

A neural network model of the attentional blink phenomenon

Kleanthis C. Neokleous^{1*}, Marios N. Avraamides², Costas K. Neokleous³ Christos N. Schizas¹

¹Department of Computer Science, University of Cyprus

²Department of Psychology, University of Cyprus

³Department of Mechanical Engineering, Cyprus University of Technology

The Attentional Blink refers to the finding that the perception of a target stimulus is often impaired when it is presented within a temporal window of 200–500 ms following another successfully-perceived stimulus. This interesting phenomenon has attracted much research in the fields of attention and perception but has also inspired the implementation of several computational models. In the present study we have implemented a model of selective attention that is capable of modelling a variety of findings related to the Attentional Blink. Importantly, the model produces synchronization of neural activity to simulate the interaction between a low-level visual system and a high-level goal-maintenance system during the deployment of attention. Synchronization of neural activity within and across brain areas is typically observed when carrying out various tasks that involve the attentional processing of information. Thus, the model provides a neurally and computationally plausible account for the Attentional Blink and potentially other attentional tasks.

Keywords: Neural network, coincidence detector neurons, visual selective attention, attentional blink.

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*. Selective attention is often portrayed as a gatekeeper responsible for selecting which stimuli will gain access to a capacity-limited memory store known as *working memory* (Awh, et al. 2006). Information represented in working memory is used to control behavior, e.g., to pre-

pare and execute motor responses, produce verbal responses etc. Attention can be guided on the basis of both top-down and bottom-up information reflecting the interplay of external stimulation with internal motivations. Evidence from single-cell recordings suggests that volitional shifts of attention are associated with neural signals in the prefrontal cortex while the exogenous orienting of attention correlates with activity in the visual cortex of the brain (e.g., Buschman & Miller, 2007).

A number of recent neurophysiological studies have shown that synchronization of neural activity in the brain occurs during the deployment of selective attention (Gruber et al., 1999; Steinmetz et al., 2000). For example, Fries et al. (2001) found increased gamma frequency synchronization (i.e., syn-

*Department of Computer Science, University of Cyprus, P.O Box 20537, Nicosia 1057 Cyprus E-mail: kleneokl@cs.ucy.ac.cy

chronized activity at around 40Hz) of neurons in area V4 of the brain of macaque monkeys when they attended target stimuli. Increased synchronization of neural activity is also observed across brain areas, reflecting possibly top-down influences on the control of attention. For example, Saalman et al. (2007) recorded neural activity simultaneously from the posterior parietal cortex as well as an earlier area in the visual pathway of the brain of macaques during the execution of a visual matching task. Findings revealed synchronization of the activity in the two regions when the monkeys selectively attended a location. More recently, Gregoriou et al. (2009) have provided evidence for enhanced oscillatory coupling between area V4 and an area in the prefrontal cortex known as the frontal eye field (FEF) when attending a stimulus. These findings are compatible with Grossberg's (1999) conjecture that the temporal patterning of activities could be ideally suited to achieve matching of top-down predictions with bottom-up inputs. Synchronization is typically found in the gamma frequency range (30-80Hz) and reflects oscillatory bursts that are loosely locked to the stimulus (i.e., their latency varies from trial to trial). This synchronization, also known as the induced-gamma response, may more generally underlie the construction of object representations by binding activity from different areas of the brain (Tallon-Baudry & Bertrand, 1999).

In the present study we have developed and implemented through appropriate simulations a model of selective attention that produces synchronization of neural activity to model the interaction between a low-level visual system and a high-level goal-maintenance system. The model is used to simulate the main findings from a well known phenomenon in the field of selective attention, known as the *Attentional Blink* (AB; Raymond, et al. 1992).

The AB occurs when the Rapid Serial Visual Presentation (RSVP) is used to present stimuli at a speeded rate of about 100ms. Participants are asked for example to identify letter targets among number distractors within the sequence of presented stimuli (Figure 1; Chun & Potter, 1995).

The AB refers to the findings that when 2 targets are presented among a sequence of distractors, the correct identification of the 1st target (T1) impairs the identification of the 2nd target (T2), provided that T2 appears within a brief temporal window 200-500 ms following T1. In cases where T2 is presented outside this temporal window, it is normally identified. Remarkably, when T2 immediately follows T1, no AB is observed; this finding is known as *Lag-1 Sparing*. Figure 2 depicts the percentage of correct T2 reports as a function of the Stimulus Onset Asynchrony (SOA; i.e., the temporal interval between T1 and T2).

Several theories as well as computational models have been formulated to account for both the AB and Lag-1 sparing. Although a comprehensive review is beyond the scope of this paper, the most popular models are reviewed next.

2. PREVIOUS THEORETICAL ACCOUNTS FOR THE ATTENTIONAL BLINK

Raymond et al. (1992) initially proposed an inhibition model to explain the AB phenomenon. According to this model,

while T1 is being processed any further visual processing is inhibited. This inhibition prevents confusion of T1 with other stimuli. In essence, the model suggests that all stimuli that are presented during the period of inhibition are not processed at all. However, this suggestion is not supported by empirical research. As Isaak et al. (1999) pointed out, several studies provide evidence that stimuli following T1 are semantically processed. For example, in a study recording Event-Related Potentials (ERPs), Luck et al. (1996) had participants report whether T2 matched semantically a word stimulus that was presented before the RSVP sequence. Although identification of T2 was reduced when it followed T1 by 250 ms, an N400 ERP component for T2 was still observed. As the N400 is generally considered an index of semantic mismatch, its presence suggests that T2, despite not being detected, was nevertheless semantically processed.

Isaak, et al. (1999) proposed an alternative model to account for empirical findings on the AB. This model, which is based on the interference between the neural activities of stimuli, assumes that representations of presented stimuli are created and compared to internal templates that define the features of the targets. When a match occurs between a stimulus and a template, the perceptual and conceptual characteristics of the stimulus receive further processing for which a pool of limited resources is engaged. This processing is assumed to take about 500 ms and has been termed by Ward et al. (1996) as the attentional *dwelt time*. According to Isaak et al. (1999), all items that are presented within this dwell time compete for access to short-term memory. Therefore, T2 has to overcome strong interference from the distractors that precede it as well as any distractors that follow it within the dwell time. As a result of this interference, an incorrect item may often be selected for report in lieu of T2.

Chun and Potter (1995) proposed a two-stage model for the AB. During the first stage of rapid detection all stimuli are processed and their features are analyzed. Transient conceptual representations are thus constructed in this stage for all stimuli and potential targets are selected. The second stage of the model involves additional limited-capacity processing that is required to build a more enduring representation of the target. An important assumption for this model is that this second-stage processing cannot begin unless the first-stage processing is concluded. As a result, when T2 is presented within the 200-500 ms temporal window, it can be detected by the first-stage but its second-stage processing is delayed until T1 is fully processed. This delay, however, increases the probability that T2's representation fades from the system. Thus, Chun and Potter (1995) attribute the AB deficit to the processing that is needed to consolidate T1 in memory.

It should be noted that a similarity between the models of both Isaak et al. (1999) and Chun and Potter (1995) is that they both explain the AB on the basis of resource depletion. That is, they assume that a limited processing resource is allocated to T1 with spare resources spreading towards other stimuli only when available. However, as pointed out by Di Lollo et al. (2005) resource depletion models predict a monotonic decrease of the AB effect as lags progress instead of the non-monotonic U-shaped functions that are typically reported by RSVP experiments. That is, these models cannot account for Lag-1 Sparing, at least without any additional assumptions.

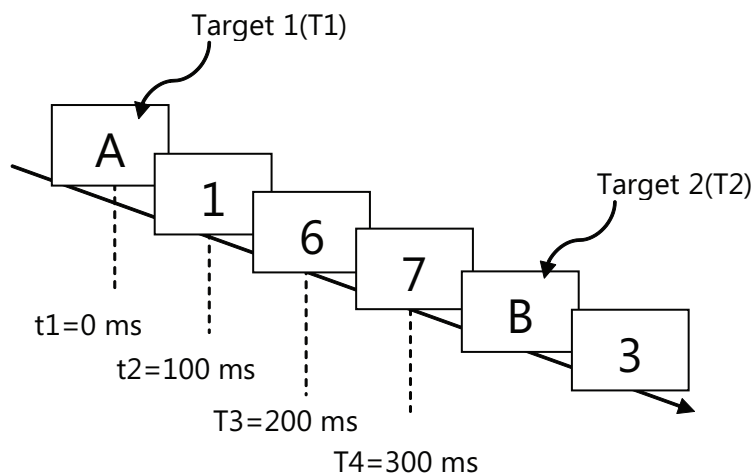


Figure 1 The use of the RSVP paradigm in attentional blink studies. Participants are asked to identify targets T1 and T2 that are presented, with a manipulated SOA, within a sequence of distractors.

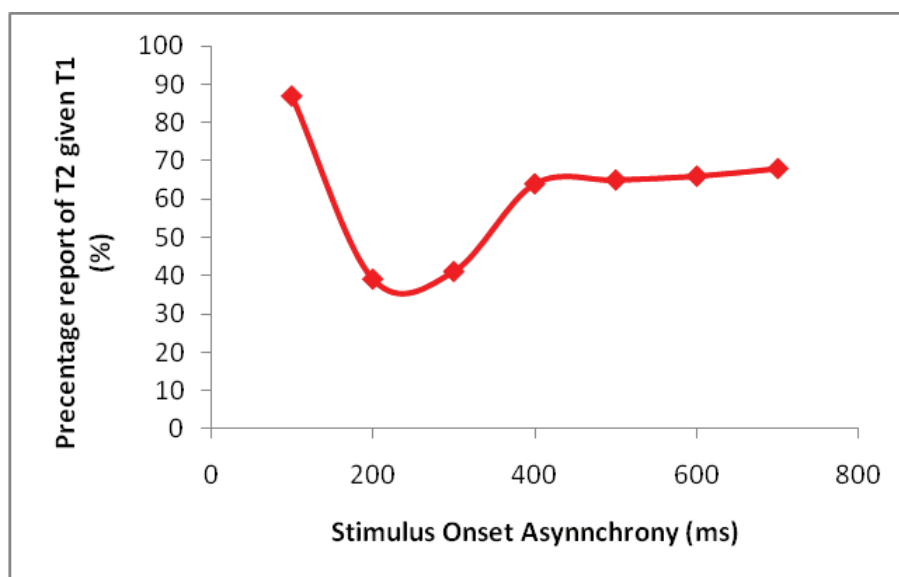


Figure 2 The basic curve from attentional blink studies based on the behavioral data from Chun and Potter (1995) showing the percentage of correct T2 identification given the successful identification of T1 as a function of SOA.

Lag-1 Sparing can be accounted by these models by allowing for the simultaneous (or near-simultaneous) processing of T1 and T2. In the case of the Isaak et al.'s (1999) model this is achieved by postulating the presence of an attentional gate that opens rapidly when T1 is presented but closes rather sluggishly allowing thus the stimulus at Lag 2 to enter.

Di Lollo et al (2005) proposed an alternative model to explain the AB. The model attributes AB to the temporary loss of control (TLC). Specifically, Di Lollo et al. suggested that in the RSVP paradigm the system responsible for processing visual input is initially configured based on endogenous signals to anticipate the features of T1. Once T1 is presented, the system is involved in stimulus processing and cannot therefore issue endogenous control signals in order to reconfigure its filter to the features of the T2. However, during this time,

exogenous information can modify the filter. If T2 has similar features with T1 and is presented at Lag 1 then it can be processed based on the filter's initial configuration. However, if a distractor is presented at Lag 1 then the filter is altered exogenously, so if T2 is presented at Lag 2 it will no longer be detected. In a series of behaviour experiments Di Lollo et al. (2005) provided evidence for the TLC hypothesis. An aspect of this model that is important for the goals of the computational model we have implemented here is the fact that it explains the AB effect and Lag-1 Sparing by proposing an interaction between bottom-up information contained in the visual input and higher-order endogenous signals representing expectations. These signals presumably originate at higher brain regions such as the prefrontal cortex.

3. COMPUTATIONAL MODELS FOR THE AB

In addition to the various theoretical accounts for the AB, several computational models have been implemented to simulate the AB findings.

One such model is the CODAM model which was proposed by Taylor (2002) and was used to simulate findings from the AB by Fragopanagos, Kockelkoren, and Taylor (2005). An important assumption in the CODAM model is that attention functions in the brain as a general control system; therefore, a control engineering approach is followed in the model. The model in its initial form is composed by several modules on the basis of neurobiological theories of attention. First, the Input Module represents the neural activity at very early stages of visual hierarchy and it has its output directly connected to the Object Map, where the specific neural activity representing information is registered. The Input Module also activates the Goals Module which guides the top-down deployment of attention. An Inverse Model Controller (IMC) is also included to generate an attention control signal for the amplification of the attended stimulus activity based on the activity in the Goals Module. The model contains also a Working Memory buffer whose contents define what information is available for report as well as a Corollary Discharge buffer which uses a copy of the attention control signal to predict forthcoming input by pre-activating the buffer working memory site. Finally, a Monitor Module provides a measure of the error occurring during an attention movement by comparing actual and desired attentional movements.

The CODAM model simulates the AB effect by allowing inhibitory signals towards the Corollary Discharge nodes during the time the Working Memory module is occupied. As a result, when T1 is active in working memory, all Corollary Discharge nodes are turned off.

This prevents other stimuli from getting through and interfering with the processing of the first target. Therefore, if T2 appears within the specific time window when the Corollary Discharge nodes are ineffective, no Working Memory pre-activation will occur and thus T2 will not be able to reach awareness.

Another influential AB model is the Simultaneous Type/Serial Token model (ST₂) proposed by Bowman and Wyble (2007). The model consists of two processing stages of neural activity representing visual stimuli. The first stage includes parallel visual processing while the second stage encodes information into working memory in a serial manner. In order to encode the visual stimuli the model employs two factors referred to as types. These types provide information about the feature properties of an item as well as tokens to mark the occurrence of visual stimuli. The first stage in the ST₂ model is responsible for implementing the standard visual processing. That is, during this stage the visual features of stimuli are extracted and each stimulus is semantically categorized. As processing during the first stage takes place in a parallel manner, the system may simultaneously process multiple items with little interference between them. However, a durable representation and thus access to working memory is only achieved when an item makes it to the second stage.

Thus, the second stage can be considered as the entrance to working memory and in contrast to the first stage, it imposes constraints that arise from the fact that the system attempts to associate items with discrete episodic contexts. Between the first and the second stage there is a salience filter which can be seen as an intermediate component responsible for enhancing task-relevant items and enabling them to progress into the second stage. Additionally, the saliency filter ensures that task-irrelevant items do not reach Stage 2. However, despite the amplification of the neural activity of a salient item by the salience filter, the authors of the model suggest an additional mechanism similar to the control signal suggested by the CODAM model. More precisely, when an item passes the salience filter in a strongly active form, a separate mechanism represented by the Transient Attentional Enhancement (TAE) will provide a temporally brief (but spatially specific) enhancement. This helps the item to proceed into a later level of Stage 1 and subsequently into working memory. The TAE in the model is realized with a mechanism that the authors termed the blaster. For the simulations of the AB, the first target initially triggers the blaster. The blaster will then enhance the first target (T1) as well as a subsequent item before it is held offline as long as it is necessary for T1 to be encoded. This takes place so that the second target (T2) is prevented from interfering with T1. Thus, if T2 arrives during this time it will receive no blaster enhancement and will therefore fail to reach awareness.

A model that uses a slightly different approach than the CODAM and the ST₂ models is the Global Workspace Model of Dehaene, et al. (2003). This model is biologically detailed and anatomically prescribed. The general functionality of the model is based on the competition between stimuli to engage a global workspace access. However, stimuli first need to pass through neural processing pathways that originate from early sensory regions to higher association areas of the temporal, parietal, frontal, and cingulate cortex. The authors suggest that when a stimulus accesses a sufficient number of workspace neurons, the activity of the neurons becomes self-sustained. Thus, it can be broadcasted via long-distance connections to different areas and create therefore a global and exclusive availability for a specific stimulus. At this point, the stimulus is considered as having reached consciousness. Another important characteristic of the model is the inhibition that is exerted by neurons processing a stimulus that has accessed workspace towards other surrounding workspace neurons. Unlike the CODAM and the ST₂ models, the Global Workspace Model has no control signal to amplify neural activity. Instead, when intrinsic fluctuations are in phase with stimulus presentation, the total activation is enhanced. This results in biasing neurons of adjacent areas and therefore increasing the probability for the entire network to fall in a global active state. Furthermore, global activity can be more easily achieved when there is "resonance" between bottom-up sensory information and top-down signals.

Recently, Taatgen (2009) implemented using the ACT-R cognitive architecture a model for the AB that attributes the effect to an overexertion of cognitive control. ACT-R includes a procedural memory store that contains production rules in the form of "if...then" statements. According to this model,

while a target is being consolidated in memory, a production rule fires to inhibit target detection. As a result, no target can be detected while other information is being consolidated. The model of Taatgen (2009) is thus similar to other models of AB (e.g., the CODAM model) in that it includes a mechanism that postpones the processing of other information while T1 is processed. A similar mechanism is included in the present model which is described next.

4. THE PROPOSED SYNCHRONIZATION MODEL OF THE AB

4.1 Overview

In line with Global Workspace Model of Dehaene et al. (2003), the proposed model is constructed with the assumption that the resonance of incoming stimuli with spontaneous or top-down brain activity is essential to create a perception. In contrast with the Global Workspace Model, but in line with the CODAM (Fragopoulos et al., 2005) and ST₂ (Bowman & Wyble, 2007) models, our model generates a control signal that amplifies the neural activity of the stimulus that is to be selected. In addition, our model provides a mechanism that allows the temporary suppression of target detection while working memory is occupied; such a mechanism is included in both the CODAM model and the threaded cognition model of Taatgen (2009). The novelty of the proposed model is that it models various empirical findings related to the AB while producing synchronization of neural activity during the deployment of attention. As discussed in the introduction, the presence of synchronization is reported by many neurophysiological studies and it has even been proposed as the activity underlying the construction of object representations (Tallon-Baudry & Bertrand, 1999). Thus, the present model relies on previous accounts for the AB but also on what is currently known about the processing of visual stimuli by the brain, to provide biologically-plausible explanation for the main findings on the AB. The model is presented schematically in Figure 3.

The model comprises of two processing stages. The first stage is responsible for the initial processing of visual stimuli based on the saliency filters in the *primary visual cortices* while the second stage of processing is more related to top-down interference. Stimuli are represented as spike trains whose bins are marked with 1's and 0's representing the presence or absence of an action potential (see section 3.2.2). The saliency of stimuli determines the firing rates (i.e., the frequency of spikes) of the spike trains that represent the stimuli. To that respect, the primary visual cortices can be regarded as a saliency map for incoming stimuli (Zhaoping 1999). Encoded stimuli compete for access to working memory with forward and lateral inhibition among stimuli influencing the strength of the neural response. In the second stage of processing, information from the first stage passes through the *semantic correlation control* module. In this stage of processing, a network comprised of integrate and fire neurons combined with coincidence detection neurons measures the degree of correlation between the neural activity representing visual stimuli and that of a module that maintains the current goals. Based

on the degree of correlation a control signal is generated in this module which can be linked to the combined firing of a neural network. Therefore, an amplification or attenuation of the neural activity that corresponds to each incoming stimulus may take place depending on the control signal. Subsequently, a working memory node will be excited causing inhibition to other working memory nodes. After a threshold is passed, the working memory node will fire an action potential to represent the perceptual awareness of a specific visual stimulus and the preparation of a response.

4.2 Detailed description of the model

The two systems of the model correspond to the early visual areas at the occipital regions of the brain (e.g., V1) and the higher order fronto-parietal network responsible for maintaining goal-directed activity. The interaction of these two systems is accompanied by synchronization of neural activity and results to the selection of particular stimuli for further processing. Thus, selective attention is modelled as the interaction between the processing of low-level information and the maintenance of endogenous expectations. We now discuss the main aspects of the model.

4.2.1 Neural elements of the model

The basic computational units used in the model are simple graded response neurons with a membrane equation

$$\tau_m \frac{dV}{dt} = E_{\text{leak}} - V - R_m I \quad (1)$$

where V is the membrane potential of each neuron and τ_m is the time constant.

The membrane potential can be seen as a measure of the extent to which a node is excited. In equation 1, E_{leak} , corresponds to a leak current that drives the node's membrane potential towards the resting potential. The total current I is a simple combination of excitation and bias currents that cause increase of the membrane potential as well as inhibition currents that reduce the membrane potential of the node. The total summation of the excitatory and inhibitory currents influences (based on the corresponding weight) the actual membrane potential at each time instance. R_m is the total membrane resistance of the neuron.

The solution of the differential (1) is shown in (2) below, which explains how V evolves according to time.

$$V(t) = E_{\text{leak}} + R_m I + (V(0) - E_{\text{leak}} - R_m I)e^{-t/\tau}. \quad (2)$$

The generation of a spike is described by a single rule: whenever V exceeds a specific threshold (V_{th}), a spike is emitted and V resets to its initial condition or resting potential V_{reset} .

For the present simulations, the following values have been used:

$$\begin{aligned} \tau_m &= 30 \text{ ms} \\ E_{\text{leak}} = V_{\text{reset}} &= -65 \text{ mV} \\ V_{th} &= -65 \text{ mV} \\ R_m &= -90 \text{ M}\Omega. \end{aligned}$$

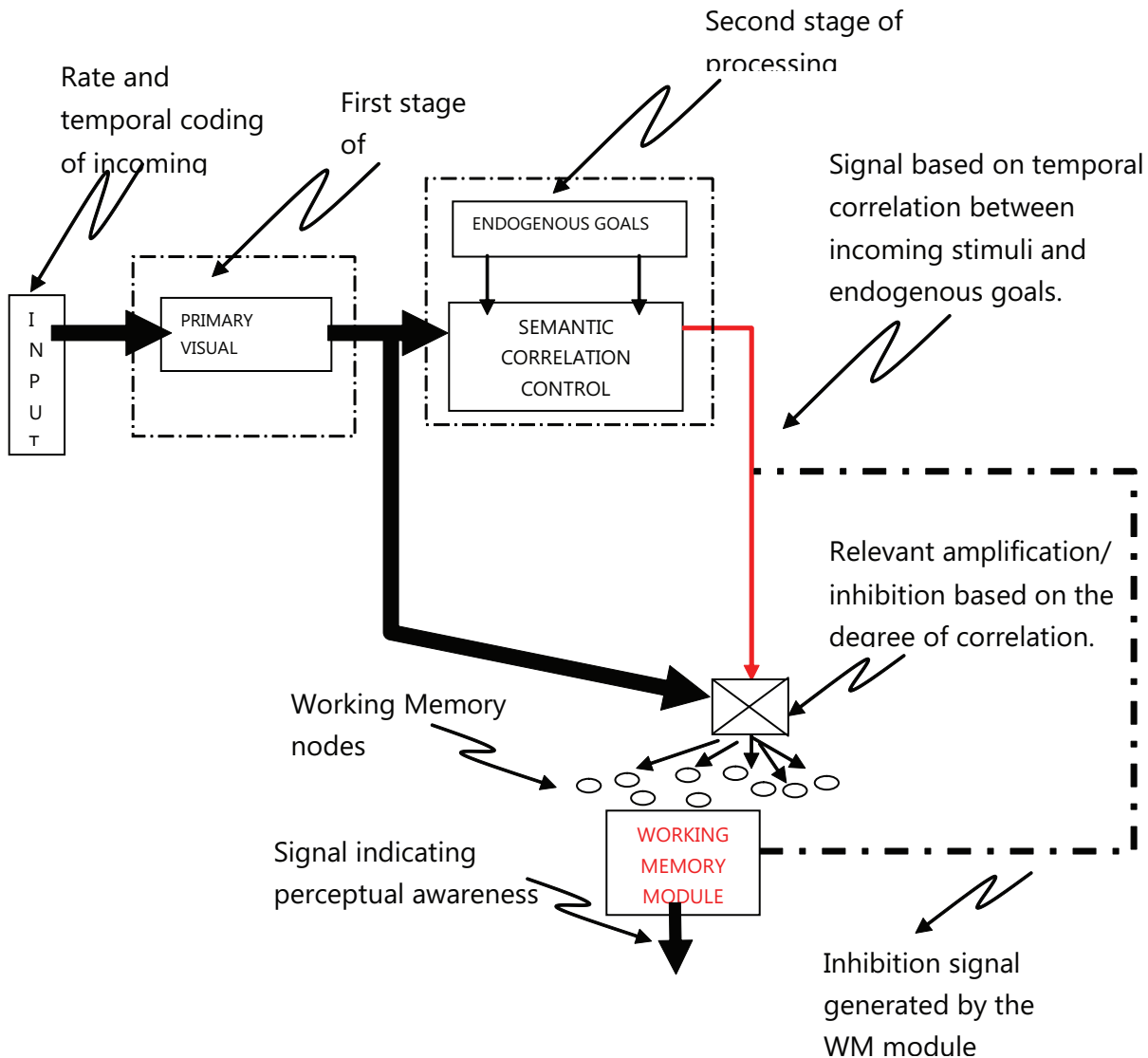


Figure 3 The proposed computational model.

Additionally, an absolute refractory period of 2 ms was applied each time a neuron fired a spike.

In the second stage of processing the model contains coincidence detection neurons. Coincidence detection is a very simplified model of neuron, which fires only if it receives two or more simultaneous inputs. In the traditional view, coincidence detector neurons can be modelled with a very short membrane time constant τ_m so that the membrane potential can change rapidly. Another way to model coincidence detection can be based on separate inputs converging on a common target. For example, let's consider a basic neural circuit of two input neurons with excitatory synaptic terminals A and B converging on a single output neuron C (Figure 4). If we assume that each spike is represented by a pulse with amplitude equal to 1 then the coincidence detector neuron C will only fire if its input is greater than 1.

4.2.2 Temporal coding of input

Each stimulus that enters the visual field is represented by a stream of binary events (called spike trains) that represent the

occurrence of an action potential or a spike, with 1s and 0s signifying respectively the presence or the absence of a potential. Two important factors determine the pattern of spike trains. First, the firing rate or the frequency of spikes is determined based on the saliency of the stimulus. Second, the exact timing with which each spike appears is produced by representing each visual stimulus as a 10 ms sequence of 1s (spike) or a 0s (no-spike) occurring at every millisecond (Figure 5).

As the correlation control module of the second stage of processing relies on the consequences of this temporal coding, it is important for the simulations to generate sets of synthetic spike trains with controlled rates and cross-correlations. The methodology used for the generation of the spike trains to represent each incoming stimulus follows the algorithm proposed by Niebur (2007) and Mikula and Niebur (2008). This algorithm generates spike trains whose mean rates as well as the cross-correlations of pairs of spike trains are free parameters that can be selected independently. The cross-correlation between any two of these spike trains can be selected to be minimal indicating completely independent spike trains or maximal representing identical spike trains. More

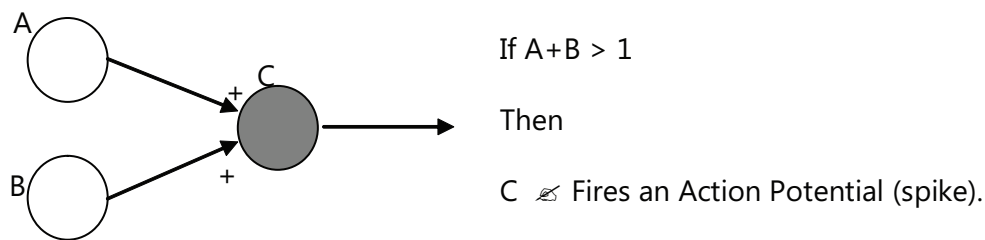


Figure 4 Simple representation of a coincidence detector mechanism.

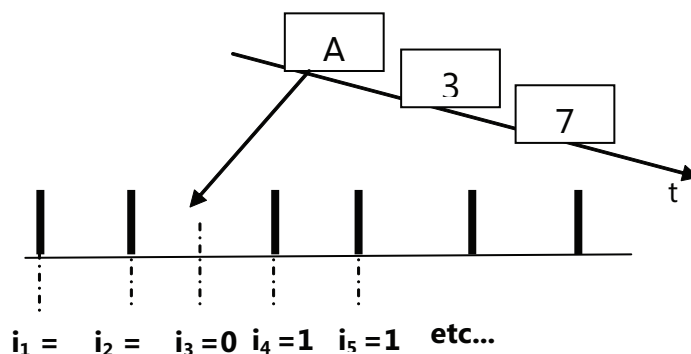


Figure 5 Coding of the incoming visual stimuli. Each stimulus is represented with a series of spikes that take values of 1 and 0 that correspond to the presence or absence of action potentials respectively.

specifically, it is assumed that all time bins (or firing times) are independent and that each spike train consists of a series of 0s and 1s. If, for example, we consider two spike trains A and B those can be seen as a Bernoulli processes with the probability $P_A = \langle A \rangle$ for spike train A to have the value 1 in each time bin ($0 \leq P_A \leq 1$) and 0 occurring with probability $1 - P_A$. In the same manner, spike train B can be generated. If now it is desired that these two spike trains have a specific degree of correlation between them, the state of spike train A can be switched (with a probability q) to that of B. That is, each bin in spike train A has a probability q to have the same state as the spike train B.

4.2.3 Representation at the Primary visual cortices (First stage of processing)

The spike trains that represent each incoming stimulus were generated based on a certain probability as explained in the previous section, defining thus their initial firing rate. Both targets and distractors were generated with the same probability to have a spike at each time bin, since both have the same saliency (i.e., they have the same brightness, intensity etc.).

In the first stage of processing, every stimulus that enters the visual receptive field, will try to “win” the race to access working memory. Therefore it acts in an inhibitory manner towards all the other competing stimuli. In the RSVP paradigm used for the AB experiments each incoming stimulus will receive inhibition from the stimuli that appeared before it as well as those that follow. This assumption is consistent with several studies of single cell recordings (e.g., Keysers & Perrett, 2002, Rolls et al. 1999) that show the effect of masking on the firing rate of neurons (that correspond to visual stimulus) in

the temporal cortex of monkeys. Masking in visual perception tasks occurs when the perception of one stimulus (i.e., the target) is influenced by the presence of another stimulus. Masking can be either forward or backward depending on whether the mask precedes or follows the target (Moore, 1998). According to Seiffert and Di Lollo (1997) backward masking causes stronger inhibition than forward masking. This finding is again consistent with the inhibitory interactions between the neurons in the first stage of processing due to the fact that feed-forward inhibition causes stronger suppression to the already presented stimulus. On the other hand, lateral inhibition between the neurons of the already presented stimulus with the corresponding neurons of the proceeded stimulus is relatively low. Thus, competition between the RSVP items, represented by lateral and feed-forward inhibition, will have the first impact on each of the neural responses.

4.2.4 Top-down influence and synchronization of neural activity

In selective attention tasks such as those that employ visual search or the RSVP paradigm, the observer knows beforehand what the target is. As suggested by the interference model of Isaak et al. (1999), the present model creates templates containing the features of the targets and uses them to evaluate visual input. In our model, these target representations are maintained in the endogenous goals module. Therefore, spike trains that represent the target letters are initially generated and saved in the endogenous goals module.

After the first stage of processing and the modulation of the firing rate from the competitive inhibition, the spike trains are adjusted again by the saliency filters, based on their charac-

teristics. Let's consider, for example, a spike train A corresponding to a target letter. The specific spike train should have strong correlation with the temporal patterns of the spike trains that describe a target letter in the endogenous goals module. Thus, the states of the spike train A will switch to the states of the spike train stored in the endogenous goals with a certain probability q . The probability q can actually be seen as the degree of resemblance to a specific stimulus. Note, however, that this procedure modulates the timing of spikes within the spike train while the firing rate of the spike train remains unchanged.

The basic component of the second stage of processing is the Correlation Control Module (CCM) which is mainly comprised of a network of coincidence detector nodes combined with basic integrate and fire neurons. Therefore, the CCM is able to capture the correlation between spike trains coming from the visual input and spike trains originating from the internal goals and produce a relevant control signal (Figure 6).

For example, if a visual stimulus has strong correlation with the template of the target letter then its neural activity is amplified. This amplification is a result of a multiplicative process between the signal generated by the CCM and the neural activity of the corresponding stimulus. The control signal is generated by a node of the CCM that represents the combined firing of a neural network. For this reason a relative refractory period exists after the firing of the CCM specific node.

The strength of the generated control signal may have many variations which are mainly based on the total firing of the coincidence detector neurons of the CCM. That is, if the two signals are correlated then the coincidence detector neurons will fire more frequently and will consequently elicit a stronger control signal. However, if a stimulus has very little correlation with the endogenous spike trains, the node responsible for firing the control signal in the CCM will fire with reduced strength. Furthermore, in the case where the presented stimulus is a target letter, then the strong correlation between the two streams of neural activity will subsequently cause a significant synchronous firing of the coincidence detector nodes.

Finally, after the handling of the neural activity of each incoming stimulus, a specific working memory node will be excited. After a specified threshold is passed, the working memory node will fire an action potential indicating perceptual awareness for the visual stimulus. At the same time the corresponding signal will act in an inhibitory manner towards the node that generates the control signal in the Correlation Control Module (Figure 7). This can be seen as a safety mechanism to prevent multiple stimuli from entering working memory while it is occupied with the processing of the previous stimulus.

5. SIMULATIONS AND RESULTS

The model was run under three conditions. One was the typical AB condition in which T2 follows the T1 after a fixed delay (SOA of T2) while distracting numbers are presented in-between the two targets as well as after T2. We will call this condition the *no-blanks* condition as all positions in the RSVP sequence were occupied by stimuli. In another condi-

tion, termed *Lag 1 blank*, neither a target nor a distractor was presented at Lag 1. Previous research has shown that the AB is eliminated when T1 is not followed by a distractor (Giesbrecht & DiLollo, 1996; Seiffert & DiLollo, 1997). Including this condition enables us to examine whether the model is able to capture this finding. In a third condition, *Lag 2 blank*, a blank was presented 200ms after T1 (i.e., after a distractor was presented at Lag 1). This condition predicts the presence of AB.

For the simulations, T1 was always presented at time $t = 0$ and T2 at each of the subsequent time lags. For each lag that T2 was presented, the simulations were run for 50 times. Results revealed a clear match between simulations (Figure 8a) and the patterns of finding obtained from previous studies (Figure 8b).

As predicted by the literature, an AB effect was observed in the no-blanks condition when T2 was presented at Lags 2, 3, and 4 (i.e., the temporal window of 200-400ms). In addition, Lag 1 Sparing was observed when T2 was presented either at Lag 1 or after lag 4. As expected based on the findings of Giesbrecht and DiLollo (1996) and Seiffert and DiLollo (1997), the AB effect was eliminated in the Lag 1 blank condition. In contrast, a normal AB effect was obtained in the Lag 2 blank condition.

Different features of the model are responsible for simulating the AB effects found in the literature. The first is the competitive inhibition between incoming stimuli during the whole process. Specifically during the first stage of processing, the inhibition caused by the masking stimuli towards the target modulates its neural activity. The inhibition in the first stage of processing is important because it actually happens at very early stages of visual processing, before any top-down interference and thus makes no distinction between distractors and targets.

The second feature and perhaps the most important component of the model is the Correlation Control Module (CCM) that generates the appropriate control signal. However, one important mechanism of the model that has a key role in the reproduction of the typical U-shape curve of AB experiments is the interaction between the signals generated by the working memory node (that represents perceptual awareness) with the control signal generated by the CCM.

For the case where a blank is presented at Lag 1 two mechanisms contribute to the attenuation of the blink. As it has been mentioned previously, the specific node of the CCM that fires the control signal represents the combined firing of a neural network and is thus influenced by a relative refractory period. However, the specific node fires an analogous signal for all incoming stimuli regardless of whether they are within the target or the distractor set. The effect of the refractory period in the strength of the following signal combined with the inhibitory interaction between the incoming stimuli in the first stage of processing are the basic features of the model that cause this attenuation

6. DISCUSSION

As seen in the previous section, the model was capable of simulating a range of findings from the AB literature includ-

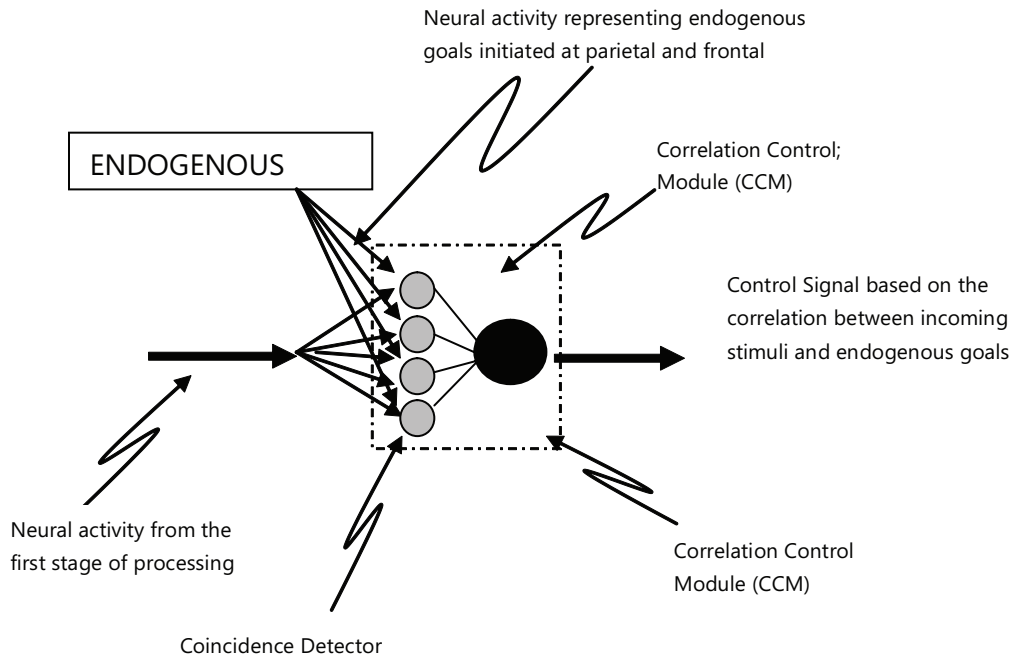


Figure 6 The functioning of the Correlation Control Module.

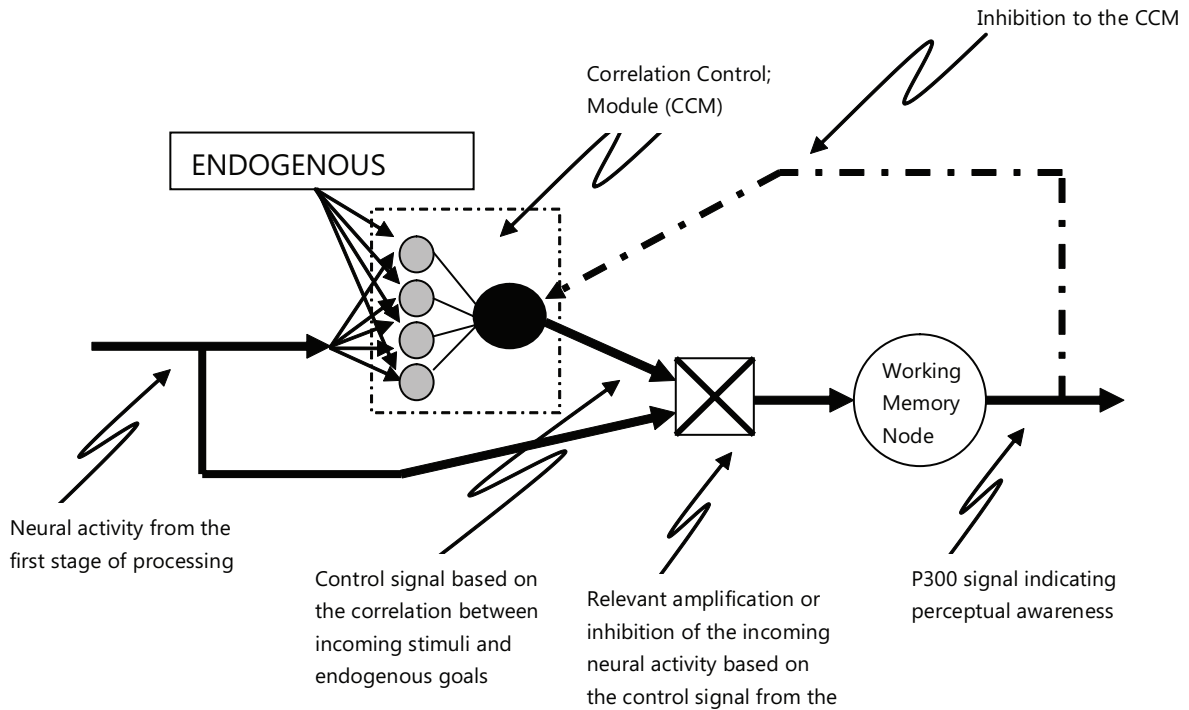
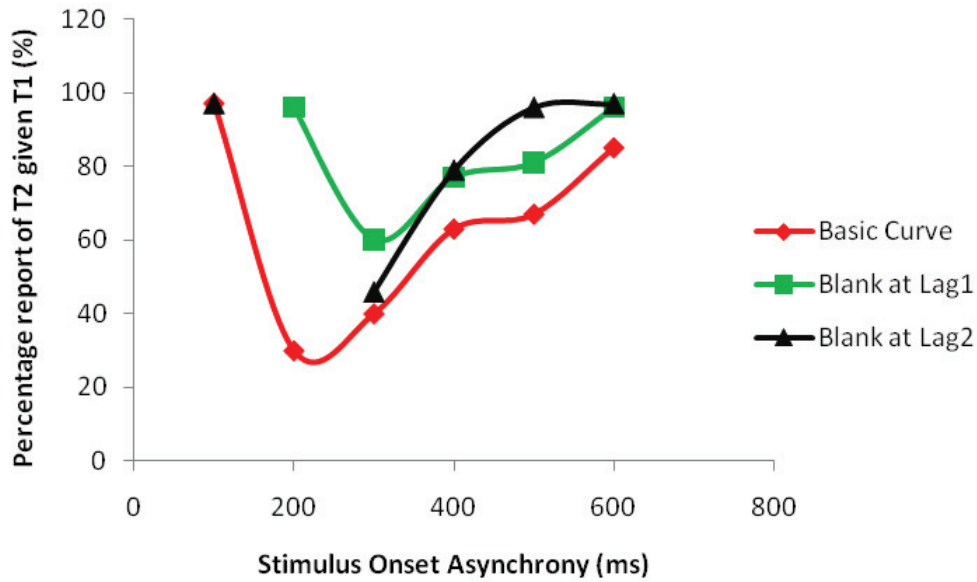


Figure 7 Working memory inhibition towards the Correlation Control Module.

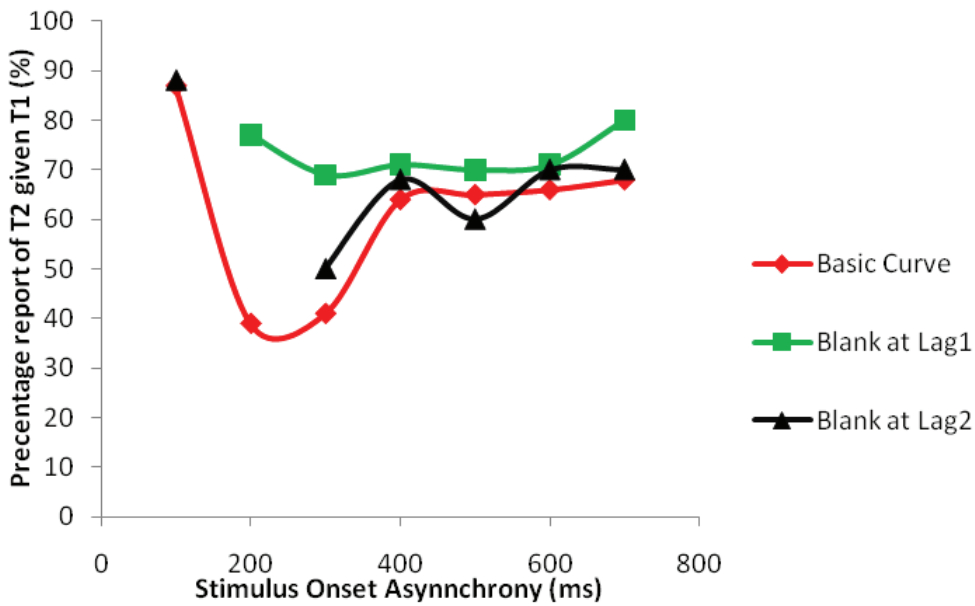
ing the basic AB effect, Lag 1 Sparing, and the elimination of the AB effect with a blank is inserted at an appropriate location. Importantly, the model accounted for these empirical findings using mechanisms that are at present popular among neuroscientists and cognitive scientists.

First, the model incorporates temporal coding of input. This is an idea proposed by Crick and Koch (1990) and it allows se-

lecting stimuli on the basis of synchrony across neurons. According to Crick & Koch, the change of the structure of spike trains that fall within the focus of attention represents selective attention at the neural level. As discussed by Niebur et al. (2002), selecting stimuli by adjusting the temporal structure of attended stimuli is a powerful mechanism as it allows selection without altering the firing rates of neurons. Although selec-



(a)



(b)

Figure 8 (a) Simulation Data from the proposed model. (b) Typical behavioral data from Attentional Blink studies (data adopted from Chun & Potter, 1995).

tion through modifying firing rates would also be a powerful mechanism, it is criticized for interfering with information that is presumably maintained in the firing rates (Niebur, et al. 2002). Specifically, Niebur and Koch (1994) suggested that attentional modulation by the saliency map in the first stage of processing influences the timing of the spikes and neurons within the focus of attention tend to fire synchronously.

As the presence of synchronization of neural activity within and across brain is well documented in the area of selective attention, we have adopted the idea of temporal coding for the present model. As the model was capable of simulating the AB findings quite well, we can argue that temporal coding is a plausible mechanism for the encoding of visual information.

Second, the model involves a first stage of processing in which incoming stimuli are allowed to interfere with one

other. Competitive inhibition, such as the one incorporated in the model, is known to take place at various levels of visual processing including the pyramidal cells of V1 (Zhaoping 1999).

Third, neural activity at the bottom-up first stage of processing is allowed to receive influence from the endogenous goals module. This way the model incorporates the well-known interaction between low-level information contained in incoming stimuli with high-level cognitive operations. Within the neuroscience literature there is indeed evidence that neural activity is affected by top-down attention in a rather later stage of processing, mostly in the area V4 of the brain which is considered an intermediate stage in the visual object-processing pathway in the occipital cortex (Moran & Desimone, 1985; Reynolds et al. 2000).

The model initially encodes all visual input with selection occurring gradually within the information processing stream. What gets selected is influenced by the result of the inhibitory interactions among visual input at the first-stage of processing and is determined after the influence – facilitatory or inhibitory – of internal volitions at a subsequent stage. This interaction between bottom-up and top-down signals may occur in area V4 of the visual cortex (Ogawa and Komatsu 2004).

Several aspects of the model can be linked directly with findings from electrophysiological studies of attention. The first distinguishable signals in these studies are obtained around 130-150ms post stimulus and are known as the P1/N1 signals. It is generally believed that these signals correspond to the initial processing that takes place in the visual cortex and the early activation of the incoming visual stimuli. At about 180-240 ms post-stimulus the P2/N2 signals are observed. These signals which are more easily obtained using Magnetoencephalography (MEG), (Ioannides and Taylor, 2003), have been proposed to represent control signals for the movement of attention (Hopf et al., 2000; Taylor 2002). In fact, several computational models for the AB contain mechanisms that are linked to these signals. For example, the CODAM model of Taylor (2002) uses the N2 signal as the signal from the controller that modulates the direction of the focus of attention. Moreover, in their Simultaneous Type Serial Token (ST2) model, Bowman and Wyble (2007) argue that when the visual system detects a task-relevant item, a spatially specific Transient Attentional Enhancement (TAE) called the blaster is triggered. This blaster is also linked to the P2/N2 component. In addition to P1/N1 and P2/N2, the P300 component which is present at about 350–600 ms post-stimulus is often regarded as an index of the availability for report of the attention-amplified input arriving from earlier sensory cortices to the associated working memory sensory buffer site. Finally, the N400 signal which is related to semantic processing is observed at around 400ms. In the present model, the spike trains generated for each stimulus during encoding can be linked to the early P1/N1 signals. The output of the Correlation Control Module can be associated with the N2/P2 signal and even more specifically with the N2pc component. The N2pc component has been considered by previous research as an index of distractor suppression in attentional tasks (Eimer 1999). Finally, the P300 which represents perceptual awareness of a stimulus can be associated with the activation of the working memory node in the model. The activation of this node also suppresses the firing of the Correlation Control Module.

Studies recording Event-Related Potentials (ERPs) with the RSVP paradigm have revealed important findings for the AB effect. For example, they have shown that even when T2 is not correctly identified, the P1/N1 and the N400 can be still obtained. On the other hand, the N2 and P300 components are no longer present (Sergent et al, 2005). This suggests that in spite of having no perceptual awareness of the presence of T2, people do process it semantically to at least some extent. The present model accounts for these findings by allowing all input to be semantic processed at the CCM. Thus, a T2 which is not available to perceptual awareness can still elicit an N400 in the event that it mismatches the semantic context.

In addition to documenting the presence or absence of ERP components, electrophysiological studies have revealed im-

portant findings regarding induced gamma activity when the RSVP paradigm is used. For example, Nakatani et al. (2005) have provided evidence that synchrony of neural activity in the 40-Hz range was substantially increased throughout the scalp for trials in which the T2 was detected compared to those trials that it did not. This finding is compatible with previous studies documenting an association between gamma-induced activity and selective attention. Furthermore, it also agrees with Tallon-Baudry & Bertrand's (1999) claim that induced-gamma activity is the neural basis of the construction of object representations by binding activity from different areas of the brain. In line with this empirical finding, the model implemented here is able to produce synchronization of activity across brain areas in order to select stimuli for attention. As with the empirical results, increased synchronization for T2 is obtained in the model when T2 is detected that when it is not.

In closing, it should be noted that although the model here was implemented to simulate the AB effect, it can be viewed as a more general model of selective attention as none of the mechanisms it contains is specific to the AB. The model was successful in simulating several findings from the AB literature. However, a more critical evaluation of the model can be made by examining whether the model can account, without modification, for other findings in the attention literature.

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