Ollscoil na Gaillimhe
University of Galway

Provided by the author(s) and University of Galway in accordance with publisher policies. Please cite the published version when available.

Title	Expectancy, not memory determines identical search rates in static and dynamic displays.
Author(s)	Elliott, Mark
Publication Date	2005
Publication Information	Shi, Z., & Elliott, M. A. (2005). Expectancy, not memory determines identical search rates in static and dynamic displays. In J. S. Monahan, S. M. Sheffert & J. T. Townsend. (Eds.). Fechner Day 2005. Proceedings of the Twenty First Annual Meeting of the International Society of Psychophysics. Traverse City Michigan, USA. The International Society for Psychophysics, (pp. 333-336).
Publisher	International Society for Psychophysics
Item record	http://hdl.handle.net/10379/1577

Downloaded 2024-04-26T16:57:47Z

Some rights reserved. For more information, please see the item record link above.

EXPECTANCY, NOT MEMORY DETERMINES IDENTICAL SEARCH RATES IN STATIC AND DYNAMIC DISPLAYS

[1]Zhuanghua Shi, [1,2]Mark A. Elliott
[1]Department Psychologie,
Ludwig-Maximilians Universität, Munich/München, Germany
[2]Department of Psychology
National University of Ireland, Galway, Ireland

Abstract

Search rates are often used as a measure of search efficiency. Horowitz & Wolfe employed this measure to compare static and dynamic visual search (Horowitz & Wolfe, 1998). Based on identical search rates, they argued that visual search operates without memory. Subsequently and in contrast a number of other authors have agued that visual search relies upon iconic memory (Bäcker & Peral, 1999; Peterson, Kramer, Wang, Irwin, & McCarley, 2001; Scheier, Khurana, Itti, & Koch, 1999). In a reanalysis of Horowitz and Wolfe's data, Kornbrot found contrary results (Kornbrot, 2004). Search rates only indicate search efficiency and the implications of this may be limited. In this commentary we propose a probability model and point out that factors such as target probability and subjective expectancy may bring about similar results.

In a typical visual search task, subjects are asked to search for a target positioned amongst distracters, for example for a red diagonal bar nested among green vertical bars. In the majority of experiments there are two common dependent variables, response time (RT) and accuracy, which are employed as indexes of search efficiency and by extension as indicators of the mechanisms of search. More specifically, search rates (or search slopes), i.e. RT increment per item, are a particular focus of interest (Wolfe, 1998) and have lead to concepts such as parallel/serial search (Treisman & Gelade, 1980) and guided search (Wolfe, 1994). A typical serial search model assumes that search rates reflect some degree of sequential processing. Once an item has been processed, it is tagged and never again reprocessed. Implicit in this assumption is the notion of memory-driven search. This assumption was questioned by Horowitz and Wolfe (1998), who used static and random displays for the presence of a target. In random display, all item locations were changed every 111 ms, whereas in static display all item locations remained the same. Based on identical search rates and the impossibility of a memory-driven strategy in random displays they argued visual search operates without memory. This was soon subject to criticism by a number of researchers citing eye movement data (Peterson et al., 2001), the inadequacy of Horowitz and Wolfe's data (Bäcker & Peral, 1999), and more recently reanalysis of their data (Kornbrot, 2004) as indicating quite the contrary. The counter claim being that visual search does have a memory.

In spite of this debate for a number of years Townsend and others have repeatedly warned against using the method of varying set size and measuring response time for differentiating serial and parallel search (Atkinson, Holmgren, & Juola, 1969; Townsend, 1971, 1990, 2001). In current paper we show that even adopting a strict serial processing assumption it is still dangerous to conclude anything about the role of memory in visual search from search rates alone.

Probability models in visual search

Horowitz employed two different search displays (Horowitz & Wolfe, 1998). One condition was a normal static search display with set size *n*, the second was a random dynamic display with same amount of items but with item locations shifted randomly every 111 ms. The search tasks were the

same. For simplicity, we will describe only serial self-terminating search model. It's enough to see how search rates can be identical with memory assumption, although an equivalent parallel model can be developed. A serial self-terminating model assumes that one item is processed at a time and search is terminated after a target has been found or all of the items have been examined. Furthermore, the distribution of processing time for the individual target and distracter items was also assumed to be identical. Under these assumptions, the mean RTs in Horowitz's experiments for static and random display are equivalent to average checked balls in following two classical probability questions, respectively:

1. There're *n* balls in a cloth bag with colour hidden from view. The balls are red or blue. With a 50% probability the bag contains one red ball and the experimental subjects are allowed to take out one ball at a time. What is the mean average number of times taken for a subject to find the red ball?

2. The same basic setting as above with a variation in procedure. Subjects are allowed to take out one ball at a time but if the ball is not red it must be returned to the bag. The question again asks, what is the mean average number of times taken for a subject to find the red ball?

Since Experiment 3 in Horowitz's paper is only considered in terms of a target being present, the same situation is also considered here. The answer to first question is:

$$\begin{aligned} Mean &= \sum_{i=1}^{n} i \cdot \Pr(step\ i\ get\ red\ ball) = \sum_{i=1}^{n} i \cdot \prod_{i<i} \Pr(ball\ \ j\ is\ blue) \cdot \Pr(ball\ i\ is\ red) \\ &= \sum_{i=1}^{n} i \cdot \frac{n-1}{n} \cdot \frac{n-2}{n-1} \Lambda\ \frac{1}{i} = \frac{n+1}{2} \end{aligned} \tag{1}$$

For the second question, because of replacement of distractor balls, the probability of a red ball (target) in each step is identical, i.e. $p = 1/n$ while probability of blue balls (distracters) is $q = 1\text{-}1/n$. Thus:

$$\begin{aligned} Mean &= \sum_{i=1}^{M} i \cdot \prod_{i<i} \Pr(ball\ \ j\ is\ blue) \cdot \Pr(ball\ i\ is\ red) = \sum_{i=1}^{M} i \cdot q^{i-1} \cdot p \\ &= \frac{1}{p} \cdot (1 - q^{M}) - M \cdot q^{M} \\ &= n - (n + M) \cdot \left(1 - \tfrac{1}{n}\right)^{M} \end{aligned} \tag{2}$$

Where *M* is maximum number of repeated checks, we refer to this as a stopping criterion. In an ideal model *M* should approach infinity. However, because of the small probability for very late target appearance and subject impatience, subjects always set some limited criteria (Experiments showed trials with response longer than 5s were less 2% in total, Horowitz & Wolfe, 1998). Kornbrot argued that these criteria should independent of set size due to dependent error rates (Kornbrot, 2004). Bäcker and Peral (1999) made a similar assumption since they estimated *M* around 33 for all set sizes. Whether stopping criterion *M* is set size independent or not, error rates should be detailed examined. It is quite clear, without considering misses that pure error rates when applying stopping criterion *M* are $e = (1 - \frac{1}{n})^{M}$.

Detailed relationships between error rates and stopping criterion *M* are shown in Figure 1a. The real error rates from the behavioral data (the triangles in Figure 1a, see also Figure 1 in Kornbrot) indeed suggest *M* is not independent of set size *n*. This is contrary to the conclusion reached by Kornbrot.

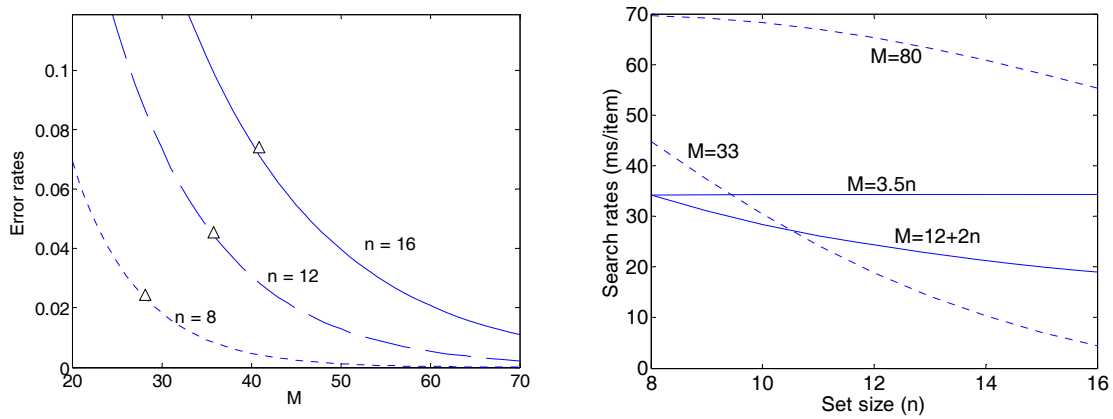

Fig. 1. a. Left panel: Error rates as functions of stopping criterion *M* (the maximum number of items checked) for different set sizes. Dot line: random display with set size 8, dash line: set size 12 and solid line: set size 16. Triangles are the empirical error data from Horowitz's Experiment 3. Right: Search rates as a function of set size for different stopping criterion *M*. dash lines: uniform stopping criteria. Solid lines: set size depended criteria.

A reasonable alternative assumption is that in dynamic search subjects set their stopping criterion *M* as a function of set size and with an initial intercept C, i.e.

$$M = C + k \cdot n \tag{3}$$

Under these conditions, set size determines stopping criterion. We further investigated how these two different conditions, i.e. static and random displays, can produce similar search rates without assuming the involvement of any other factors.

Because of linear properties (Equation 1) the search rate of static condition is straightforward,

$$s = 0.5\tau, \tag{4}$$

where τ estimated from Horowitz's experiment 3 is 70ms and search rate *s* is 35ms. The search rate of dynamic condition is a little more complex:

$$s = \left(1-(n+1+M)\left(1-\frac{1}{n+1}\right)^{M}+(n+M)\left(1-\frac{1}{n}\right)^{M}\right)\cdot\tau \tag{5}$$

Note this is a nonlinear function of set size. Principally the search rates are very different from the static condition.

Based on Equation 5, Figure 1b shows how different stopping criteria affect search rates as a function of set size. If subjects have patience and set a very large termination time, the search slopes should actually double relative to the static condition. For example search slope is near 70ms in random condition compared to 35ms in static condition for set size 8 and M equals 80 (Figure 1b M=80). This predicted the Horowitz's Monte Carlo simulation (Horowitz & Wolfe, 1998). However, in most cases subjects terminate search quite early. Bäcker estimated that subjects terminated search roughly after examining 33 items for random displays. Following this stopping criterion, however, Figure 1 b shows that search rates decrease dramatically when set size increases, although the mean average of 3 levels (set sizes of 8, 12 and 16 distracters) was similar to the empirical data. A possible ideal stopping criteria which can guarantee similar search rates to

the static condition is an absolute set size dependent termination strategy (Figure 1b. $M=3.5n$). Under this strategy search rates are kept almost the same as the static condition among a wide range of set sizes. Furthermore the error rates should also remain as low as under static conditions (Figure 1a). However, the real data suggests that slopes decrease slightly with increasing set size (Figure 2a in Horowitz, 1998) while error rates increase as a function of set size (c.f. Figure 1a triangles). Consequently, the most probable strategy undertaken by subjects would be to relative set size dependent termination strategy (Figure 1b. $M=12+2n$). With this strategy the model predicts both Horowitz's error rates and search slopes more precisely.

Discussion

Search rates and memory

Inferring mechanisms from search rates has been counselled against for a number of years (Atkinson et al., 1969; Townsend, 1971, 2001). These commentators warned that search rates are inadequate a means to discriminate between parallel and serial search. The above probability models also show there is a similar danger in inferring whether search is memory driven or not. The first non-replacement probability model presented here has an implicit memory assumption. By contrary, there's no memory assumption in the second replacement model. Even with these two different assumptions modelled search rates can be identical by using set size dependent termination criteria (Figure 1b). Search rates merely reflect the search efficiency. On this basis one should exercise considerable caution in inferring from search rates alone, especially when examining a very few levels of set size.

Stopping criteria and expectancy

Contrary to the set size independent strategies proposed by Kornbrot and Bäcker (Baecker & Peral, 1999; Kornbrot, 2005), the above analyses indicated that stopping criteria M are dependent of set size n. In random search displays, target probability is an inverse property of set size n. Therefore, stopping criteria is actually related to target probability. A lower target probability makes for an expectancy of longer search. When set size increases and target probability decreases in random search display, subjects implicitly increase stopping criteria M, with the result that, as a by product –both static and dynamic search produce similar search rates.

Acknowledgements

This research was supported by German research council (DFG) grant EL 248/1 to MAE.

References

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

Bäcker, A., & Peral, E. (1999). *Visual search: amnesic or undecided?* Paper presented at the Proc. 3rd Annual Vision Research Conference, Fort Lauderdale, FL.

Horowitz, T. S., & Wolfe, J. M. (1998). Visual search has no memory. *Nature, 394*(6693), 575-577.

Kornbrot, D. E. (2004). *In the glimpse of an eye: decision making and vision.* Fechner Day 2004: Proceedings of the Twentieth Annual Meeting of the International Society for Psychophysics. Coimbra: Gráfica de Coimbra, Lda. (pp. 252-257

Peterson, M. S., Kramer, A. F., Wang, R. F., Irwin, D. E., & McCarley, J. S. (2001). Visual search has memory. *Psychol Sci, 12*(4), 287-292.

Scheier, C., Khurana, B., Itti, L., & Koch, C. (1999). *Visual Search Amnesic or Memory Driven?* Paper presented at the Proc. 3rd Annual Vision Research Conference, Fort Lauderdale, FL.
Townsend, J. T. (1971). A note on the identifiability of parallel and serial processes. *Perception & Psychophysics, 10*, 161-163.
Townsend, J. T. (1990). Serial vs. parallel processing: Sometimes they look like tweedledum and tweedledee but they can (and should) be distinguished. *Psychological Science, 1*, 46-54.
Townsend, J. T. (2001). A clarification of self-terminating versus exhaustive variances in serial and parallel models. *Percept Psychophys, 63*(6), 1101-1106.
Treisman, A., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12*, 97-136.
Wolfe, J. (1998). *Visual Search*. London, UK: Universitz College London Press.
Wolfe, J. M. (1994). Guided Search 2.0: A revised model of visual search. *Psychonomic Bulletin and Review, 1*(2), 202-238.