Cognitive Modeling of Dilution Effects in Visual Search

Kleanthis C. Neokleous[1,3], Marios N. Avraamides[1],
Costas K. Neocleous[2], and Christos N. Schizas[3]

[1] Department of Psychology, University of Cyprus
P.O. Box 20537, 1678 Nicosia, Cyprus
mariosav@ucy.ac.cy
[2] Department of Mechanical Engineering, Cyprus University of Technology,
Archbishop Kyprianou 31, P.O. Box 50329, 3036 Lemesos, Cyprus
{kleneokl,schizas}@cs.ucy.ac.cy
[3] Department of Computer Science, University of Cyprus
P.O. Box 20537, 1678 Nicosia, Cyprus
costas.neocleous@cut.ac.cy

Abstract. A biologically plausible neural network model of selective attention has been implemented to account for discrepant findings on the source of distractor interference in visual search tasks. The model successfully simulated the findings from an experiment by Benoni and Tsal (2010) documenting the effects of dilution on distractor interference. In conjunction with previous implementations of the model, we have been able to offer a unifying account that settles the controversy between the Perceptual Load and the Dilution theories of selective attention.

Keywords: Computational Modeling, Spiking Neural Networks, Perceptual Load Theory, Dilution theory.

1   Introduction

Performing the various tasks of daily life entails selecting from the vast amount of information registered by our sensory systems only what is relevant to the task at hand and discarding the rest. The mechanism that allows us to do so is generally known as selective attention. While some theories of selective attention argue that selection of relevant stimuli occurs at early stages of processing (e.g., Broadbent, 1958), others claim that it takes place at a later stage, and only after the meaning of stimuli has been processed (e.g., Deutsch & Deutsch, 1963).

As a solution to the early vs. debate concerning on the locus of selection, Lavie and colleagues (e.g., Lavie & Tsal, 1994) proposed the Perceptual load theory (PLT, Lavie &Tsal, 1994) of attention. The PLT claims that selection of stimuli may take place early or late depending on the perceptual load of the visual scene.

In a paradigmatic study supporting the PLT, Lavie and Cox (1997) manipulated perceptual load by means of a difficult or easy visual search with distractor interference being the dependent measure. Participants in the high load condition searched for one of two target letters (X or N) among 5 similarly-shaped letters arranged in a circular array.

In the low load condition, the participants searched for the target that was surrounded by five instances of the letter "O". In both conditions, a distractor letter was presented to the left or to the right of the array. Depending on condition, the distractor letter could either be congruent with the target (i.e., the same letter as the target), or incongruent (i.e., the other target), or neutral (i.e., the letter "L"). Results from this experiment that participants in the low load condition were slower to find the target in incongruent than congruent or neutral trials. However, in the high load condition participants found the target equally fast in all congruency conditions. According to the PLT, this occurs because in the low load condition only minimum resources are consumed by the main task of identifying the target, which allows spare resources to spill over to the processing of the distractor. In that case, all stimuli are initially processed and selection must occur late. In the high load condition all available resources are consumed by the difficult visual search leaving no spare resources for processing the distractor. Thus, the distractor in this condition is excluded early on.

Although many studies have provided evidence to support the PLT, a few studies however present results that challenge it. For example, using visual task similar to the one of Lavie and Cox (1997), Johnson, McGrath, and McNeil (2002) showed that when the target location was primed by preseting a 100%-valid cue ahead of the array, the interference exerted by an incompatible distractor in the low load condition was significantly reduced compared to the uncued control condition. As the presentation of a cue does not alter the amount of spare resources available during the search, this result is problematic for at least a strong version of the PLT.

In previous work of us (Neokleous, Koushiou, Avraamides, &Schizas, 2009), we implemented a computational model of selective attention and succesfully simulated both the findings from the basic load manipulations of Lavie and Cox (1997) and the modulating effects of cueing reported by Johnson et al., 2002. To do so, the model took into account the patterns of saliency of visual stimuli, their completion for cortical representation, and the interaction of top-down factors. Through the simulations, we were able to provide a more concrete account for perceptual load effects and the possible neural mechanisms that give rise to them.

Recently, a new theoretical account that resembles the one we presented with our model, was put forth by Benoni &Tsal (2010; see also Wilson, Muroi & MacLeod, 2011). This theory, named the Dilution Theory (DT), proposes that the distractor is processed in both load conditions, yet distractor interference in the high load condition is eliminated due to dilution exerted by the non-target letters of the search array on the distractor. Empirical findings from studies using low load conditions with high dilution suggested that dilution, and not perceptual load, is the critical factor for the presence of distractor interference (Benoni & Tsal, 2010).

In this paper we apply our model to conditions included in the study of Benoni and Tsal (2010), to examine whether the pattern of findings supporting the DT can be accounted for by our existing conceptualization of perceptual load. In one condition of the behavioral task, termed as the low load-high dilution condition, participants had to identify a red target among three other green neutral letters (or a green target among red neutral letters) when all four letters were presented on the four possible corners of an imaginary square centered on fixation. At the same time participants had to ignore a larger white flanker presented on the left of the visual scene. In the high load-high dilution condition the neutral letters and the target were of the same color

(red or green) while in the low load- low dilution condition the red (or green) target was presented along with the white distractor but without any neutral letters. The main finding reported by Benoni and Tsal (2010) was that distractor interference was eliminated in the low load-high dilution condition but not in the low load- low dilution and the high load-high dilution conditions.

In the next sections we provide an overview of the model and we present simulation data for the three conditions included in the Benoni and Tsal (2010).

2   The Computational Model

The computational model is a spiking neural network model that has been previously used in similar form to simulate findings from other attentional paradigms (e.g, the attentional blink phenomenon, Neokleous, Avraamides, Neokleous, &Schizas, 2009, and the relation between attention and consciousness, Neokleous, Avraamides, &Schizas, 2011) The model is comprised of integrate-and-fire (I&F) neurons combined with coincidence detector (CD) neurons and simulates attention as a continuous stream of neural activity that is initially based on bottom-up information and gradually incorporates biases from top-down processes. The graded response of the I&F neurons is defined by the membrane eq. 1.

$$V_i(t+\delta t) = (E_L - V(t))(1+\frac{\delta t}{\tau_m}) + \frac{R_m}{\tau_m}I_s(t)\delta t \tag{1}$$

where V is the membrane potential of each neuron, τ_m is the membrane time constant, E_L is the resting potential of the membrane, Is(t) represents the total synaptic current and is a simple combination of pre-synaptic excitation and bias currents that increase the membrane potential, with inhibition currents that reduce the membrane potential of the node. The total summation of the excitatory and inhibitory currents influences the actual membrane potential at each time instance. Finally, R_m is the membrane resistance of the neuron.

The inclusion of coincidence detector (CD) neurons in the model is inspired by neurophysiological evidence about the functional role of the pyramidal neurons which have been observed to respond best to the coincident activation of multiple dendritic compartments (Spruston, 2008). Traditionally CD neurons are modeled with a very short membrane time constant τm that can change rapidly. However, another way to model coincidence detection is based on a simple case in which separate inputs converge on a common target. More precisely, if Ψ(t) is a binary row vector denoting the states of neuron A and B at time t and C(t + 1) the state of neuron Cat t + 1, then the outcome of Cat t +1 can be expressed as:

$$C(t+1) = \Theta(\Psi(t) - \theta) \tag{2}$$

with Θ being the Heaviside step function, and θ the specific threshold for the number of pre-synaptic spikes that are needed to arrive synchronously in order for the output neuron C to induce a spike.

The structure of the model (Fig. 1) involves two stages of processing implemented through spiking neural networks (SNN). The first stage corresponds to the initial bottom-up competitive neural interactions among visual stimuli and corresponds to the early visual areas in the occipital regions of the brain (e.g., V1, V2). The second stage of processing extends the neural pathway towards working memory and allows for relevant top-down goals (e.g. based on semantic information) to exert an influence on neural activity.
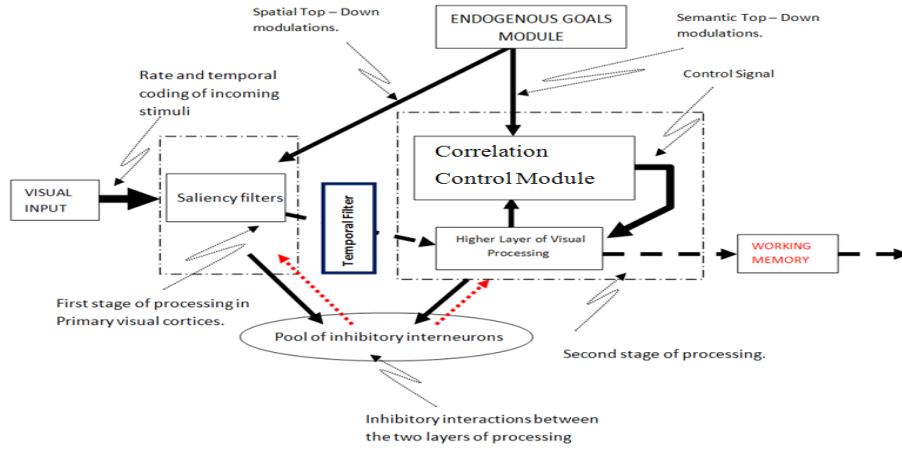

Fig. 1. The different modules of the computational model of visual selective attention

In the first stage of processing, the initial representations of any incoming stimuli are created in the model on the basis of a saliency map. The manipulation of visual activity by means of a saliency map in the early stages of visual processing is supported by numerous neurophysiological studies including findings that in the primary visual cortex and in area V1 in particular, a neuron's response can be significantly suppressed or enhanced in correlation with stimulations in the vicinity of its receptive field (e.g. Nothdurft, Gallant, & Van Essen, 1999; Shibata et al, 2008). In our model, we adopted a saliency map algorithm that was originally proposed by Koch and Ullman (1985). This algorithm was implemented by Walther and Koch (2006) into a Matlab toolbox (Saliency Toolbox - http://www.saliencytoolbox.net), and is used in the model for producing saliency values for spatial locations in the visual field. These values are calculated according to a simple transformation algorithm (eq.3) that links grayscale pixel values into frequency of spikes to establish the initial firing rates of the neurons that encode visual stimuli (see also Fig.2).

$$FR_{si} = \alpha(Max(Pj)) + \beta(\sum_{j=1}^{n} Pj) \tag{3}$$

In eq. 3, FR_{si} represents the firing rate of each of the 12 input neurons that correspond to the receptive field of stimulus Si. Max (Pj) is the maximum value of all the pixels

that correspond to stimulus Si, and $\sum\limits_{j=1}^{n} Pj$ is the total summation of the n pixel values (Pj) that correspond to stimulus Si. The terms α and β are weighting constants. The maximum value of the pixels for each stimulus reflects the general saliency of the stimulus while the summation value was used to incorporate the size of the stimulus in the calculations, since the model always uses 12 neurons to encode incoming stimuli regardless of their size.
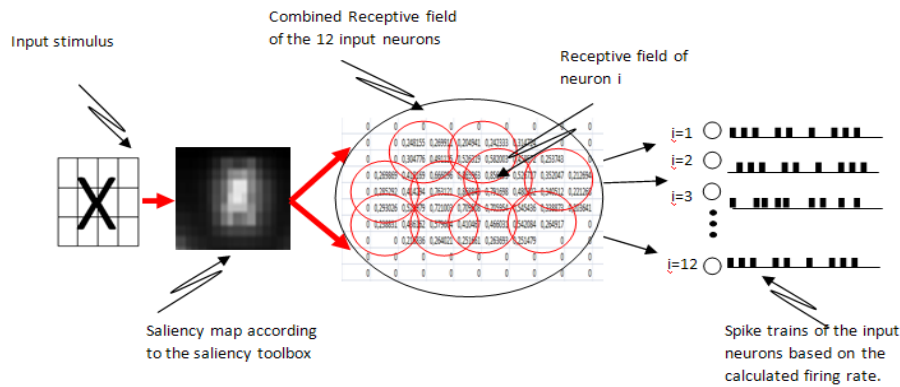

Fig. 2. Generation of initial firing rate according to the Saliency map algorithm

In addition to saliency values, spatial top-down interactions are also considered in the first stage of processing. More precisely, when perceptual cues are used to prime the spatial location of an upcoming stimulus, top-down spatial factors in the model, will exert their influence on the initial firing rate of the input neurons. This interaction is compatible with findings from several studies documenting that cues may increase the neural activity of neurons that correspond to visual stimuli very shortly after the presentation of the cue (e.g., Shibata et al., 2008; Silver, Ress, &Heeger, 2007).

The top-down effects in the second stage of processing are implemented in the model in a way that produces both rate amplification and synchronization of neural activity as suggested by neurophysiological evidence (e.g., Womelsdorf and Fries 2007; Gregoriou, Gotts, Zhou & Desimone, 2009). More precisely, during a visual task, templates that contain features of targets are created and maintained in the endogenous goals module of the model and are used to evaluate the resemblance between incoming visual input and the target. The evaluation of each stimulus takes place by computing the correlation between spike trains representing the stimulus and the spike trains maintaining target identity in the endogenous goals module. This is performed in the Correlation Control Module (CCM) of the model (Fig.1).

During the progression of neural activity through the two stages of processing, the encoded stimuli compete for access to working memory (WM) through forward and lateral inhibitory interactions (from the pools of inhibitory interneurons), resulting into modulation of the strength of their neural response.

3   Computational Simulations

In this section simulation results are compared to the empirical findings of Benoni and Tsal (2010) in an attempt to account for dilution effects in perceptual load tasks.

Fifty simulation trials were run for each of the combinations of load and compatibility in the three conditions (high low-high dilution, low load-low dilution, and low load-high dilution). Median latencies from the model are shown in Fig.4. As seen in the figure, the model successfully produced the pattern of latencies reported by Benoni and Tsal (2010), although overall latencies from the simulations were slower than those in the experimental data[1]. Specifically, a compatibility effect (i.e., slower latency for incongruent vs. congruent distractors) was only produced in the low load-low dilution condition. Although latencies were overall shorter in the low load-high dilution condition than in the high load-high dilution condition, no difference between congruent and incongruent distractors was present in either condition.

The successful simulation of the behavioral data relied on three aspects of the model. First, spatial top-down signals were allowed to interact with the neural activity of the neurons whose receptive field fell within the area of the imaginary square. This was done to simulate instructions to participants to search for the target within that area. Second, the saliency analysis using the saliency map algorithm produced different values for each condition (Fig.3) leading to different initial neural activities for each stimulus in the display.
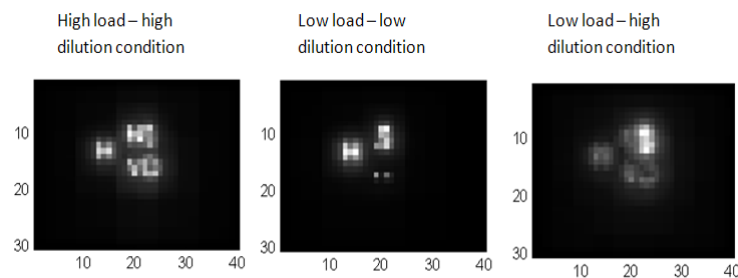

Fig. 3. Output of the saliency map algorithm for the three conditions

Finally, the neural activity of both the target and the distractor were biased in the second stage of processing due to their high correlation with the top-down signals maintaining the current goals (i.e., the identities of the possible targets).

Based on the above, the target letter was able "win" the race to working memory in all three conditions, but with different average reaction time in each condition due to differences in the level of inhibitory neural interactions exerted among stimuli in the display. This was the case because the inhibitory interactions in the model depend on the level of neural activation that each stimulus has during its progression in the model.

---

[1] No parameter tuning to the model described by Neokleous et al.. (2009) was carried out to achieve a closer fit with the experimental data in terms of overall latency.
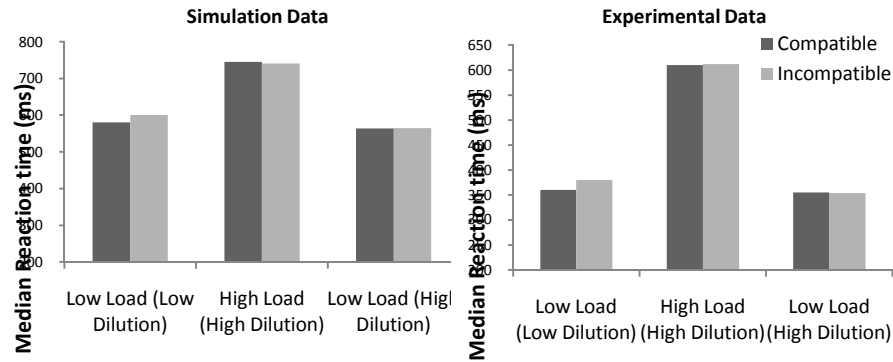
Fig. 4. Simulation data from the model and experimental data from Benoni and Tsal (2010)

4   Discussion

The described computational model represents an attempt to provide a comprehensive and concrete account for perceptual load findings that is also able to simulate findings that pose challenges to the PLT. In the present study, we demonstrated that the model is capable of explaining the finding from dilution experiments based on what is currently known about the neural mechanisms of selective attention. The model does not rely on any formal definition of concepts such as high or low perceptual load, and dilution. Instead, based on the interactions between low-level saliency and top-down spatial and semantic goals, the model is capable of reproducing the empirical findings. On one hand, the model includes continuous inhibitory interactions among the stimuli in the visual field whose relative saliency determines the strength of the inhibitions that are exerted. On the other hand, the model allows for top-down signals to bias this competition by amplifying the activity of neurons representing stimuli that match the spatial and semantic goals. The model demonstrates that the by combining the effects of low-level visual information such the saliency of stimuli with top-down processing, one can provide a unifying account that settles the controversy between the PLT and the DT.

References

1. Benoni, H., Tsal, Y.: Where have we gone wrong? Perceptual load does not affect selective attention. Vision Research 50, 1292–1298 (2010)
2. Broadbent, D.: Perception and Communication. Pergamon Press, London (1958)
3. Crick, F., Koch, C.: Some reflections on visual awareness. Cold Spring Harbor Symposia on Quantitative Biology 55, 953–962 (1990)

4. Deutsch, J.A., Deutsch, D.: Attention: Some theoretical considerations. Psychological Review 70, 80–90 (1963)
5. Gregoriou, G.G., Gotts, S.J., Zhou, H., Desimone, R.: High-frequency, long-range coupling between prefrontal and visual cortex during attention. Science 324, 1207–1210 (2009)
6. Johnson, D.N., McGrath, A., McNeil, C.: Cuing interacts with perceptual load in visual search. Psychological Science 13, 284–287 (2002)
7. Koch, C., Ullman, S.: Shifts in selective visual attention: towards the underlying neural circuitry. Human Neurobiology 4, 219–227 (1985)
8. Lavie, N., Cox, S.: On the efficiency of attentional selection: Efficient visual search results in inefficient rejection of distraction. Psychological Science 8, 395–398 (1997)
9. Lavie, N., Tsal, Y.: Perceptual load as a major determinant of the locus of selection in visual attention. Percepion & Psychophysics 56, 183–197 (1994)
10. Moran, J., Desimone, R.: Selective attention gates visual processing in the extrastriate cortex. Science 229, 782–784 (1985)
11. Neokleous, K.C., Avraamides, M.N., Neocleous, C.K., Schizas, C.N.: Selective attention and consciousness: Investigating their relation through computational modeling. Cognitive Computation 3, 321–331 (2011)
12. Neokleous, K.C., Avraamides, M.N., Neocleous, C.K., Schizas, C.N.: A neural network model of the attentional blink phenomenon. International Journal of Engineering Intelligent Systems 17, 115–126 (2009)
13. Neokleous, K.C., Koushiou, M., Avraamides, M.N., Schizas, C.N.: A coincidence detector neural network model of selective attention. In: Proceedings of the 31st Annual Meeting of the Cognitive Science Societ, Amsterdam, The Netherlands (2009)
14. Nothdurft, H.C., Gallant, J.L., Van Essen, D.C.: Response modulation by texture surround in primate area V1: correlates of "popout" under anesthesia. Visual Neuroscienc 16, 15–34 (1999)
15. Reynolds, J.H., Desimone, R.: Interacting roles of attention and visual salience in V4. Neuron 37, 853–863 (2003)
16. Reynolds, J.H., Chelazzi, L., Desimone, R.: Competitive mechanisms subserve attention in macaque Areas V2 and V4. Journal of Neuroscience 19, 1736–1753 (1999)
17. Reynolds, J.H., Chelazzi, L.: Attentional modulation of visual processing. Annual Review of Neuroscience 27, 611–647 (2004)
18. Shibata, K., Yamagishi, N., Goda, N., Yoshioka, T., Yamashita, O., Sato, M.A., et al.: The effects of feature attention on prestimulus cortical activity in the human visual system. Cerebral Cortex 18, 1664–1675 (2008)
19. Silver, M.A., Ress, D., Heeger, D.J.: Neural correlates of sustained spatial attention in human early visual cortex. Journal of Neurophysiology 97, 229–237 (2007)
20. Torralbo, A., Beck, D.M.: Perceptual-load-induced selection as a result of local competitive interactions in visual cortex. Psychological Science 19, 1045–1050 (2008)
21. Tsal, Y., Benoni, H.: Diluting the burden of load: Perceptual load effects are simply dilution effects. Journal of Experimental Psychology:Human Perception and Performanc 36, 1645–1656 (2010)
22. Walther, D., Koch, C.: Modeling attention to salient proto-objects. Neural Networks 19, 1395–1407 (2006)
23. Wilson, D.E., Muroi, M., MacLeod, C.M.: Dilution, not load, affects distractor processing. Journal of Experimental Psychology: Human Perception and Performance 37, 319–335 (2011)
24. Womelsdorf, T., Fries, P.: The role of neuronal synchronization in selective attention. Current Opinion in Neurobiology 17, 154–160 (2007)