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IN THE GLIMPSE OF AN EYE: DECISION MAKING AND VISION

Diana Eugenie Kornbrot
Psychology Department, University of Hertfordshire. d.e.kornbrot@herts.ac.uk.

Abstract

Rapid visual search, depending on iconic memory, is a core but controversial psychophysical topic. A key example is the claim by Horowitz & Wolfe (1998a) that 'visual search has no memory. Their evidence is the effect of increasing search set size in a letter identification task. Search *time* per item was unimpaired when all letters were randomly relocated during the search. This paper presents additional analyse showing strong deleterious effects of randomly relocating letters, on error rates, and on total reaction time. Thus visual search *does* have a memory. A psychophysical information accrual model is presented to account for these data and other key studies on visual search. The model includes decision criteria as well as sensory parameters. Criterion adjustments, which depend on numbers of distractors, predict the lower mean search times and the lower error, rates observed for non-random presentations.

Humans have evolved to be extremely effective visual searchers, whether for edible morsels in the forest, or for amusing titbits on the Internet. Furthermore, many cognitive scientists have used visual search through physical space as a model for cognitive search through mental space. Consequently, the mechanisms underlying visual search are of central psychological. Generally, there have been three strands of research. The first examines easy tasks using reaction time as a measure of performance (Luce, 1986) for review. Sternberg's classic work being an example (Sternberg, 1969). Error rates are generally noted, but frequently not analysed, (Horowitz & Wolfe, 1998b; Townsend & Roos, 1973; Treisman, 1988). Notable exceptions include Treisman and Gormican (1988) and some of Wolfe's work (Wolfe, 1998; Wolfe, Butcher, Lee, & Hyde, 2003). The second strand examines hard discrimination tasks using measures based on errors, such as d' from the theory of signal detectability or ln (η) from Luce's choice theory. The third strand brings together reaction time and error performance by modelling information accrual mathematically via processes such as random walks (Kornbrot, 1988, 1991; Laming, 1968; Luce, 1986; Usher & McClelland, 2001). The first two strands have typically been concerned with understanding perception via stimulus features, such as colour or shape. By contrast, the mathematical modellers have been more interested in general decision making. Furthermore, their methods tend not to be taken up more generally because of mathematical intractability. This is changing. One reason is the availability of techniques like logistic regression in statistics packages. Random walk models typically generate linear functions of logit (error) as key sensitivity and bias parameters. Another reason is that more sophisticated versions of random walks can now be analysed (Diederich & Busemeyer, 2003; Roe, Busemeyer, & Townsend, 2001; Usher & McClelland, 2001). Here the methods are applied to visual search. We aim to evaluate whether 'visual search has no memory' (Horowitz & Wolfe, 1998a). We also aim to show how information accrual models can account for both errors and latencies.

Howrowitz and Wolfe's Iconic Memory Experiment

In this ingenious paradigm, people are given the task of searching a display with a set of *N* letters for pre-specified target letter(s). Response times (RTs) and accuracy are recorded. As in numerous previous studies, mean RTs are found to be a linear function of set size, *N*. The clever part is that there are two kinds of presentation of the display to be searched - static and random. Presentations comprise several frames following one after the other. For static presentations the target and distractor letter locations remains fixed. For random presentations, all letter locations change every 111 msec. The 'natural' prediction is that the slope of the linear function relating mean correct RT to *N* for random presentations will be twice that for static presentations. This is because if people remember where they have already searched, they will on average search only half as many items in the static condition. However, the surprising finding is that the slopes for random and static displays are not reliably different. Horowitz and Wolfe's conclusion on the amnesiac nature of visual search is based on the assumption that not only, the search *time* per item, but also search *efficiency* per item is identical for both presentation modes. They argue that although error rates are higher for random presentations, the lower than predicted slopes for random presentations cannot be due to speed-accuracy trade-offs, with guessing occurs if a target is not found by some deadline (Horowitz & Wolfe, 1998b).

Todd Horowitz kindly provided the raw data from Horowitz and Wolfe's Experiment 3 (1998a). So it has been possible to further investigate the relationship between error rates and set size, and between RT and set size, for different presentation modes. The results lead to the conclusion that search *efficiency* per item *is* substantially impaired for random presentations. An explanation is provided using a theoretical approach that explicitly describes the effects of presentation mode and set size on decision criteria.

Analysis of Horowitz & Wolfe Results

Horowitz and Wolfe's Experiment 3 has a within participants design with 2 presentation modes (static, random); 3 set sizes (8, 12, 16) and 2 targets (E, N). Error rates are analysed using logistic regression (Agresti, 1996; Agresti & Hartzel, 2000). Figure 1 shows the effects of presentation mode and set size on performance. The dependent variables are mean RT in the top panel and logit (error rate) shows in the bottom with the (non-linear) scale for probability marked on the right axis. For RT, the effect of condition on slope was not significant, F (1, 10) = 3.07, p = .110 with a mean slope of 32.1 msec/item (as described by Horowitz & Wolfe); the large difference of 188 msec in intercept was significant, F (1, 10) = 18.7, p = .0015. The logistic regression analysis of the error rates showed no effect of presentation mode, χ^2 (1) = .99, p = .32; a main effect of set size, χ^2 (1) = 20.8 for 1 df, p = .000005; and an interaction of set size and presentation mode, χ^2 (1) = 8.2 for 1 df, p = .0042. Separate logistic regressions for static and random presentations showed no effect of set size for static presentations, χ^2 (1) = 1.11, p = .292; but a strong effect for random presentations, χ^2 (1) = 38.1, p < 10^{-6}. The set size effects on error rate evident in Figure 1 are thus highly reliable.

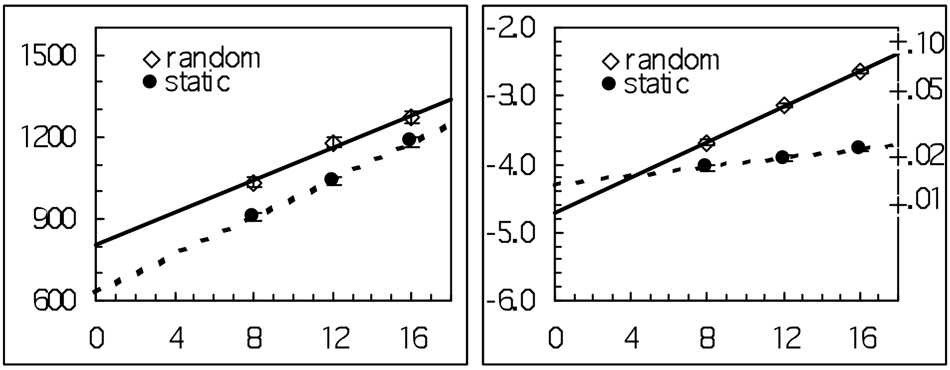

Figure 1. Performance as a function of set size for random and static presentations. Left panel mean RT msec. Right panel errors: left axis logit scale, right axis probability scale. Dashed line static; solid line random.

The finding of a set size dependent error rate only in the random condition surely contradictsˆ the claim of equal 'efficiency' per item. The difference in RT intercept of 188 msec, equivalent to searching six more items, surely cries out for a theoretical explanation.

Eccentricity

The pattern of higher intercepts of the RT versus set size function for random presentations; together with a reliable effect of set size on error rates for random presentations only is distinctive. In order to see if this pattern would hold up when other variables were taken into account the effect of eccentricity (distance from the centre of visual fixation) in experiment 3 was also investigated[2]. The results are shown in Figure 2. For static presentations, RT slope increases with eccentricity, F (2,10) = 15.1, p = .0001. For random presentations RT intercepts increase with eccentricity, F (2,10) = 7.66, p = .0034. The slope for static presentations, 44.4 msec per item, is significantly larger than for random presentations, 32.3 msec per item, for the most eccentric stimuli, F (1, 10) = 7.54, p = .006. The error functions in Figure 2 show the same pattern at each eccentricity, as do the aggregated results in Figure 1. For random presentations, there is a large effect of set size on logit (error rate), χ^2 (1) = 38.02, p < .00001. Eccentricity has a significant effect on the intercept of the logit (error rate) versus set size function, χ^2 (2) = 8.73, p = .013; but no reliable effect on the slope, χ^2 (2) = 3.70, p = .157. There is no effect of eccentricity, or indeed set size, on logit error rates for static presentations

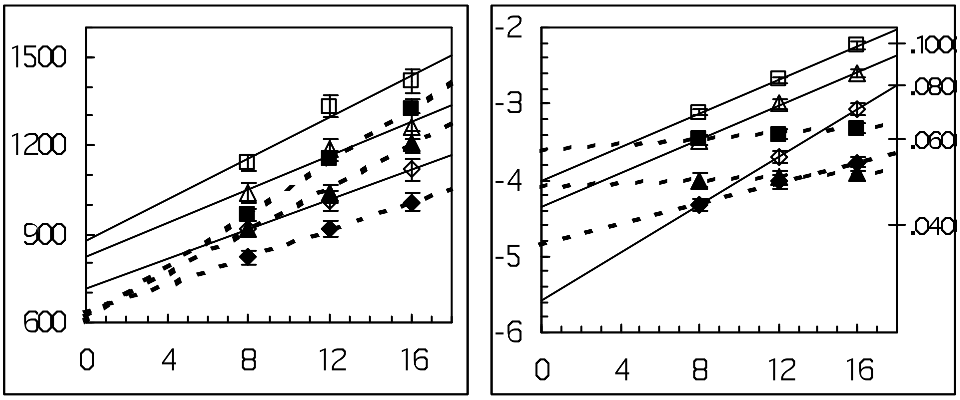

Figure 2. Performance as a function of Set Size and Eccentricity for Random and Static Presentations. Dashed static; solid random. Diamond eccentricity 0 or 1; triangle eccentricity 2; square eccentricity 3. Top Panel mean RT msec. Bottom Panel Logit (Errors): left axis logit scale, right axis probability scale.

A Model of Visual Search

A successful model should account for the following salient features of the data.

- RT slopes are sometimes lower for random than static presentations.
- RT intercepts are always higher for random than static presentations.
- Error rates are independent of set size for static presentation.
- Error rates increase with set size for random presentations.

These features are present for each of the Horowitz and Wolfe experiments, and separately at each eccentricity in Experiment 3. They may all be accounted for by a model where people make rational changes in their decision criteria in response to the manipulation of experimental variables. There is considerable work modelling error rates and latency intercepts as well as slopes in visual search. However only discriminability has been modelled explicitly (Bundesden, 1996; Duncan & Humphreys, 1989; Treisman, 1988). The present approach also models criterion setting.

The model postulates that observers accumulate information for each of two possible responses in location independent accumulators, by a process such as a random walk. People set a criterion for each response, and make whichever response first reaches criterion. The rate of information accumulation is postulated to be inversely related to set size, *N*. Consequently the time needed to achieve a fixed criterion, *C*, will be *C*N,* giving the standard linear RT versus set size function. So how might people adjust their decision criteria when some variable, *V*, is manipulated to make a task more difficult? 'More difficult' may be interpreted as lowering the rate of information accumulation. The new feature is an explicit model of two heuristics for criterion setting. The first heuristic is that people increase their criteria by an amount S_V that is proportional to the set size, in an attempt to maintain accuracy. This causes a RT *slope* increase of S_V. Furthermore, if more distractors means more 'noise' as well as more locations, then the increase in criterion may be greater for distractors. This will generate the, frequently observed, higher *slopes* when targets are absent. Since the increases in decision criteria caused by more difficult tasks are usually not sufficient to maintain accuracy, speed and accuracy will decline together. Set size *dependent* increases in criteria thus cause set size *independent* error rates. The second heuristic is to increase the criterion by a fixed amount I_v that is independent of set size. This causes an RT *intercept* change of I_V. This heuristic may be used when there is a loss of information over time. So any manipulation that increases such loss, masking and random relocation of targets being prime examples, will lead to a fixed, set size independent increase in RT, that is an increase in *intercept.*

Summary

People are both more accurate and faster at visual search for static than random presentations. Maintaining equal-processing rates per item for random presentations incurs costs in increased error rates that rise with the number of items. Thus, the static task is easier than the random task in terms of both speed and accuracy. It is easier precisely because more information (either letter identity or location) is retained from each presentation frame than in the random task. In any event, static presentation leads to enhanced performance, so the new conclusion is that visual search *does* have a memory.

Thus, considering intercepts as well as slopes may radically change important theoretical conclusions. Also, using logistic regression, available in standard packages, enables efficient analysis of error rates, thus enabling further theoretical insights.

A new model shows how rational adjustment of search time decision criteria can account for the effects of random presentation, number of items and eccentricity. An important feature of this model is that it distinguishes for the first time set size dependent criteria shifts that lead to changes in slope, from set size independent shifts in criteria that lead to changes in intercept. This explicit modelling of decision making is unusual for visual search, and has the potential to account for the sometimes conflicting effects of other variables such as stimulus presence or absence, masking, duration, and search instructions.

REFERENCES

Agresti, A. (1996). *Introduction to categorical data analyses*. Chichester: Wiley.

Agresti, A., & Hartzel, J. (2000). Tutorial in biostatistics: strategies for comparing treatments on a binary response with mulit-centre data. *Statistics in Medicine, 19*, 1115-1139.

Bundesden, C. (1996). Formal models of visual attention: a tutorial review. In A. F. Kramer, M. G. H. Coles & G. D. Logan (Eds.), *Converging operations in the study of visual selective attention* (pp. 1-43). Washington, DC: American Psychological Association.

Diederich, A., & Busemeyer, J. R. (2003). Simple matrix methods for analyzing diffusion models of choice probability, choice response time, and simple response time. *Journal of Mathematical Psychology, 47*(3), 304-322.

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review, 96*, 433-458.

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

Horowitz, T. S., & Wolfe, J. M. (1998b). *Visual search has no memory: additional information*, from http://search.bwh.harvard.edu/RECENT%20PROJECTS/nature/speed_error.htm

Kornbrot, D. E. (1988). Random walk models of binary choice. *Acta Psychologica, 69*, 109-127.

Kornbrot, D. E. (1991). Levels of organisation and the planning of movement sequences: evidence from sequential trends. In J. Requin & G. E. Stelmach (Eds.), *Tutorials in Motor Neuroscience* (pp. 385-396). Dordrecht: Kluwer.

Laming, D. R. J. (1968). *Information theory of choice reaction times*. London: Academic Press.

Luce, R. D. (1986). *Response times*. Oxford: Clarendon Press.

Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multialternative Decision Field Theory: A Dynamic Connectionist Model of Decision Making. *Psychological Review, 108*(2), 370-392.

Sternberg, S. (1969). Memory scanning: mental processes revealed by reaction time experiments. *American Scientist, 57*.

Townsend, J. T., & Roos, R. N. (1973). Search reaction time for single targets in multiletter stimuli with brief visual displays. *Memory and Cognition*.

Treisman, A. (1988). Features and objects: The fourteenth Bartlett Memorial Lecture. *Quarterly Journal of Experimental Psychology, 40A*, 201-237.

Treisman, A., & Gormican, S. (1988). Feature analysis in early vision: Evidence from search asymmetries. *Psychological Review, 95*, 15-48.

Usher, M., & McClelland, J. L. (2001). The Time Course of Perceptual Choice: The Leaky, Competing Accumulator Model. *Psychological Review, 108*(3), 550-592.

Wolfe, J. M. (1998). What can 1 million trials tell us about visual search? *Psychological Science, 9*, 33-39.

Wolfe, J. M., Butcher, S. J., Lee, C., & Hyde, M. (2003). Changing your mind: on the contribution of top-down and bottom-up guidance in visual search for feature singletons. *Journal of Experimental Psychology: Human Perception and Performance, 29*, 483-502.

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