Modeling dilution effects in perceptual load search tasks

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Abstract

A computational model of selective attention has been previously used to provide a concrete and comprehensive account for perceptual load findings in visual search tasks (Neokleous, Koushiou, Avraamides, & Schizas, 2009). Here, the same model was used to simulate findings from an experiment in which perceptual load effects were attributed to distractor dilution (Benoni & Tsal, 2010). By modeling at the neural level the continuous inhibitory interactions that take place among visual stimuli competing for cortical representation, the model reproduced successfully the behavioural pattern of results. The model thus offers a biologically-plausible way to reconcile findings that contradict Perceptual Load theory with those that support it.

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

Introduction

The *Perceptual Load* theory was proposed by Lavie and Tsal (1994; Lavie, 1995) to resolve the early vs. late debate concerning the locus of attention (e.g., Broadbent, 1958; Deutsch & Deutsch, 1963). It posits that selection of stimuli may take place early or late depending on the perceptual load of the task.

In a paradigmatic study of perceptual load Lavie and Cox (1997) had participants carry out a *high load* or a *low load* visual search task. In the high load task participants searched for two target letters (X and N) among 5 similarly-shaped letters arranged in a circular array. In the low load task, they searched for these targets among five instances of the letter O. In both conditions, a distractor letter, which participants were asked to ignore, 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), incongruent (i.e., the other target), or neutral (i.e., the letter "L"). Results revealed that in the low load task participants took longer to identify the target in the presence of an incongruent distractor compared to when the disctractor was congruent or neutral. In contrast, in the high load task, no difference between the three distractor conditions was found. Lavie and Cox (1997) argued that distractor interference was absent in the high load task because all attentional resources were consumed by the task leaving none to process the irrelevant distractor. In contrast, in the low load task only minimal resources were devoted to the task allowing spare resources to spill over to the processing of the distractor. Thus, the Perceptual Load theory posits that selection is early under high load conditions and late in low load conditions.

Despite its appeal, the Perceptual Load theory has been criticized on various grounds. First, a number of studies have provided findings that seem at odds with the theory (Eltiti, Wallace, & Fox, 2005; Johnson, McGrath, and McNeil, 2002; Torralbo & Beck, 2008). For example, Johnson et al. (2002) showed that cueing the target location with a 100%-predictive central cue in a low load visual search task eliminates distractor interference despite the fact that it does not alter the load of the task. Neokleous et al. (2009) reported the same result using an 80%-predictive peripheral cue. Second, Torralbo and Beck (2008) argued that the theory is unsatisfying because it does not provide a clear definition for perceptual load, and because the concept of exhaustive capacity cannot be easily reconciled with what is known about brain mechanisms.

To provide a more concrete formulation of the Perceptual Load Theory we have previously presented a biologically-plausible computational model, capable of simulating both the basic pattern of findings from Lavie and Cox (1997)and findings considered contradictory to the theory(e.g., Johnson et al., 2002). The model offered an explicit account for the possible neural mechanisms that give rise to perceptual load findings without relying on vague terms such as high and low load. The model simulated the data by modeling at the neural level the continuous inhibitory interactions that take place among visual stimuli competing for cortical representation. The strength of these inhibitory interactions is determined by the saliency of stimuli whereas top-down signals are allowed to bias this competition by amplifying neural activity that matches the current goals.

Recently, Benoni and Tsal (2010) proposed a theoretical account for perceptual load effects that resembles the one implemented in our model. In their *Dilution* account, Benoni and Tsal (2010; see also Tsal & Benoni, 2010; Wilson, Muroi, & MacLeod, 2011) claim that the distractorsin the visual search tasks employed by Lavie and Cox (1997) are processed regardless of load. However, distractor interference in the high load condition is eliminated due to diluting effects exerted by non-target letters in the search array towards the distractor.

Benoni and Tsal (2010) provided support for the Dilution account by showing that distractor interference is absent in a low load condition with high dilution (Exp.1). In this condition, participants searched for a red target in an array with three additional green letters or a green target in an array with three additional red letters, while ignoring a larger white distractor presented adjacently to the array. In the high load-high dilution condition the 4 letters of the search array, including the target, were displayed in the same color, either red or green. Finally, in a low load-low dilution condition the red or green target was presented without any accompanying letters in the search array.

Results showed that, as predicted by the Perceptual Load theory, (1) overall latencies were shorter for the low load-low dilution than the high load-high dilution, and (2) distractor interference was present in the low load-low dilution condition but not in the high load-high dilution condition. However, in contrast to the predictions of the Perceptual Load theory, no distractor interference was observed in the low load-high dilution condition despite the fact that latencies in this condition were as short as those of the low load-low dilution condition. Benoni and Tsal (2010) interpreted this finding as evidence that the perceptual load effects reported in the literature previously are caused by dilution.

Although the Dilution account aspires to offer a more concrete explanation of perceptual load effects than the Perceptual Load theory itself, it is also somewhat vague in some respects. For example, Benoni and Tsal (2010) argued that dilution requires the mere presence of non-target letters "...whose features are visually similar to those of the distractor" (p.1293). It is not very clear what constitutes a visually similar feature and how exactly a task can be cateogorized as high-dilution or low-dilution. Benoni and Tsal (2010) employed a low load task in which the target was presented alone in the search array thus no dilution was possible. However, Lavie and Cox (1997) have used a low load task in which the target is presented among flanking O's. Are O's expected to exert diminished dilution effects or none at all?

Here, we use the same computational model we described in Neokleous et al. (2009) to simulate the findings from Benoni and Tsal (2010; Experiment 1). The model requires neither a definition of load nor an explicit differentiation of tasks in terms of dilution. Also, in contrast to the Dilution account in which inhibitory signals originate only from non-target letters in the search array and are directed only towards the distractor (i.e., the target is considered immune to inhibition), our model allows for inhibitory signals among all stimuli in the display.

The computational model

The computational model has been previously used in similar form to simulate findings from the attentional blink phenomenon (Neokleous, Avraamides, Neokleous, &Schizas, 2009)and the relation between attention and consciousness(Neokleous, Avraamides, & Schizas, 2011). It 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 model (Fig.1) involves two stages of processing implemented as spiking neural networks (SNN). The first stage involves the initial bottom-up competitive neural interactions among visual stimuli and corresponds to 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 information to exert an influence on neural activity.

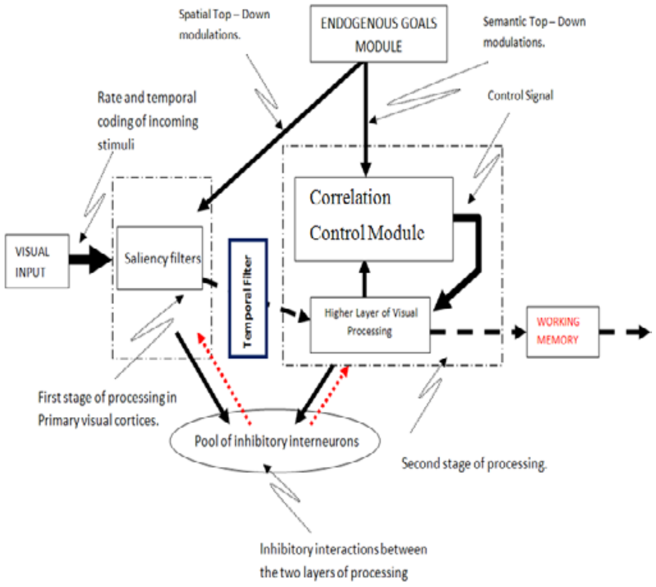

Figure 1. The modules of the computational model of visual selective attention.

In the first stage of processing, the initial representations of visual stimuli are created in the model on the basis of a saliency map. The modulation of visual activity by saliency in the early stages of visual processing is supported by neurophysiological findings that in area V1 of the visual cortex a neuron's response can be significantly suppressed or enhanced by stimulation in the vicinity of its receptive field (Nothdurft, Gallant, & Van Essen, 1999; Wachtler, Sejnowski, & Albright, 2003; Shibata et al., 2008). In our model, we adopted a saliency map algorithm 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), that is used in the model to produce saliency values for spatial locations in the visual field. These values are produced based on a simple transformation algorithm that converts grayscale pixel values into frequency of spikes to establish the initial firing rates of the neurons that encode visual stimuli (Fig.2).

During the first stage of processing, neural activity can be modulated by spatial top-down factors. For example, when a cue is used to prime the location of a stimulus ahead of presentation, the neural activity corresponding to the stimulus is amplified. This implementation is based on findings from several studies showing that cues may enhance the neural activity of neurons that encode visual stimuli (e.g., Shibata et al., 2008; Silver, Ress, &Heeger, 2007).

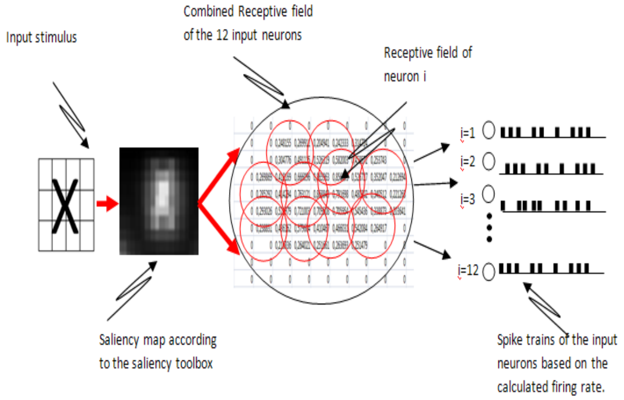

Figure 2. Initial firing rate computations based on a saliency map algorithm.

The second stage of processing simulates the modulation of neural activity that represents visual stimuli by activity that maintains information about the targets as specified by the set of instructions (e.g., “Find x or y in the central array”). Support for such modulations stems from studies showing that neural activity in area V4 of the cortexis influenced by top-down activity (e.g., Moran & Desimone, 1985; Reynolds & Desimone, 2003). 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., Fries, Reynolds, Rorie & Desimone 2001; Gregoriou, Gotts, Zhou & Desimone 2009). That is, according to the model, attending a stimulus enhances the firing rates of neurons that correspond to that stimulus and at the same time forces them to fire in a more synchronous rhythm. Similarly, the firing rates of neurons that correspond to unattended stimuli are suppressed.

The main components in the second stage of processing of the model have been inspired by Crick and Koch’s (1990) theoretical analysis on the role of attention and neural synchronization for the establishment of awareness. Crick and Koch (1990) based on neurophysiological findings showing that visual stimuli can elicit synchronized activity in the visual cortex, suggested that a prerequisite for the presence of neural synchronization is to have synchronous impulses in selected neuronal populations. Therefore, they proposed that visual selective attention may function in a way that it causes changes to the temporal structure of the neural spike trains that represent the information to be selected, and that this temporal structure may facilitate the transfer of the encoded information to working memory.

The idea presented by Crick and Koch (1990) was later supported by experimental evidence. In a comprehensive review, Womelsdorf and Fries (2007) presented evidence showing how attention selectively modulates the neurons that represent the attended stimulus feature or spatial location in a way that it synchronizes their responses. For example, Bichot, Rossi and Desimone (2005) recorded the neuronal spiking responses and LFPs in the visual area V4 of macaque monkeys and demonstrated that the allocation of attention towards a particular feature synchronizes the responses of selective sensory neurons, tuned to the attended feature. They suggested that feature salience is not only demonstrated with an increasing firing rate, but also by selectively synchronizing specific neuronal responses based on the similarity between feature preferences and the attended stimulus feature.

To incorporate these ideas in our model, templates that contain features of visual search targets are created and maintained in the endogenous goals module of the model and are used to evaluate the resemblance between any incoming visual input and a 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).However, before the neural activity of each incoming stimulus is processed in the CCM, it passes through a temporal filter that reorganizes the timing of spikes without altering the average firing rate. This mechanism is implemented in the model according to a pre-defined probability that reflects the degree of resemblance between the features of the incoming stimulus and those of a target. Thus, only the spike train patterns of a stimulus that shares features with the target will significantly change and become closer to the distinct spike train pattern of the target. The temporal filter mechanism used in the model is in line with Crick and Koch’s (1990) suggestion about the impact of selective attention on neural synchronization.

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(Fig.3). This implementation is based on neurophysiological findings showing that competition for neural representation in visual areas V1 and V2 is initiated when two or more stimuli fall within the receptive fields of the same or nearby cells (Reynolds & Chelazzi, 2004; Reynolds &Desimone, 1999).

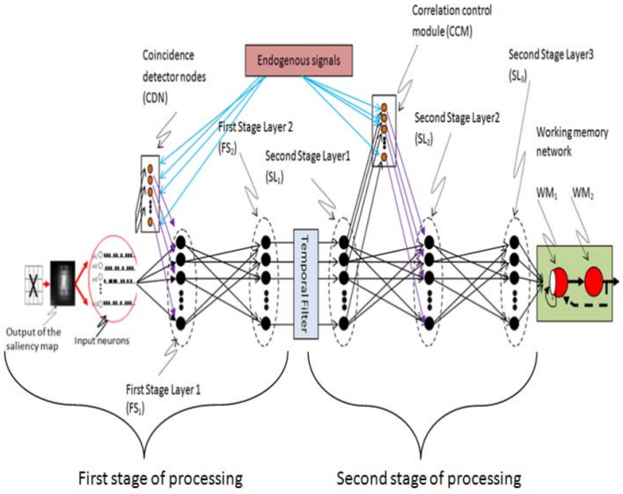

Figure 3. Top-down and bottom-up interactions during the progression of neural activity in the two stages of processing.

These interactions during the progression of neural activity produce enhancement and synchronization of neural activity that eventually lead to the selection of a particular stimulus for further processing.

Computational Simulations

The computational model described in the previous section was used to simulate the pattern of findings reported by Benoni and Tsal (2010). Three aspects of the model are important for simulating the data: (1)spatial top-down signals enhance the neural activity of the neurons whose receptive fields fall within the area of the search array, (2)the saliency analysis produced different values for stimuli in each condition of the experiment (Fig.4)and led as a result to different initial firing rates, and (3) stimuli whose neural representation matches that of a target template held in the endogenous goals module are biased regardless of whether they appear, at a given trial, in the search array or as a distractor.

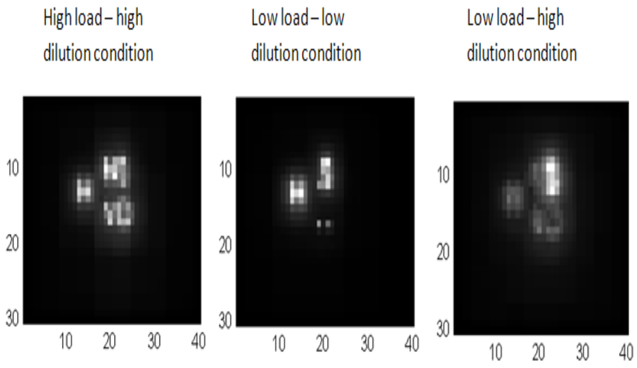

Figure 4.The three conditions and the output of the saliency map algorithm.

These aspects of the model allow the target to "win" the race to working memory but with different speed depending on the combination of load/dilution (low load-low dilution, low load-high dilution, high load-high dilution) and distractor compatibility (congruent vs. incongruent).

Fifty simulation trials were run for each of the combinations of load and compatibility. Median latencies from the model are shown in Fig.5. As seen in the figure, the model successfully produced the pattern of latencies reported by Benoni and Tsal (2010). Specifically, a compatibility effect (i.e., slower latency for incongruent vs. congruent distracters) was produced in the low load-low dilution condition only. Latencies were overall shorter in the low load-high dilution condition than in the high load-high dilution condition, but no difference between congruent and incongruent distractors was present in either condition. It should be noted that although the model successfully produced the patterns reported by Benoni and Tsal (2010), it was in all conditions slower that human participants by 150-200ms. However, it should also be pointed out that the simulations were run with exactly the same parameter settings that were previously used to simulate the findings of Lavie and Cox (1997; see Neokleous et al., 2009). That is, no effort was made to fit the behavioral data by tweaking the parameters of the model.

In the next section we discuss how exactly the model simulates the behavioral data.

How the model simulates the experimental data

High Load-High Dilution Condition

In this condition the saliency analysis produced similar values for the target and the non-target letters in the search array. Saliency was somewhat higher for the distractor due to its larger size. As the task instructs participants to focus on the search array, the effects of spatial top-down signals were modeled by raising the firing rate for the four letters of the array. The higher neural activations for theseletters resulted in greater inhibition from the letters of the search array (both target and non-target letters)towards the distractor. As a result, the neural activity of the distractor was significantly reduced from the very early stages of processing, thus reaching the second stage of processing with low activation. Due to its low activation, the distractor, regardless of begin congruent or incongruent with the target, could not influence much the response latency.

Besides inhibition exerted towards the distractor, the non-target letters of the search array produced strong inhibitory signals towards each other and towards the target. As a result, the neural activity of the target was reduced and the time needed to pass the set response threshold was increased. This accounts for the long response latencies observed in this condition.

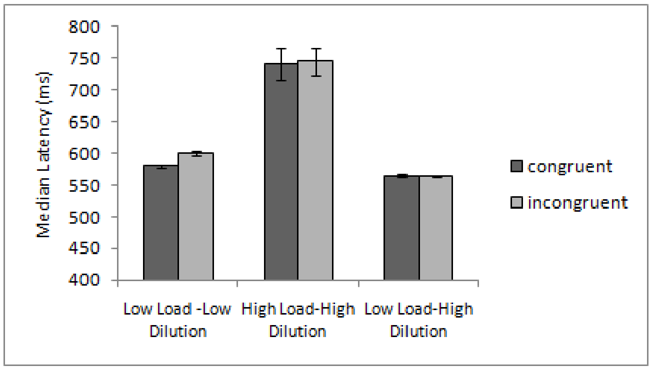

Figure 5. Experimental data for the conditions reported by Benoni and Tsal (2010) compared to the simulation results from the computational model.

Low Load -Low Dilution Condition

Due to the absence of non-target letters in the search array of the low load-low dilution condition, the target and the distractor had about the same saliency. In fact, due to its larger size, the distractor initially had a somewhat higher saliency value than the target. The neural activity of the target was, however, amplified as it fell within the area that participants are instructed to attend. Although inhibitory interactions take place between the target and an incongruent distractor, both enter the second stage of processing with enough activation to produce a match with the goal templates held in the endogenous goals module. While a congruent distractor assists the target's processing, an incongruent distractor inhibits it. This results into (1) overall shorter latencies than in the high load condition, and (2) longer latencies for trials with incongruent than congruent distractors.

Low Load-High Dilution Condition

The low load-high dilution is the critical condition for differentiating the Dilution account from the Perceptual Load theory. The saliency analysis resulted in a higher value for the target letter than for the non-target letters of the search array because it was presented in a different color. In addition, the neural activity for all letters in the search array was amplified to model top-down spatial effects. As a result, the target accumulated substantial activation which allowed it to exert strong inhibition towards the other elements of the display, including the distractor. As in the high load condition, the distractor reached the second stage of processing with low neural activation and was thus unable to exert strong influence on the processing of the target. The main difference between this condition and the high load condition, is that here, because of the initial amplification of the target's neural activity, the neural activations of the non-target letters in the search array were suppressed which allowed the target to be processed easier and faster.

Discussion

The computational model of selective attention that was described in the present paper was previously implemented to account for the basic pattern of findings from the Perceptual Load paradigm (Lavie & Cox, 1997). The model was capable of simulating not only the basic pattern of load findings, but also findings that were considered contradictory to the theory (Johnson et al., 1992). Here, the same model, with no tuning whatsoever, was able to reproduce the pattern of findings from a study manipulating dilution (Benoni &Tsal, 2010).

Although the Dilution account of Benoni and Tsal (2010) resembles the functioning of the model we had presented earlier (Neokleous et al., 2009), its premises are not entirely in line with the way our model reproduces the behavioral data. According to the Dilution account, the representation of the distractor in high dilution conditions and in the typical high load conditions is degraded by inhibitory signals exerted from the non-target search array letters towards the distractor. Although we agree that such inhibitions take place, our model posits that in some cases, such as the in low load-high dilution of Benoni and Tsal (2010), the major source of inhibition on the distractor originates from the target. In contrast to the Dilution account, our model allows for inhibitory signals among all elements of the display. The amount of inhibition that any stimulus exerts on others depends on the strength of its neural activity, which according to the model, is based on its initial saliency and the biasing from top-down factors.

The computational model presented here is an attempt to provide a comprehensive and concrete account for Perceptual Load findings based on what is currently known about the neural mechanisms of selective attention. The way the model is implemented allows for modeling a wide range of empirical data related to perceptual load effects. Future empirical research will allow us to test predictions from the model and evaluate its validity.

Acknowledgments

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