In Proceedings of the Sixth International Conference on Cognitive Modeling, 64-69.
Mahwah, NJ: Lawrence Earlbaum.

A Connectionist Model of the Attentional Blink Effect During a Rapid Serial Visual Presentation Task

Sylvain Chartier (chartier.sylvain@courrier.uqam.ca)
Département de psychologie, Université du Québec à Montréal
C.P. 8888, succ. Centre-ville, Montréal, H3C 3P8 CANADA

Denis Cousineau (denis.cousineau@umontreal.ca)
Département de psychologie, Université de Montréal
C.P. 6128, succ. Centre-ville, Montréal, H3C 3J7 CANADA

Dominic Charbonneau (dominic.charbonneau@umontreal.ca)
Département de psychologie, Université de Montréal
C.P. 6128, succ. Centre-ville, Montréal, H3C 3J7 CANADA

Abstract

We introduce a connectionist model that reproduces the attentional blink effect during a rapid serial visual presentation task. The model is composed of two layers, a competitive one that acts as an identification layer and a recurrent one that acts like short term memory where the main mechanisms is the presence of an inhibition gate and a neural fatigue. Simulations show that the model generates data that are as variables as the one obtained from human participants and the mean performance is identical to the performance obtained by human participants.

Introduction

During visual scanning, the eyes gaze at a given area then make a saccade to another area. Between the saccades, they receive brief images. How the brain can process such a flow of information is studied in the laboratory using the Rapid Serial Visual Presentation (RSVP) task. In this experimental setting, stimuli are presented in rapid succession, usually, 6 to 20 stimuli per second, at a same spatial location. Within the stream, there is usually a target which is marked by a different attribute (e.g. color) and the task is to identify it. Thus, the RSVP can be seen as a visual search without saccade.

The attentional blink (AB) effect is characterized by a decrease in performance for a second target when a first target has been identified (T2|T1). The performance for recalling a second target will decrease if it is presented within 200 to 500 milliseconds of the first. However, if the second target is presented next to the first target, there is no decrease in performance. This phenomenon is called lag of 1 sparing effect. Figure 1 shows a typical AB curve with human participants obtained from our lab.

Many independent models have been postulated to explain the AB phenomenon.The first explanation is given by Raymond, Shapiro & Arnell (1992) and is based on the postulate of an inhibition process. When a first target is perceived, the perceptual system is inhibited to avoid confusion with subsequent items. However, the inhibition is slow to start, so that if a second target is next to the first, it will be processed along the way.

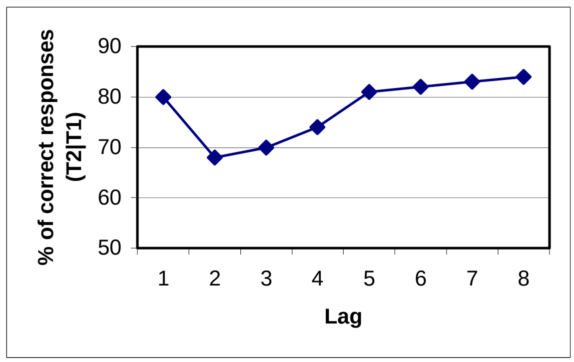

Figure 1: Results with human participants in the AB task from our lab.

Shapiro, Ward & Duncan (1997) challenged this explanation by showing that the second target could facilitate the processing of a third target. If perception was inhibited, there should be no facilitation, according to Raymond & al. (1992).

Another explanation was proposed by Chun & Potter (1995) who postulated a two-stage model. The first stage operates rapidly and decides which of the stimuli is sent to the second stage for encoding. The second stage is slow and can process only one item at a time. Meanwhile, the second target is left in a waiting stage. Thus, as time passes the probability of encoding the second target correctly decreases. However, if the second target is presented next to the first target, it will be encoded

Finally, the most recent explanation comes from Jolicoeur (1998). He proposed a modified version of the two-stage model by adding a third stage. According to Jolicoeur, the first and last stages are the perception and recall stage respectively. The second stage is used to encode the targets in short term memory and is characterize by its limited capacity (1 item at a time). This bottleneck delays the processing of a second target. The probability of correctly encoding the second target decreases as a function of the delay.

These three explanations seem to capture the data in a qualitative manner. However, few formal simulations were ever proposed (Bowman, Wyble and Barnard, 1994). Without form simulation it is difficult to evaluate them quantitatively. This paper introduces a connectionist model of perception and short-term memory that accounts for the AB effect. The paper is divided as follow: the first section presents the general methodology used with human participant to obtain the AB effect. The second section presents the model, and gives the methodology used for the simulations. The third section compares the results obtained by the model with the one obtain by human participants. Finally, the last section gives a brief conclusion.

Description of the RSVP Task

The typical task used to obtain the AB effect consists in presenting a RSVP stream of 16 items. Each item is a number between 0 and 9. A target item is red whereas a distractor is green. An item is presented during a period of 100 milliseconds. What is controlled is the position of the second target relative to the first target, a variable named lag. For example, a lag of 1 indicates that the second target is presented immediately after the first target and a lag of 2 indicates that there is one distractor between the first and the second target. The participant performances are obtained by calculating the recall percentage of the second target when the first target is correctly detected. Figure 2 shows a typical RSVP used to obtain AB effect.

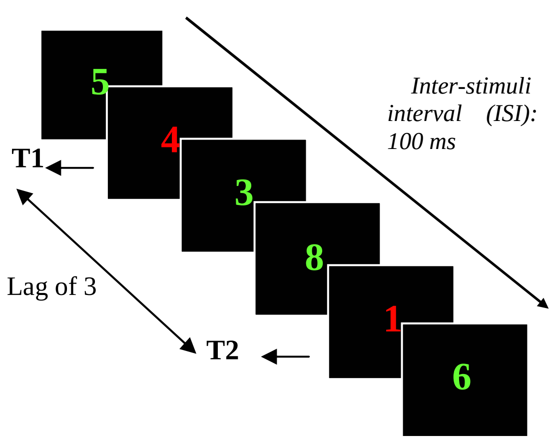

Figure 2: Six frames of an RSVP stream showing the two targets (4 and 1), the second occurring at a lag of 3.

Description of the AB Model

The proposed model is based partially on Chun & Potter (1995) and Jolicoeur (1998) models, where the first stage identifies the stimulus and the second stage stores the input into a short term memory (STM). The overall model is illustrated in Figure 3. However, as seen latter, the model also has the characteristic of Raymond, Shapiro and Arnell (1992) model, an inhibition process.

As seen in Figure 3, the input is distributed and is decomposed into its attributes. The identification stage is composed of 2 competitive networks (Kohonen, 1982, 1984). One competitive network identifies which letter is presented and the second network identifies which color is presented. In this modelization, the color determines if the stimulus is a target or a distractor. This information is thus the decision criterion used to decide if a given letter must proceed to STM. The STM memory is represented by an autoassociative layer (Hopfield, 1982).

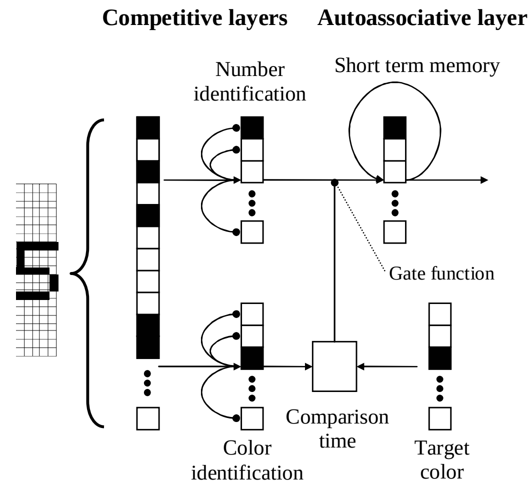

Figure 3: Model architecture

The main characteristic of the model is the presence of a dual mechanism that accounts for the decrease in the overall performance and the lag of 1 sparing effect. The first mechanism is the comparison process: once a target has been identified, it is compared to the desired attributes. If the stimulus attribute corresponds to the desired one, two things occur: a) a gate to STM is open so that the stimulus starts being encoded; b) an inhibitive process takes place making further comparison harder for a given period of time. This can be viewed as a psychological refractory period (PRP) as described by Pashler (1994). In addition, the comparison time is also involved to close the gate to STM.

The second mechanism takes place at the STM layer. At this stage, while learning of the first target occurs, a neural fatigue takes place diminishing the learning strength over time (Tsodyks & Markam, 1997). These mechanisms are illustrated in Figure 4 for a target presented at lag of 1, 2 and 3. The figure shows that the memory trace is function of both learning strength and comparison time. Thus, the amount of learning is given by the trapezoidal area.

The responses of the model are the two items that are the most learned in STM. Yet, the memory is not perfect: because the comparison time is slow, not only the targets are memorized but also the distractor following a target. As a consequence the model predicts intrusion effects (the participant reports the distractor following a target instead of the target) as well as inversion effects (the participant reports the two targets in reversed order).

Model Description

In this section, we give the details of the identification network, implemented by a competitive model, and the short-term memory, implemented by an autoassociative model. As for any artificial neural network, these networks are entirely described by their architectures, their transmission rules and their learning rules.

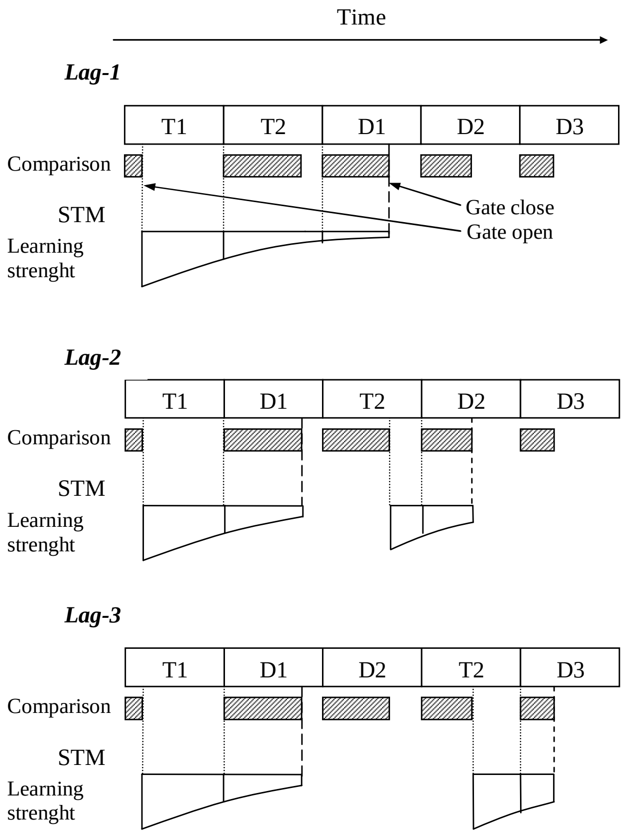

Figure 4: Illustration of the model main mechanisms

Competitive Model of Identification

Figure 5 illustrates the architecture of a typical competitive model (Kohonen, 1982). As we can see, each unit inhibits its neighbors. Thus after some times only one unit will remain active. This unit will be the one whose weights are closer to the input. As a consequence the network's output is localist (Page, 2000): each unit is responsible for the perception of a given input. In our simulations, we used the digits from 0 to 9 so that there are 10 units.

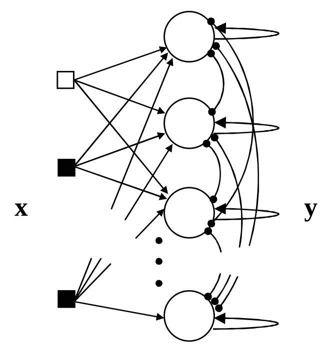

Figure 5: architecture of the competitive layer

The network's transmission rule is given by the following equation:

$$\mathbf{a} = \mathbf{W}\mathbf{x} \qquad (1)$$

where **a** represents the activation vector, **W** the weight matrix, and **x** an input vector. The inhibitive function is usually modeled by the Mexican hat function. However, we can use the following Winner-Take-All (WTA) simplification: the most active unit is set to 1 and all the others are shut down to zero, so that:

$$\mathbf{y} = WTA(\mathbf{a}) \qquad (2)$$

where **y** represents the output of the network. Learning in the model is usually carried out by an unsupervised algorithm (Kohonen, 1982). However, in our case, learning at this layer is not a preoccupation because the participant should already be able to identify a letter or a color. Consequently, for simplification, the network was trained to identify colors (7 possible colors) and identity (10 possible identities) before it was submitted to the RSVP task using the supervised delta rule (Widrow & Hoff, 1960) described by the following expression

$$\mathbf{W}_{[k+1]} = \mathbf{W}_{[k]} + \eta(\mathbf{z} - \mathbf{y})\mathbf{x}^{\mathrm{T}} \qquad (3)$$

where η represents the learning parameter, **z** the desired output, T the matrix transposition operator, and k the learning trial.

Autoassociative Model of Short-Term Memory

This network is usually used to model unsupervised memorization process (Hopfield, 1982, Anderson, Silverstein, Ritz and Jones, 1977). Figure 6 shows the network's architecture. The output vector **y** computed from the identification network is the original input used for the autoassociative memory, so that $\mathbf{x}_{[0]} = \mathbf{y}$. Because the memory is fed by the output of the competitive network, the STM also has 10 units. As we can see, the model is recurrent and the input is associated with its-self.

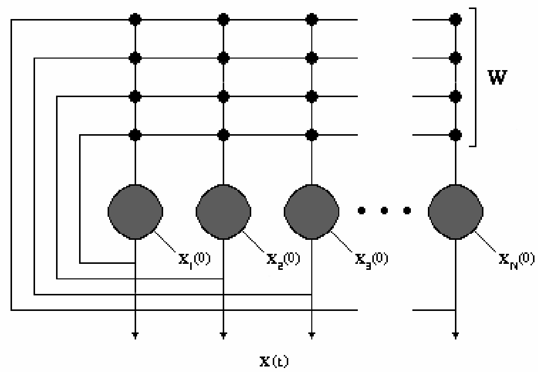

Figure 6: Architecture of the autoassociative layer

Memorizing an item was carried out by the following equation:

$$\mathbf{W}_{[k+1]} = \mathbf{W}_{[k]} + \eta(\mathbf{x}_{[0]}\mathbf{x}_{[0]}^{\mathrm{T}} - (\mathbf{W}\mathbf{x}_{[t]})(\mathbf{W}\mathbf{x}_{[t]})^{\mathrm{T}}) \tag{6}$$

We used this learning rule instead of a strictly hebbian learning rule found in (Silverstein, Ritz and Jones, 1977) for the simple reason that the hebbian does not converge whereas this one converge in a finite number of learning trial (Chartier & Proulx, 2001). Because the inputs to be learned are not linearly dependant, this autoassociative model can memorize up to 10 items with different memory strength for each, depending on the study time.

Methodology

Stimulus Composition

The inputs were simplified digits made from a 5 × 7 array of pixels. However, to model the presence of color, we used one such array for each color channel (red, green, blue). Therefore, the full input is composed of 3 arrays of 5 × 7. This input is separated in two sections. The first section consisted of the pixel information. This stimulus is thus an array of 5 × 7 given a 35 dimensions input vector. The second section consisted of the color information. The color information is thus a 3-dimensions input vector, corresponding to the RGB channels. An example of a RSVP stream is illustrated at the Figure 7.

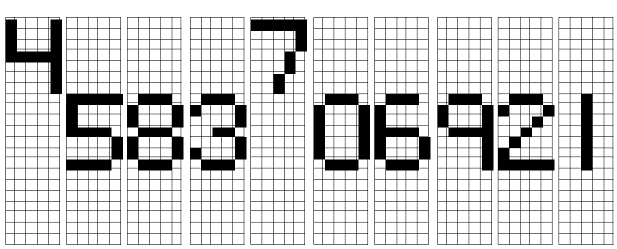

Figure 7: One possible RSVP stream composed of 10 digits. The two targets are red (top channel) and the remaining distractors are green (middle channel).

Variables

The independent variable, were the learning strength and the comparison time, which is implemented by an inhibition time function. The initial learning strength was varied from 0.001 to 0.02, whereas the inhibition time function varied from 0 to 100 time step. It is noted the inhibition function decrease following a linear function

$$inhib_{[t+1]} = inhib_{[t]} - 1 \tag{7}$$

whereas the learning strength decrease following a simple exponential function described by

$$\eta_{[t+1]} = \eta_{[t]} * \gamma \tag{8}$$

where t represents the time step and γ a general constant (γ was set to 0.997 for all the simulation). The dependant variables were the memory strength in STM for each stimulus, the average model performance and the probabilistic output. Moreover, to generate data that are closely related to human performance simple uniformed noise were introduced to both learning strength and comparison time. The random component was 30% of a given parameter initial value. To have a good idea of the variability obtained in the model's response, we performed 100 simulations. From those outputs, we compute the mean to see if, the network was able to reproduce mean performance obtained by the participants.

Results

Figure 8 shows the different AB curve obtained from the variation of the learning strength and the inhibition time. We can see that the learning strength is responsible for the vertical movement of the curve, higher the learning strength is, higher the overall performance. The inhibition time is responsible for the depth of the blink effect. Higher is the amount of inhibition, lower will be the recall performance, creating a bigger blink.

From these results, we selected a learning strength of 0.017 and inhibition value of 85 to be used for the probabilistic network. Figure 9 shows the results obtained from the simulations and the one obtained from human participants. We can see that the simulations yield similar results as the one obtained by human. Moreover if we look at Figure 10 we can see that the mean performance gives the same as the one obtained by human participants (Figure 1).

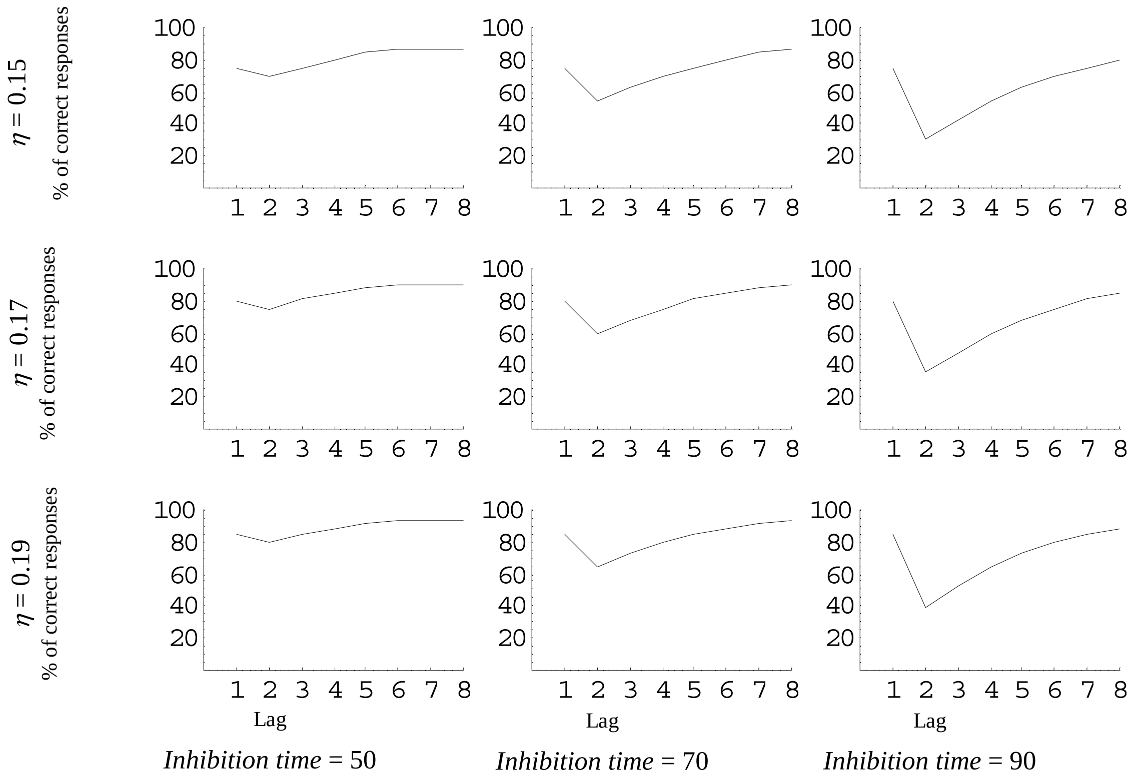

Figure 8: Various performances obtained by varying the parameters.

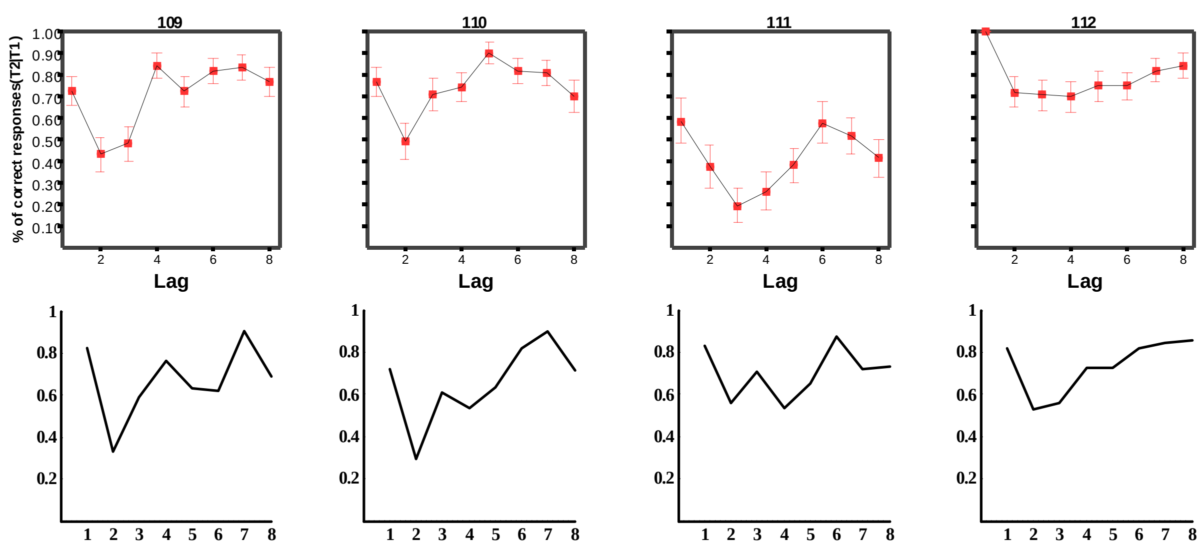

Figure 9: Examples of individual data from 4 participants (top row) and from the simulations (bottom row).

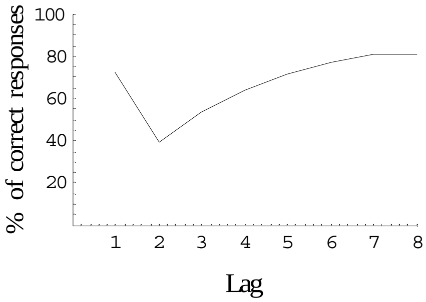

Figure 10: Mean results over 100 simulations

Conclusion

Experiments conducted with human participants showed the presence of an attentional blink if stimuli are presented within a rapid serial visual task. Many authors have proposed different mechanism that could account for the data but none have tested their affirmations using simulations. We proposed a two stage model composed of an identification stage and a memorization stage where the mains characteristic are an inhibition gate and neural fatigue. The important point is that the two-stage model alone or the inhibition model alone cannot account for the standard results.

We performed several simulations that shown that the model can reproduce the average performance of the human subjects. Moreover, under its probabilistic version the model generates data that are as variables as the one obtained from human participants. If we average those data we have shown that mean performance is the same as the one obtained by human participant. It is thus concluded that model can describe accurately the AB effect during a RSVP task.

References

Anderson, J. A., Silverstein, J. W., Ritz, S. A. & Jones, R. S. (1977). Distinctive features, categorical perception, and probability learning: Applications of a neural model. *Psychological Review, 84*, 413-451.

Bowman, H., Wyble, B. and Barnard, P.J. (2004). Towards a Neural Network Model of the Attentional Blink. In H. Bowman and C. Labiouse, editors, *Proceedings of the Eighth Neural Computation and Psychology Workshop, Connectionist Models of Cognition and Perception II, volume 15 of Progress in Neural Processing*, 178 - 187, Singapore.

Chartier, S. & Proulx, R. (2001). A new online unsupervised learning rule for the BSB model, *Proceeding of the International Joint Conference on Neural Networks (IJCNN'01)*, 448 - 453, Washington D.C.

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

Hopfield, J. J., (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences, 79*, 2554-2558.

Jolicoeur, P. (1998). Modulation of the attentional blink by on-line response selection : Evidence from speeded and unspeeded Task1 decisions. *Memory & Cognition, 26*, 1014-1032.

Kohonen, T. (1982). Self-organized formation of topologically correct feature maps. *Biological Cybernetics, 43*, 59-69.

Kohonen, T. (1984). Self-organization and associative memory. Springer Verlag.

Page, M. (2000). Connectionist modelling in psychology: A localist manifesto. *Behavioral and Brain Sciences, 23*, 443-512.

Pashler, H. (1987). Detecting conjunctions of color and form: Reassessing the serial search hypothesis. *Perception and Psychophysics, 41*, 191-201.

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

Shapiro, K., Driver, J., Ward, R. & Sorensen, R. E. (1997). Priming from the attentional blink: A failure to extract visual tokens but not visual types. *Psychological Science, 8*, 95-100.

Tsodyks, M. V., & Markam, H. (1997). The neural code between neocortical pyramidal neurons depends on neurotransmitter release probability. *Proceedings of the National Academy of Science, 94*, 719-723.

Widrow, B. & Marcian E. H. (1960) Adaptive switching circuits, *IRE WESCON Convention Record*, New York: IRE, pp. 96-104.