Available online at www.sciencedirect.com

ScienceDirect

ELSEVIER

Neural Networks

Neural Networks xx (xxxx) xxx–xxx

www.elsevier.com/locate/neunet

2006 Special Issue

What has been learned from computational models of attention

Marius Usher*

Department of Psychology, Birkbeck College, London, UK

There are few fields where neurocomputational modelling is as necessary as in that of attention — a multifaceted and elusive process that is at the very core of cognition and consciousness (James, 1890). While descriptive theories of attentional functions, relying on a plethora of metaphors (spotlight/zoomlens, increased-gain, biased-competition), abound, computational models that are simple enough to promote understanding of the phenomena and make testable predictions are relatively scarce. As models are often criticised for their ability to 'fit everything', imposing some degree of constraint is essential. Neurocomputational models can answer this challenge by taking on neurophysiological constraints and by addressing not only behavioural but also physiological data. I start with some functional considerations of the attention process, followed by examples of models that help to explicate these processes and some suggestions for future work.

The most central characteristic of attention, common to all its subtypes, is a limited capacity bottleneck (Broadbent, 1958; James, 1890). The nature of this bottleneck, however, is likely to vary with the various types. One aspect of the bottleneck (the *late* one) involves the selection of information for transfer (consolidation) to (in) short-term memory (Chun & Potter, 1995; Duncan, 2006). Target selection is thought to involve a type of top-down control characterised by biased-competition (Desimone & Duncan, 1995) and is subject to capacity limitations. The bottleneck is demonstrated in multiple target paradigms (Duncan, 1980), where a strong interference takes place (unlike in single target with multiple distractors paradigms). In the attentional blink (AB) paradigm (Raymond, Shapiro, & Arnell, 1992), for example, the detection of the second target (T2) is considerably depressed when it follows a previous (detected) target (T1) up to intervals of about 500 ms. Interestingly, when the interval between the two targets is only 100 ms, the interference is minimal, posing stringent constraint on computational models. Finally, a different (earlier) type of bottleneck appears to be involved in bottom-up processing, where visual attention seems to have the function of enhancing the rate of information accrual (Smith, 2000) and of enhancing spatial resolution (Carrasco, Williams, & Yeshurun, 2002), via a gain-enhancing type of mechanism. A number of models addressing these processes have been developed in the last 15 years; due to space limitations, only a few of these important models are addressed.

1. Biased-competition

The principle of biased-competition (Desimone & Duncan, 1995) has been explicitly explored in a number of computational models. Usher and Niebur (1996) have shown that a system using lateral inhibition between object representations can make use of top-down input (or bias), corresponding to goal information, in order to select a target among multiple distractors in an effective way. The model accounts for physiological data (Chelazzi, Miller, Duncan, & Desimone, 1993) and shows that the selection time depends on the similarity between the target and the distractors (Duncan & Humphreys, 1989). More recent models have examined precise physiological measurements of attentional enhancements in V2/V4 (Deco & Rolls, 2005; Reynolds & Desimone, 1999). The most precise of these models, recently proposed by Deco and Rolls (2005), relies on biologically realistic simulations of neural activity in the V2/V4 areas and demonstrates that within a very specific area of the parameter-space (intra- and inter-area connectivity) one can explain, both, the various attentional modulations and their interactions with top-down factors (contrast). The model (like that of Usher and Niebur) assumes that bias is implemented via an additive synaptic input. This poses the problem of avoiding 'hallucinations' (responses in the absence of input), a problem which can be solved with multiplicative schemes (Spratling & Johnson, 2004). However, as demonstrated by Deco and Rolls, an

* Corresponding address: Department of Psychology, Birkbeck College, University of London, Malet Street, WCIE 7HX London, UK. Tel.: +44 207 631 6312; fax: +44 207 531 6201.

E-mail address: m.usher@bbk.ac.uk.

0893-6080/$ - see front matter © 2006 Published by Elsevier Ltd
doi:10.1016/j.neunet.2006.09.004

additive synaptic bias (complemented by the nonlinearity inherent in the neural response function) goes a large way towards solving this problem, as the largest effect of the bias is at intermediate levels of contrast (Martinez-Trujillo & Treue, 2002; Reynolds & Desimone, 2003). A different type of top-down attentional control, involves control over stimulus dimensions (rather than features). This type of control is exercised, both in tasks that make explicit reference to the dimensions (such as Stroop) and in tasks where the dimensions are implicit (such as visual search; Weidner, Pollmann, Müller, and von Cramon (in press)). Although more work is needed to explore this type of control, it is remarkable that one of the earlier and most successful models of attentional control relies on additive dimensional bias (Cohen, Dunbar, & McClelland, 1990).

2. Attentional blink

A number of recent models have addressed the nature of the capacity limitation inherent in the blink phenomena (Battye, 2003; Bowman & Wyble, in press; Frogopanagos, Kockelkoren, & Taylor, 2005; Nieuwenhuis, Gilzenrat, Holmes, & Cohen, 2005). One interesting idea is that the blink reflects the opening and closing of a transient attentional gate (Weichselgartner & Sperling, 1987). The nature of the gate mechanism was proposed to reflect neuromodulatory responses in the Locus Coeruleus (LC) in response to salient/target information (Nieuwenhuis et al., 2005; Usher, Cohen, Servan-Schreiber, Rajkowsky, & Aston-Jones, 1999), which boosts the neural responses and may contribute to the process of consolidation in STM. Alternatively, the gate may reflect a mechanism of creating online episodic token representations (Bowman & Wyble, in press), which is distinguished from the type-representations (this can help for the encoding sequences with repeated items: same type but different tokens). These models account for the lack of interference at 100 ms post T1 (lag-1 sparing), as a result of having both targets benefiting from the attentional gate (which last for about 100 ms). Moreover, the models make a specific prediction: with faster presentation times (of 50 ms/item) the lack of interference should extend to lag-2, as it falls within the gate-window (see Bowman and Wyble for experimental results confirming this prediction). Still the models need to account for the virtual disappearance of the blink when T1 is followed by a blank (rather than a distractor). One possibility is that targets followed by blanks trigger a stronger and faster gate response, which terminates sooner (Bowman and Wyble (in press); this should further predict a blink attenuation when T1 is a salient item, such as the observer's name). It is unclear, however, if such a mechanism is robust enough to account for the near abolishment of the blink with T1+blank stimuli. Alternatively, the attention-gate may be triggered by the distractor that follows T1, in order to protect it from interference (Shapiro, Raymond, & Arnell, 1994). If the gate has a width of about 100 ms, this can also explain the lag-2 sparing in fast 50 ms/item sequences. This idea was implemented in an interesting model, which assumes a fast system that monitors conflict and modulates lateral inhibition to protect the targets from interference (Battye (2003); see also, Usher and Davelaar (2002) for a model where inhibition is neuromodulated to satisfy task demands).

3. Bottom-up processing

Attention enhances visual processing even in the absence of top-down (target) information. A number of models have addressed this type of attentional enhancement and I will only mention two approaches. The first one involves an increase in the gain-function mediated by competitive interactions between alternative detectors. This approach was used by Lee, Itti, Koch, and Braun (1999), who demonstrated that the best account for the attentional enhancement of discrimination thresholds, obtains in a model where a second layer of detectors sharpens the response tuning of simple responses; such sharpening can be the result of a type of shunting inhibition. Increasing the gain (or the lateral inhibition) can optimise choice, in situations with mutually exclusive stimuli (e.g., vertical vs horizontal gratings; see also Bogacz, Usher, Zhang, and McClelleland (in press)). However, there are situations where such a strategy will be counterproductive (when plaid stimuli have to be observed). Thus, a fruitful idea for further exploration is that the level of lateral inhibition is modulated to optimise task demands. Attention may also enhance processing via a more sophisticated mechanism than gain-enhancement, which involves active recruitment of representational resources. This idea is now incorporated in the various versions of the TVA theory (e.g., Bundensen, Habekost, and Kyllingsbaek (2005)). Finally, more work is also needed to examine the relation between attentional allocation and visual grouping. Models based on neural synchrony may play an important role in bridging these two processes (Gross et al., 2004; Singer & Gray, 1995).

References

Battye, G. (2003). Connectionist modelling of attention and anxiety. Unpublished Ph.D. Cambridge, England: The MRC Cognition and Brain Science Unit.

Bogacz, R., Usher, M., Zhang, J., & McClelleland, J. L. Extending a biological inspired model of choice:multialternatives, nonlinearity and value based multidimensional choice. *Philosophical Transactions of the Royal Society, B* (in press).

Bowman, H., & Wyble, B. The simultaneous type, serial token model of temporal attention and working memory. *Psychological Review* (in press).

Broadbent, D. E. (1958). *Perception and communication*. London: Pergamon.

Bundensen, C., Habekost, T., & Kyllingsbaek, S. (2005). A neural theory of visual attention: bridging cognition and neurophysiology. *Psychological Review*, *112*, 291–328.

Carrasco, M., Williams, P. E., & Yeshurun, Y. (2002). Covert attention increases spatial resolution with and without masks: support for signal enhancement. *Journal of Vision*, *2*, 467–479.

Chelazzi, L., Miller, E., Duncan, J., & Desimone, R. (1993). A neural basis for visual search in inferior temporal cortex. *Nature*, *363*, 345–347.

Chun, M. M., & Potter, M. C. (1995). A two-stage model for multiple target detection in rapid serial visual presentation. *Journal of Experimental Psychology Human Perception Performance*, *21*, 109–127.

Cohen, J. D., Dunbar, & McClelland, (1990). On the control of automatic processes: A parallel distributed processing model of the Stroop task. *Psychological Review*, *97*, 332–361.

Please cite this article in press as: Usher, M. What has been learned from computational models of attention. Neural Networks (2006), doi:10.1016/j.neunet.2006.09.004

Deco, G., & Rolls, E. T. (2005). Neurodynamics of biased competition and cooperation for attention: a model with spiking neurons. *Journal of Neurophysiology*, *94*, 295–313.

Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, *18*, 192–222.

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

Duncan, J. (1980). The locus of interference in the perception of simultaneous stimuli. *Psychological Review*, *87*, 272–300.

Duncan, J. (2006). Brain mechanisms of attention. *Quarterly Journal of Experimental Psychology*, *59*, 2–27.

Frogopanagos, N., Kockelkoren, S., & Taylor, J. G. (2005). A neurodynamic model of the attentional blink. *Cognitive Brain Research*.

Gross, J., Schmitz, F., Schnitzler, I., Kessler, K., Shapiro, K., Bernhard Hommel, B., et al. (2004). Modulation of long-range neural synchrony reflects temporal limitations of visual attention in humans. *PNAS*, *101*, 13050–13055.

James, W. (1890). The principles of psychology.

Lee, D. K., Itti, L., Koch, C., & Braun, J. (1999). Attention activates winner-take-all competition among visual filters. *Nature Neuroscience*, *2*(4), 375–381.

Martinez-Trujillo, J., & Treue, S. (2002). Attentional modulations strength in cortical area MT depends on stimulus contrast. *Neuron*, *35*, 365–370.

Nieuwenhuis, S., Gilzenrat, M. S., Holmes, B. D., & Cohen, J. D. (2005). The role of the Locus Coeruleus in mediating the attentional blink: a neurocomputational theory. *Journal of Experimental psychology: General*, *134*, 291–307.

Raymond, J. E., Shapiro, K. L., & Arnell, K. M. (1992). Temporary suppression of visual processing in an RSVP task: an attentional blink. *Journal of Experimental Psychology Human Perception Performance*, *18*, 849–860.

Reynolds, J., & Desimone, R. (1999). The role of neural mechanisms of attention in solving the binding problem. *Neuron*, *24*, 19–29.

Reynolds, J., & Desimone, R. (2003). Interacting roles of attention and visual saliency in V4. *Neuron*, *37*, 853–863.

Singer, W., & Gray, C. M. (1995). Visual feature integration and the temporal correlation hypothesis. *Annual Review of Neuroscience*, *18*, 555–586.

Shapiro, K. L., Raymond, J. E., & Arnell, K. M. (1994). Attention to visual pattern information produces the attentional blink in rapid serial visual presentation. *Journal of Experimental Psychology Human Perception Performance*, *20*, 357–371.

Smith, P. L. (2000). Attention and Luminance detection: effects of cues, masks and pedestals. *Journal of Experimental Psychology Human Perception Performance*, *26*, 1401–1420.

Spratling, M. W., & Johnson, M. H. (2004). A feedback model of visual attention. *Journal of Cognitive Neuroscience*, *16*, 219–237.

Usher, M., & Davelaar, E. J. (2002). Neuromodulation of decision and response selection. In Computational models of neuromodulation [Special issue] *Neural Networks*, *15*, 635–645.

Usher, M., & Niebur, E. (1996). Modelling the temporal dynamics of IT neurons in visual search: a mechanism for top-down selective attention. *Journal of Cognitive Neuroscience*, *8*, 305–321.

Usher, M., Cohen, J., Servan-Schreiber, D., Rajkowsky, J., & Aston-Jones, G. (1999). The role of Locus Coereleus in the regulation of cognitive performance. *Science*, *283*, 554–589.

Weichselgartner, E., & Sperling, G. (1987). Dynamics of automatic and controlled visual attention. *Science*, *238*, 778–780.

Weidner, Pollmann, S., Müller, H., & von Cramon, D. Y. Neural correlates of visual dimension weighting. *Visual Cognition* (in press).

Please cite this article in press as: Usher, M. What has been learned from computational models of attention. Neural Networks (2006), doi:10.1016/j.neunet.2006.09.004