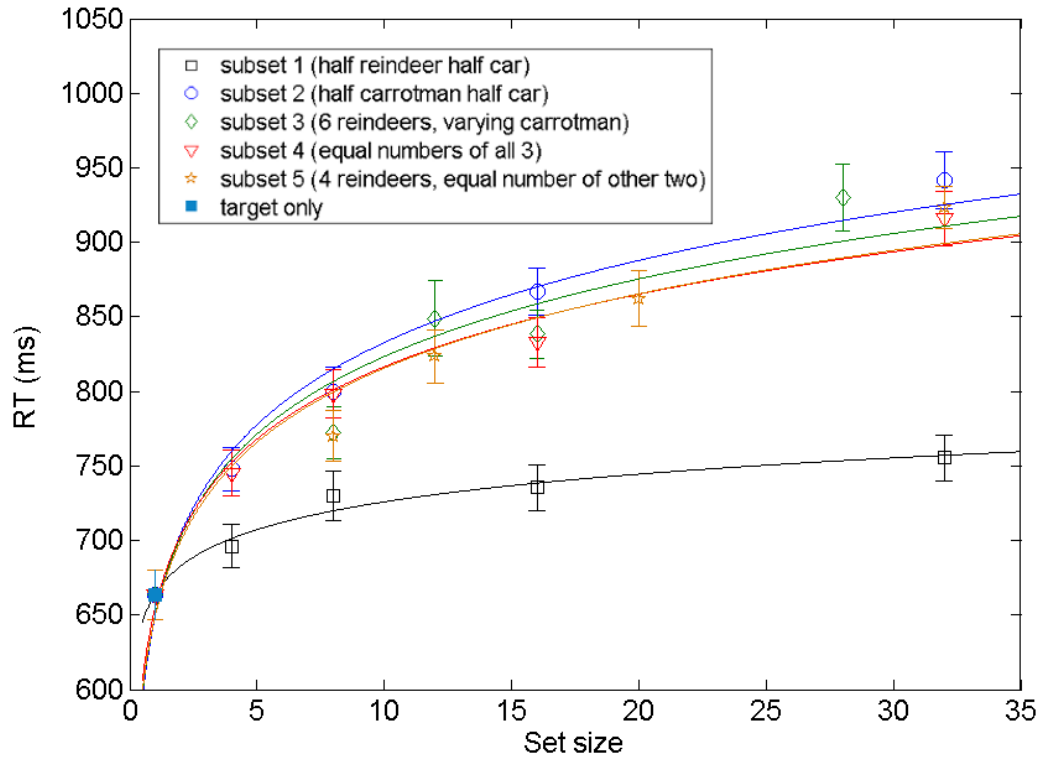


Figure 4. Reaction times in Experiment 2 as a function of set size, grouped by the different subsets of conditions. Error bars indicate one standard error of mean. Curves are best-fitting logarithmic functions, see Table 4 for model coefficients and R squares.

Table 5. Linear regression results of predicted RT to observed RT in Experiment 2

	Equation 1	Equation 2	Equation 3	Equation 4
R squared	0.9681	0.9178	0.9480	0.9153
AICc	174.533	194.392	184.757	195.003
RMSE (ms)	14.520	23.298	18.522	23.639

Table 6. Regression coefficients for the regression of Eq 1's predicted stage-one processing times to observed values

	Intercept			Slope		
	Estimate	Std. Error	T test against 0	Estimate	Std. Error	T test against 1
All subsets	-10.961	7.268	p=0.148	1.3328	0.0555	p<0.001
Subset 1	0.948	5.986	p=0.884	0.9554	0.0938	p=0.667
Subset 2	-4.392	6.585	p=0.553	1.3587	0.0515	p=0.0061
Subset 3	2.038	16.573	p=0.910	1.2063	0.1179	p=0.179
Subset 4	-1.242	10.217	p=0.911	1.2905	0.0857	p=0.043
Subset 5	-1.242	6.277	p=0.856	1.2890	0.0474	p=0.0089

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Appendix A: Conditions Used in Simulation

The combinations of the 3 types of lure items used in Chapter 2: Predictive Simulation are listed in the following table.

Lure 1	Lure 2	Lure 3
0	1	1
0	1	3
0	1	7
0	1	15
0	3	1
0	3	3
0	3	7
0	3	15
0	7	1
0	7	3
0	7	7
0	7	15
0	15	1
0	15	3
0	15	7
0	15	15
1	0	1
1	0	3
1	0	7
1	0	15
1	1	0
1	1	1
1	1	3
1	1	7

Lure 1	Lure 2	Lure 3
1	1	15
1	3	0
1	3	1
1	3	3
1	3	7
1	3	15
1	7	0
1	7	1
1	7	3
1	7	7
1	7	15
1	15	0
1	15	1
1	15	3
1	15	7
1	15	15
3	0	1
3	0	3
3	0	7
3	0	15
3	1	0
3	1	1
3	1	3
3	1	7

Lure 1	Lure 2	Lure 3
3	1	15
3	3	0
3	3	1
3	3	3
3	3	7
3	3	15
3	7	0
3	7	1
3	7	3
3	7	7
3	7	15
3	15	0
3	15	1
3	15	3
3	15	7
3	15	15
7	0	1
7	0	3
7	0	7
7	0	15
7	1	0
7	1	1
7	1	3
7	1	7

7	1	15
7	3	0
7	3	1
7	3	3
7	3	7
7	3	15
7	7	0
7	7	1
7	7	3
7	7	7
7	7	15
7	15	0
7	15	1

7	15	3
7	15	7
7	15	15
15	0	1
15	0	3
15	0	7
15	0	15
15	1	0
15	1	1
15	1	3
15	1	7
15	1	15
15	3	0

15	3	1
15	3	3
15	3	7
15	3	15
15	7	0
15	7	1
15	7	3
15	7	7
15	7	15
15	15	0
15	15	1
15	15	3
15	15	7