

A Neural Network Computational model of visual selective attention

Kleanthis C. Neokleous¹, Marios N. Avraamides², Costas K. Neocleous³, Christos N. Schizas¹

¹Department of Computer Science, ²Department of Psychology, University of Cyprus, 75 Kallipoleos, 1678, POBox 20537, Nicosia, CYPRUS, ³Department of Mechanical Engineering, Cyprus University of Technology, Lemesos, CYPRUS

Abstract. One challenging application for Neural Networks would be to try and actually mimic the behaviour of the system that has inspired their creation as computational algorithms. That is to use Neural Networks in order to simulate important brain functions. In this report we attempt to do so, by proposing a Neural Network computational model for simulating visual selective attention, a specific aspect of human attention. The internal operation of the model is based on recent neurophysiologic evidence emphasizing the importance of neural synchronization between different areas of the brain. Synchronization of neuronal activity has been shown to be involved in several fundamental functions in the brain especially in attention. We investigate this theory by applying in the model a correlation control module comprised by basic integrate and fire model neurons combined with coincidence detector neurons. Thus providing the ability to the model to capture the correlation between spike trains originating from endogenous or internal goals and spike trains generated by the saliency of a stimulus such as in tasks that involve top – down attention (Cobetta and Shulman, 2002). The theoretical structure of this model is based on the temporal correlation of neural activity as initially proposed by Niebur and Koch (1994). More specifically; visual stimuli are represented by the rate and temporal coding of spiking neurons. The rate is mainly based on the saliency of each stimuli (i.e. brightness intensity etc.) while the temporal correlation of neural activity plays a critical role in a later stage of processing where neural activity passes through the correlation control system and based on the correlation, the corresponding neural activity is either enhanced or suppressed. In this way, attended stimulus will cause an increase in the synchronization as well as additional reinforcement of the corresponding neural activity and therefore it will “win” a place in working memory. We have successfully tested the model by simulating behavioural data from the “attentional blink” paradigm (Raymond and Sapiro, 1992).

Keywords: Neural Network, coincidence detector neurons, visual selective attention.

1 Introduction

Due to the great number of sensory stimuli that a person experiences at any given point of conscious life, it is practically impossible to integrate available information into a single perceptual event. This implies that a selective mechanism must be present in the brain to effectively focus its resources on specific stimuli; otherwise we would have been in constant distraction by irrelevant information. Attention can be guided by top-down or via bottom-up processing as cognition can be regarded as a balance between internal motivations and external stimulations. Volitional shifts of attention or endogenous attention results from "top-down" signals originating in the prefrontal cortex while exogenous attention is guided by salient stimuli from "bottom-up" signals in the visual cortex (Corbetta and Shulman, 2002). In this paper we emphasize and try to simulate the behaviour of selective attention, especially in top-down tasks, mostly based on the theoretical background behind neural mechanisms of attention as it is explained by the field of neuroscience.

The underlying mechanisms of the neuronal basis of attention are supported by two main hypotheses. The first is known as "biased competition" (Moran and Desimone, 1985) and it originated from studies with single-cell recordings. These studies have shown that attention enhances the firing rates of the neurons that represent the attended stimuli and suppresses the firing rates of the neurons encoding unattended stimuli. The second more recent hypothesis, places emphasis on the synchronization of neural activity during the process of attention. The second hypothesis stems from experiments showing that neurons selected by the attention mechanism have enhanced gamma-frequency synchronization (Steinmetz et al., 2000; Fries et al., 2001). More specifically, Fries et al. (2001) measured activity in area V4 of the brain of macaque monkeys while they were attending behaviorally relevant stimuli and observed increased gamma frequency synchronization of attended stimuli compared to the activity elicited by distractors.

The proposed computational model for endogenous and exogenous visual attention is based on the second hypothesis for the neural mechanisms behind attention. The basic functionality of the model is based on the assumption that the incoming visual stimulus will be manipulated by the model based on its rate and temporal coding. The rate of the visual stimuli will have important role in the case of exogenous attention since this type of attention is mainly affected by the different features of the visual stimuli. More salient stimuli will have an advantage to pass in a further stage of processing and finally to access working memory. On the other hand, endogenous or top-down attention is mainly affected by the synchronization of the corresponding neural activity that represents the incoming stimuli with the neural activity initiated by internal goals that are setup when the individual is requested to carry out a specific task. These goals are possibly maintained in the prefrontal cortex of the brain. The direct connection of top-down attention with synchronization is supported by many recent studies (Niebur et al 2002, Gross et al 2004). For example, Saalman et al (2007) recorded neural activity simultaneously from the posterior parietal cortex and an earlier area in the visual pathway of the brain of macaques while they were performing a visual matching task. Their findings revealed that there was synchronization of the timing activities of the two regions when the monkeys selectively attended to a location. Thus, it seems that parietal neurons which

presumably represent neural activity of the endogenous goals may selectively increase activity in earlier sensory areas. Additionally, the adaptive resonance theory by Grossberg (1999) implies that temporal patterning of activities could be ideally suited to achieve matching of top-down predictions with bottom-up inputs, while Engel et al in their review (2001, p.714) have noted that “If top-down effects induce a particular pattern of subthreshold fluctuations in dendrites of the target population, these could be ‘compared’ with temporal patterns arising from peripheral input”.

2 Proposed Computational Model of Visual selective attention

Therefore, based on the above theories for visual selective attention, we suggest that a correlation control module responsible for comparing temporal patterns arising from top-down information and spike trains initiated by the characteristics of each incoming stimuli could be applied in the proposed computational model. If we extend this assumption based on relevant anatomical areas of the brain then the possible existence of such a correlation control module, would more ideally fit somewhere in the area V4 of the visual cortex were synchronization of neural activity has mostly been observed as can be seen in figure 1 below.

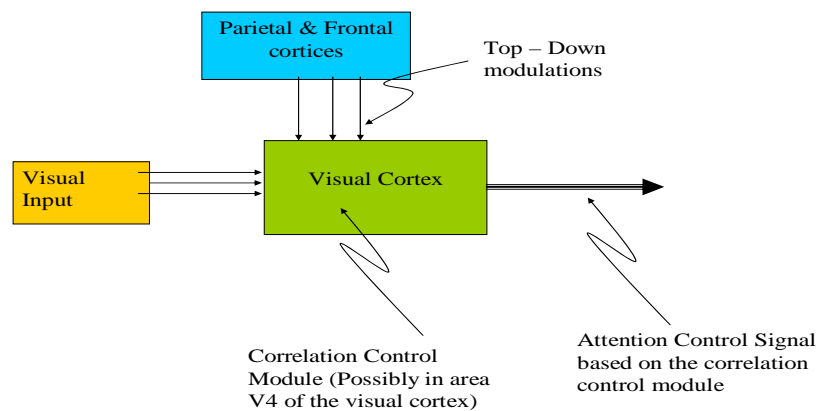


Fig. 1. Neural activity that corresponds to a specific visual input propagates along the visual cortex and initially to area V1. Furthermore, the corresponding neural activity continues into the visual hierarchy and specifically to area V4. Additionally, top-down signals originate from “higher” brain areas such as parietal and frontal lobe were possibly interact with the neural activity from the incoming stimuli. Correlation between these two streams of information could be examined in area V4 of the visual cortex.

The schematic representation of the proposed computational model is depicted in Figure 2 below. Specifically, each stimulus that enters the visual field is represented by a stream of binary events. Part of the stream represents no action potential occurrence ('zeros') and an isolated '1' that represents an action potential or spike. These binary waveforms are generated in order to represent the different spike trains initiated by each incoming stimulus. However, two important factors define the generation of these spike trains. The first is the firing rate or the frequency of spikes which is mainly based on the saliency of each stimulus, and the second factor is the exact timing that each spike appears. This means that in the race between the different visual stimuli to access working memory, both of their characteristics will contribute (Niebur and Koch 1994). The model can be seen as a two stage model where in the first stage, spike-trains representing each incoming stimulus enters into a network comprised by integrate and fire neurons. As a result, the corresponding neural activity will propagate along the network with the task to access a working memory node. Based on the firing rate of each incoming stimulus, a different neural activation will reach the working memory node and if the corresponding neural activity is strong enough to cause the working memory node to fire, then what can be inferred is that the specific stimulus that caused this activation has accessed working memory and thus it has been attended. However, in a later stage of processing, top-down signals coming from parietal and frontal lobes enter the network and try to influence the selection based on internal goals. For example, suppose that a person is asked to identify and respond if the letter A appears in the visual field. Then, information represented by spike trains that encode how letter A is stored in long term memory will enter the network as top-down signals. As a result, if a visual stimulus enters the visual field and has strong correlations with the corresponding top-down information, it will be aided in its attempt to access working memory.

The interaction between top-down information and the neural activity generated by each incoming stimulus is performed in the correlation control module which is the major component of the model (Figure 2).

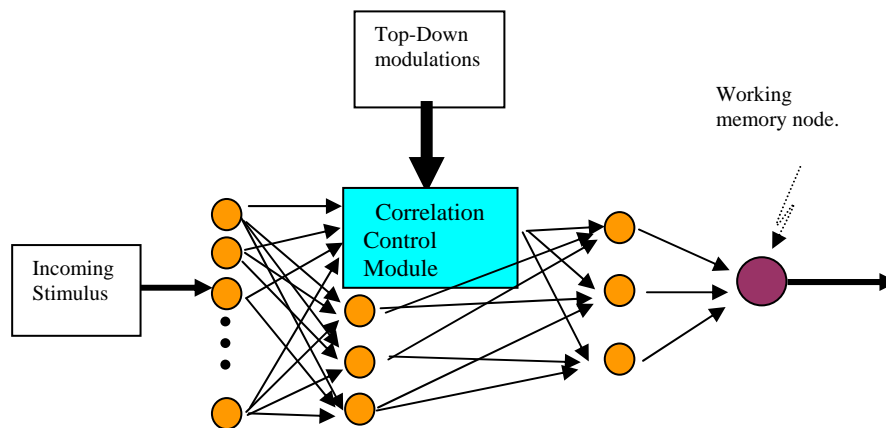


Fig. 2. A schematic representation of the proposed computational mode of visual selective attention.

One possible explanation of the mechanism behind the correlation control theory proposed in this report can be made based on coincidence detector neurons.

3. Coincidence Detector Neurons and the correlation control module

Coincidence detection is a very simplified model of neuron, however there is considerable experimental evidence signifying that under certain conditions, such as high background synaptic activity, neurons can function as coincidence detectors (Niebur, & Koch, 1994; Kempster, Gerstner, & van Hemmen, 1998).

Specifically as far as the neurophysiology of vision is concern, the main neurons found in several layers of the visual cortex are the **Pyramidal cells**. More importantly though is a recent theory about the function of pyramidal neurons which implies that the neurons responds best to coincident activation of multiple dendritic compartments. An interesting review about coincidence detection in pyramidal neurons is presented by Spruston (2008).

A plausible way to model coincidence detection can be based on separate inputs converging on a common target. For example let consider a basic neural circuit of two input neurons with excitatory synaptic terminals, A and B converging on a single output neuron, C (Figure 3). The output target neuron C will only fire if the two input neurons fire synchronously. Thus it can be inferred that a coincidence detector is a neuron model that can detect synchronization of pulses from distinct connections.

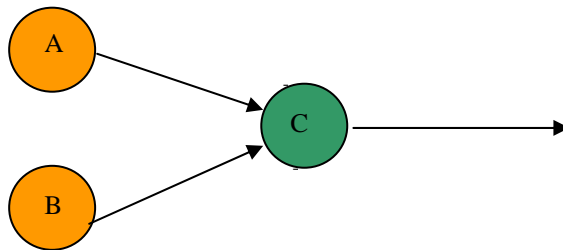


Fig. 3. A coincidence detector neuron C will fire only if the two input neurons A and B fire synchronously.

In Figure 4 is shown with a simple representation, how the correlation control module adjusts the neural activation of each incoming stimuli.

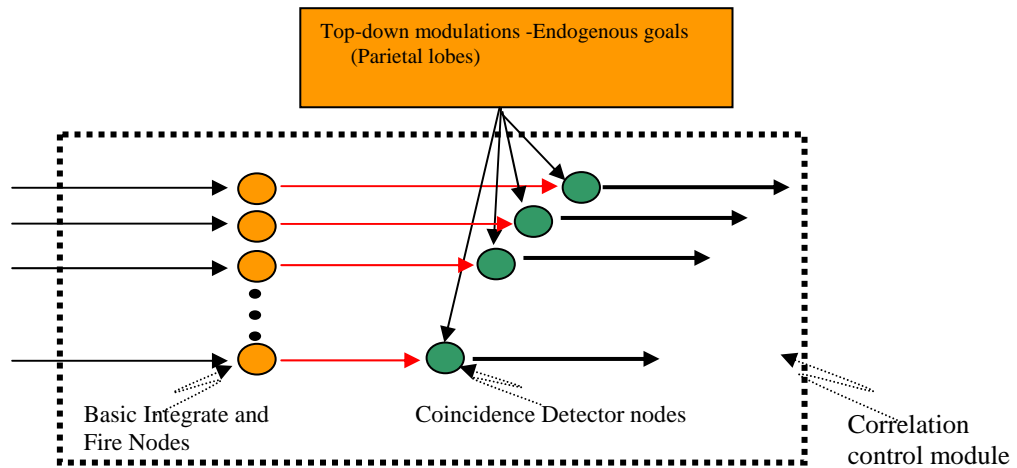


Fig. 4. Correlation control mechanism between the endogenous goals and the incoming stimuli.

4. Simulations and Evaluation of the model

In order to examine the model's validity we have attempted to reproduce behavioral data from a famous attention-related task named the attentional blink which is explained with more detail in the next section.

4.1 Attentional Blink Explanation – Theory

Attentional blink (AB) is a phenomenon observed in the rapid serial visual presentation (RSVP) paradigm and refers to the finding that when 2 targets are presented among distractors in the same spatial location, correct identification of the 1st target, usually results in a deficit for identification of a 2nd target if it appears within a brief temporal window of 200-500 ms. When the 2nd target appears before or after this time window it is identified normally (Figure 5.b). More specifically, in the original experiment by Raymond and Sapiro (1992), participants were requested to identify two letter targets T1 and T2 among digit distractors while every visual stimulus appeared for about 100ms as shown in Figure 1.a.

Another important finding from the AB paradigm is that if T1 is not followed by a mask (distractor), the AB impairment is significantly reduced. That is if lag 2 ($t=100\text{ms}$) and/or lag 3 ($t=300\text{ms}$) are replaced by a blank then the AB curve takes the form shown in Figure 5 by the green and black series.

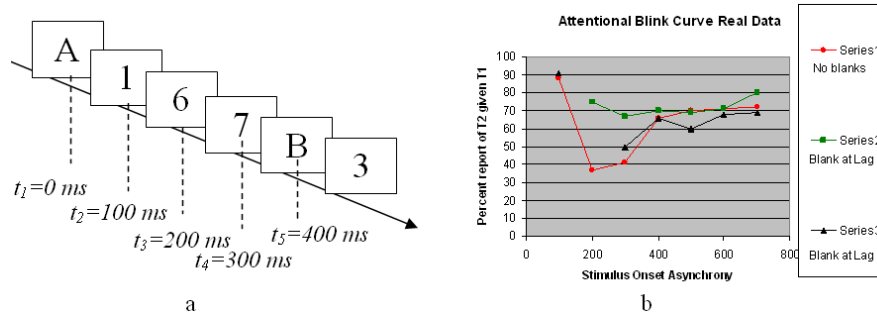


Fig. 5. Presentation of the RSVP for the “attentional blink” experiment (Figure5.a) and the attentional blink basic curve with no blanks (red series), with blank at lag 1 (green series) and blank at lag 2 (black series) based on the behavioral data of Raymond and Sapiro (1992) (Figure5.b).

One possible explanation for the classic U-shaped curve of Figure 5.b (red series) is based on Electroencephalography (EEG) measurements and more importantly on two attention related Event Related Potentials (ERPs). The first ERPs appear at about 180-240 ms post-stimulus and are referred to as the P2/N2 signals. These signals have been proposed as control signals for the movement of attention (Hopf et al., 2000, Taylor 2002). The second component is the P300 signal at about 350–600 ms post-stimulus which is associated with the working memory sensory buffer site and is taken to be the signal of the availability for report. Therefore the explanation for the U- shaped curve lies in the assumption that the P300 signal generated by the first target falls into the time window that the P2/N2 component of the second target was about to be generated. However due to this interaction, the P2/N2 component of the second target is inhibited.

The explanation behind the curves of figure 5.b (with blank at lag 1 (green series) and blank at lag 2 (black series)) is based on the neural mechanisms behind selection at attentional tasks. Mostly is based in the competition process between various stimuli in order to access working memory. This competition is reflected through relevant inhibition between the neural activities that corresponds to each stimulus.

The proposed computational model has been implemented in the Matlab-Simulink environment. Each of the visual stimuli has been represented by a 10 ms sequence of spikes and in each ms there is a one (spike) or a zero (no-spike) as seen in Figure 6. For coding both the distractors and the targets, the same firing rate has been used since both (targets and distractors) have the same effect from the salience filters (same brightness, intensity etc.). However, the difference between the spike trains generated by the targets and the spike trains generated by distractors is in the temporal patterns. Therefore, it is possible through the coincidence detector module to capture the correlation between the spike trains generated by the targets and spike trains initiated by internal goals if those two sources have similar temporal patterns in their spike trains. Based on the degree of correlation between the incoming stimulus and the internal goals, a relevant control signal is generated that could be associated with the N2/P2 component explained in the previous section. Additionally, once a specific working memory node that corresponds to a specific stimulus fires, then another signal is generated that inhibits at that timing any attempt for the coincidence control

module to generate a new control signal.

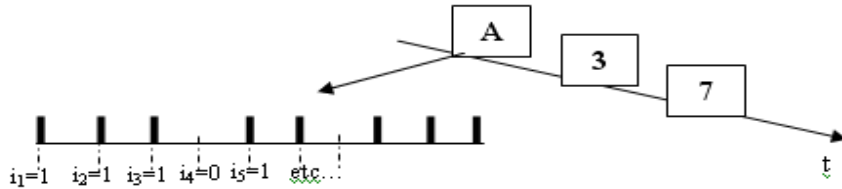


Fig. 6. Coding of the incoming visual stimuli.

As a consequence, three important features of the model that rely on neurophysiologic evidence have given the ability to reproduce the behavioural data from the attentional blink experiment as shown in Figure 7 below. These important features of the model are: a) The correlation control module that generates a control signal relevant to the degree of correlation b) the interaction between the signals related to identification and respond (P300) with the control signal and c) the competitive inhibition between each incoming stimuli.

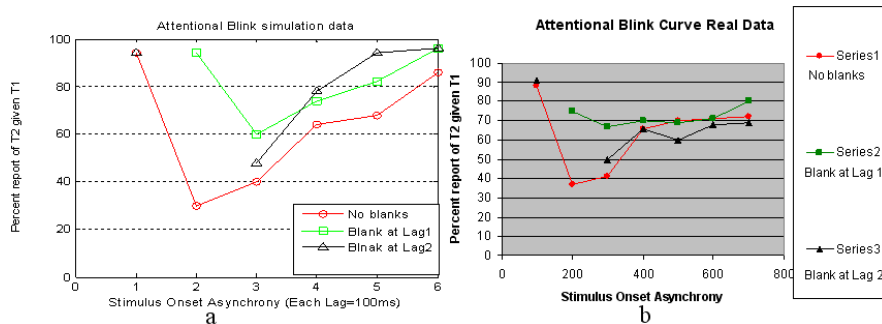


Fig. 7.. Comparison between simulation data (7.a) and experimental data (7.b).

5. Discussion

The main advantages of the implementation of a computational model of specific brain functions can be seen in a twofold manner. First, a biologically plausible model will give the ability to perform appropriate and detailed simulations in order to study the most important aspects of the specific brain function as well as to magnify or weaken related theories. On the other hand, the detailed study of the psychological and neurophysiological approach will aim into an improved understanding of the specific functionality in the brain. This, combined with knowledge from computer science, will provide the potentials to advance in neurally inspired computing and information processing. Robots and other engineered systems that mimic biological

capabilities as well as brain-computer interfaces are some of the potential applications that can be benefit and improved by this knowledge.

References

1. Corbetta, M., Shulman, G.L. (2002). "Control of goal-directed and stimulus-driven attention in the brain". *Nature R. Neuroscience* 3:201-215.
2. Engel A. K., Fries P., Singer W.(2001) "Dynamic predictions: Oscillations and synchrony in top-down processing" *Nature*, Volume 2 pp.704-716
3. Fries P, Reynolds JH, Rorie AE, Desimone R (2001). "Modulation of oscillatory neuronal synchronization by selective visual attention". *Science* 291:1560-1563.
4. Grossberg, S. (1999). "The link between brain learning, attention, and consciousness". *Conscious. Cogn* 8, 1-44
5. Gross J., Schmitz F., Schnitzler I. et al (2004). "Modulation of long-range neural synchrony - reflects temporal limitations of visual attention in humans." *PNAS* August 31, 2004 vol. 101 no. 35 pp13050-13055
6. Hopf, J.-M., Luck, S.J., Girelli, M., Hagner, T., Mangun, G.R., Scheich, H., Heinze, H.- J., (2000). "Neural sources of focused attention in visual Search". *Cereb. Cortex* 10, 1233-1241.
7. Kempter, R., Gerstner, W., & van Hemmen, J. (1998). How the threshold of a neuron determines its capacity for coincidence detection. *Biosystems*, 48(1-3), 105-112.
8. Moran J, Desimone R (1985). "Selective attention gates visual processing in the extrastriate cortex". *Science* 229:782-784.
9. Niebur E., Hsiao S.S., Johnson K.O., (2002) "Synchrony: a neuronal mechanism for attentional selection?" *Cur.Op. in Neurobio.*, 12:190-194
10. Niebur E, Koch C (1994). "A Model for the Neuronal Implementation of Selective Visual Attention Based on Temporal Correlation Among Neurons". *Journal of Computational Neuroscience* 1, 141-158.
11. Raymond JE, Shapiro KL, Arnell KM (1992). "Temporary suppression of visual processing in an RSVP task: an attentional blink?". *J.of exp. psyc. Human perc, and performance* 18 (3): 849-60
12. Saalmann Y.B., Pigarev I.N., et al. (2007) "Neural Mechanisms of Visual Attention: How Top-Down Feedback Highlights Relevant Locations" *Science* 316 1612
13. Spruston, N. (2008) Pyramidal neurons: dendritic structure and synaptic integration. *Nature Reviews Neuroscience* 9:206-221.
14. Steinmetz PN, Roy A, et al.(2000) "Attention modulates synchronized neuronal firing in primate somatosensory Cortex". *Nature* 404:187-190.
15. Taylor J.G., Rogers M. (2002). "A control model of the movement of attention". *Neural Networks* 15:309-326