# Parallel attentive processing and pre-attentive guidance

Hermann J. Müller[a,b], Heinrich René Liesefeld[c], Rani Moran[d], and Marius Usher[e]
[a]*Department of Psychology, Ludwig-Maximilians-Universität München, Leopoldstr. 13, Munich D-80802, Germany;*
[b]*Department of Psychological Sciences, Birkbeck College, University of London, Malet Street, London WC1E 7HX, UK*;
[c]*Department of Psychology, Ludwig-Maximilians-Universität München, Leopoldstr. 13, D-80802 Munich, Germany*;
[d]*School of Psychological Sciences and Sagol School of Neuroscience, Tel Aviv University, Ramat Aviv, POB 39040, Tel-Aviv 69978, Israel*;
[e]*School of Psychological Sciences and Sagol School of Neuroscience, Tel Aviv University, Ramat Aviv, POB 39040, Tel-Aviv 69978, Israel*;

**ubjta52@bbk.ac.uk**
**http://www.bbk.ac.uk/psychology/our-staff/academic/hermann-muller**

**Heinrich.Liesefeld@psy.lmu.de**
**www.psy.lmu.de/exp/**

**rani.moran@gmail.com**

**marius@post.tau.ac.il**
**http://socsci.tau.ac.il/psy-eng/index.php/staff/faculty/32-marius-usher**

**Abstract:** This commentary focuses on two related, open questions in Hulleman & Olivers' proposal: (i) the nature of the parallel attentive process that determines target presence within, and thus presumably the size of, the functional visual field, and (ii) how the pre-attentive guidance mechanism must be conceived to also account for search performance in tasks that afford no reliable target-based guidance.

Hulleman & Olivers (H&O) make an interesting case for an approach that takes eye fixations, rather than individual items, as its central unit. Within the fixational "functional field of view" (FFV), items are processed in parallel. The size of the FFV is adjusted according to search (target discrimination) difficulty, determining the number of fixations and thus RTs. While H&O's, and previous (e.g., Zelinsky 2008), arguments that eye movements and the FFV play a role in realistic visual search are persuasive, their model leaves (i) the *attentional* process that detects targets and (ii) the pre-attentive process that guides fixations underspecified. Here, we discuss point (i) in relation to Humphreys and Müller's (1993) "Search via Recursive Rejection" (SERR) model (discussed by H&O on pp. 9–10), which, arguably, anticipated some of the ideas advocated by H&O, and (ii) the need for a *pre-attentive* search-guidance mechanism in both SERR and H&O's model.

(i) Like H&O's model, SERR deploys a sequence of parallel search steps to decide whether or not a target is present in the display. While H&O are silent about the process that determines whether the target is present in each FFV region (a process their model considers as error-free), SERR – a connectionist implementation of Duncan and Humphreys' (1989) "Similarity Theory" – posits an error-prone mechanism. In SERR, items, the target and the distractors, within some FFV of spatially parallel processing compete for activating their (higher-level) template representations. When there are multiple distractors of the same complex feature description in the FFV, they are likely to win the competition over the single target, whereupon they are top-down suppressed “as a group”. This process operates recursively until either (i) the target activates its template, triggering a target-present (TP) decision; or (ii) all items are “removed” from the FFV, leading to a target-absent (TA) decision. This dynamics is influenced by target-distractor similarity: the more similar the target is to (some of) the distractors, the more likely it is to be rejected along with a distractor group, yielding increasing miss rates. To bring the rate of target misses down to acceptable levels (matching those exhibited by humans), SERR must make several rechecking “runs” at the items in the FFV, until the target is either detected or consistently not found. Importantly, SERR produces miss rates that accelerate positively with the number of items in the FFV (especially with multiple distractor groups), in which case the rechecking strategy can become prohibitively expensive. “A solution [discussed by Humphreys & Müller, (1993)] is to limit SERR’s functional field so that there is a balance between the first-pass miss rate and the time cost incurred by rechecking” (p. 105) – providing an explicit, error-based “rule” for the FFV size adjustment. The adjusted FFV would then have to be deployed serially across the display (whether this involves covert or overt attention shifts). This resembles some of H&O’s central ideas concerning discriminability-dependent FFV adjustments, which would be reflected in the number of attention shifts necessary to perform the task. – As an aside, H&O are not quite right in stating that “the … empirical work [associated with SERR] focused on relatively small slopes” (p. 11): Müller et al. (1994) present simulations of human slopes (with slope estimates derived from simulated mean RTs and RT distributions) ranging, for example, in their Experiment 1, from around 30 to well over 200 ms/item.

(ii) Given a need for overt or covert attention shifts, efficient search would require an element of pre-attentive “guidance” for the FFV to be directed to (only) the most “promising” regions of the display. In principle, guidance can be provided by a combination of bottom-up and top-down mechanisms, for example, through the computation of local feature-contrast signals and their summation, across dimensions, on some search-guiding “overall-saliency” or “priority” map of the field. Note that this map is generally conceived as a pre-attentive representation, even though it is subject to top-down (feature- and dimension- as well as memory-based) biasing. Notions of guidance are at the heart of models from the Guided-Search (GS) family, including our “Competitive GS” model (e.g., Liesefeld et al. 2016; Moran et al. 2013; 2015), and well supported empirically. Although feature contrast computations themselves are not necessarily “item-based” (see, e.g., Itti & Koch 2001), much of what is known about their workings stems from item-based search experiments! Arguably, then, as acknowledged by H&O (on pp. 56–59), their model (and SERR!) would need to incorporate some notion of “guidance” to fully account for human search performance – which would bring it closer into line with "traditional", two-stage models of visual search like GS.

Note that H&O "buy in" guidance from models such as Zelinsky's (2008) "Target Acquisition Model" or Pomplun et al.'s (2003) "Area Activation Model". In these types of model, guidance is exclusively top-down: target- (template- or feature-) based. In fact, Zelinsky (2008) finds it "arguable whether a model that combines both top-down [target-template-based] and bottom-up [saliency] signals would be more successful than TAM in describing human behavior, at least in tasks in which the top-down target information [is] highly reliable" (p. 825). Such models, however, fail to address what determines target detection in search for (feature or feature conjunction) singleton targets, where there is no (reliable) target template to top-down guide the search (Müller et al. 1995; Weidner & Müller 2013); for example, is target "pop-out" based on a parallel attentive process operating over the whole display or a pre-attentive, salience-based process? One interesting possibility is that, on TP trials, detection decisions are triggered directly by the salience map – consistent with studies showing pop-out detection with no or minimal target identity processing (e.g., Müller et al. 2004; Töllner et al. 2012) and some process of parallel distractor rejection taking place on TA trials (e.g., Müller et al. 2007). On more difficult search trials, the pre-attentive guidance mechanism could direct the attentive process to sample an area that surrounds the location of the highest salience. Here models such as H&O's may indeed add to the traditional item-based models.

## References


Duncan, J. & Humphreys, G. W. (1989) Visual search and stimulus similarity. *Psychological Review*96:433–58. doi:10.1037/0033-295X.96.3.433.

Humphreys, G. W. & Müller, H. J. (1993) SEarch via Recursive Rejection (SERR): A connectionist model of visual search. *Cognitive Psychology* 25:43–110. doi:10.1006/cogp.1993.1002

Itti, L. & Koch, C. (2001) Computational modelling of visual attention. *Nature Reviews Neuroscience* 2:194–203. doi:10.1038/35058500

Liesefeld, H. R., Moran, R., Usher, M., Müller, H. J. & Zehetleitner, M. (2016) Search efficiency as a function of target saliency: The transition from inefficient to efficient search and beyond. *Journal of Experimental Psychology: Human Perception and Performance*. Advance online publication. doi:10.1037/xhp0000156[HJM]

Moran, R., Zehetleitner, M., Müller, H. J. & Usher, M. (2013) Competitive guided search: Meeting the challenge of benchmark RT distributions. *Journal of Vision* 13(8):24. doi:10.1167/13.8.24

Moran, R., Zehetleitner, M., Liesefeld, H. R., Müller, H. J. & Usher, M. (2015) Serial vs. parallel models of attention in visual search: Accounting for benchmark RT-distributions. *Psychonomic Bulletin & Review*. Advance online publication. doi:10.3758/s13423-015-0978-1

Müller, H. J., Humphreys, G. W. & Donnelly, N. (1994) SEarch via Recursive Rejection (SERR): Visual search for single and dual form-conjunction targets. *Journal of Experimental Psychology: Human Perception and Performance* 20:235–58. doi:10.1037/0096-1523.20.2.235

Müller, H. J., Heller, D. & Ziegler, J. (1995) Visual search for singleton feature targets within and across feature dimensions. *Perception & Psychophysics* 57:1–17. doi:10.3758/BF03211845

Müller, H. J., Krummenacher, J. & Heller, D. (2004) Dimension-specific inter-trial facilitation in visual search for pop-out targets: Evidence for a top-down modulable visual short-term memory effect. *Visual Cognition* 11:577–602. doi:10.1080/13506280344000419

Müller, H. J., von Mühlenen, A. & Geyer, T. (2007) Top-down inhibition of distractors in parallel visual search. *Perception & Psychophysics* 69:1373–88. doi:10.3758/BF03192953

Töllner, T., Rangelov, D. & Müller, H. J. (2012) How the speed of motor-response decisions, but not focal-attentional selection, differs as a function of task set and target prevalence. *PNAS* 109:E1990–9. doi:10.1073/pnas.1206382109

Pomplun, M., Reingold, E. M. & Shen, J. Y. (2003) Area activation: A computational model of saccadic selectivity in visual search. *Cognitive Science* 27:299–312. doi:10.1016/S0364-0213(03)00003-X

Weidner, R. & Müller, H. J. (2013) Dimensional weighting in cross-dimensional singleton conjunction search. *Journal of Vision* 13(3):25. doi:10.1167/13.3.25

Zelinsky, G. J. (2008) A theory of eye movements during target acquisition. *Psychological Review* 115:787–835. doi:10.1037/a0013118