A Neural Network Model of the Visual Short-Term Memory

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Abstract

In this paper a neural network model of Visual Short-Term Memory (VSTM) is presented. The model links closely with Bundesen's (1990) well-established mathematical theory of visual attention. We evaluate the model's ability to fit experimental data from a classical whole and partial report study. Previous statistic models have successfully assessed the spatial distribution of visual attention; our neural network meets this standard and offers a neural interpretation of how objects are consolidated in VSTM at the same time. We hope that in the future, the model will be able to fit temporally dependent phenomena like the attentional blink effect, lag-1 sparing, and attentional dwell-time.

Keywords: Visual Short-Term Memory, the Magical Number 4, Winner-Take-All Network

Introduction

For everyday life, it is important for us to be able to perceive, comprehend, and react to events in our environment. Often, our rate of success is heavily dependent upon how efficient and how fast we can process, interpret and react to sensory stimuli, e.g. like when we are driving a car.

In the following we shall refer to *visual attention* as the process that enables us to focus our processing resources to certain important objects in the visual scene. Following the Theory of Visual Attention (Bundesen, 1990) we assume that features have already been extracted and objects successfully segregated on the basis of their individual feature spaces. Our model deals with the important question of how only a limited sub span of all objects are actually selected and further encoded into VSTM.

Cartell already in the late 19th century demonstrated a surprising limit in how many objects that can be perceived at the same time – a limit only about 4 objects which may be held in the VSTM at the same time (Cattell, 1886; Cowan, 2000). This finding is independent of the number of objects visually presented at the same time (Sperling, 1960). Evidence further exist that the "magical number" of 3-to-4 objects is largely independent of how many features are encoded for each object, i.e. the complexity of the visual object, does not hold an influence on the memorial capacity of the VSTM; see (Luck & Vogel, 1997), but see also (Alvarez & Cavanagh, 2004).

Modelling the function of the VSTM, it is essential that the inherent capacity limitation is properly mimicked, since it seems a fundamental limit of the system. Most likely the VSTM would be heavily overloaded, should the system lack the ability to represent only the most salient of the visually appearing objects

The Model

The model that we are presenting in this paper can actually be understood as three important consecutive processes.

The first process is simply extraction of visual features, we speak of this process as *'object matching'*, since we find it relevant to think that objects in the visual field are to some extent 'matched' against objects representations in Visual Long-Term Memory (VLTM). In this paper we do not consider the problem of which feature extraction techniques are biologically most plausible or perhaps technically most appropriate to use.

The second process that we shall consider in more detail is '*the attentional race'*. According to Shibuya & Bundesen (1988), all objects in the visual scene take a place in what one could think of as a race to become encoded. In Shibuya & Bundesen's race model, the 'odds' that a given object is selected as a winner in the race is directly related to the rate value with which the object participates. It is worth noting that the race is a stochastic, rather than a deterministic process, meaning that no one can beforehand predict readily which objects will win the race.

The third and last process that we shall consider is that of '*storage'* of object representation in VSTM. Inspired by Usher & Cohen (1999) we propose a competitive neural network model of VSTM, directly linking with several important assumptions expressed in Bundesen's Theory of Visual Attention (Bundesen, 1990).

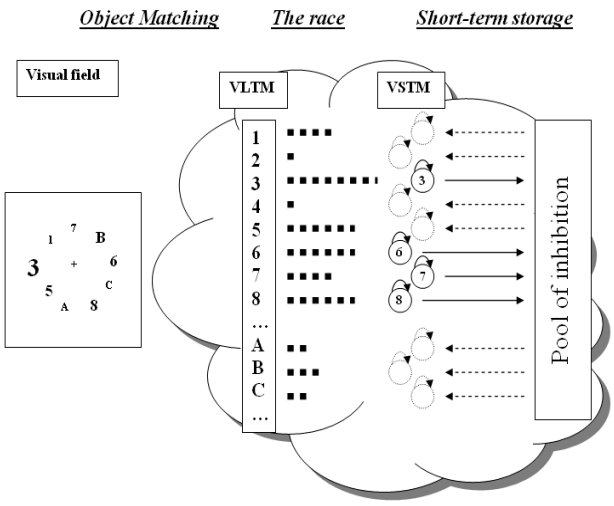

Figure 1: The Model Scheme – an example

The Neural Theory of Visual Attention

The theory of visual attention (TVA) proposed by Bundesen (1990) is a unified theory of visual recognition and attentional selection. TVA provides a mathematical framework describing how the visual system is able to select individual objects in the visual field, based on the visual evidence and the setting of two different types of visual preference parameters (pertinence and bias), representing the influence from higher cortical areas, including VLTM.

The output of the TVA-model is a set of rate parameters v that are directly related to the probability that a given characterization, *object x belongs to category i,* is encoded into the VSTM. The rate parameters are given by:

$$v(x,i) = \eta(x,i)\beta_i \frac{w_x}{\sum_{z \in S} w_z} \tag{1}$$

Where

$$w_x = \sum_{j \in R} \eta(x,j)\pi_j \tag{2}$$

Here $\eta(x,i)$ is defined as the strength of the sensory evidence that object x belongs to the visual category i. The pertinence of the visual category j is denoted by π_j and setting of these values effectively implements the so-called filtering mechanism. The perceptual decision bias of a visual category i is denoted by β_i and setting of these values conversely implements a complementary mechanism called pigeonholing.

The filtering mechanism increases the likelihood that elements belonging to a target category are perceived, without biasing perception in favor of perceiving the elements as belonging to any particular category.

Pigeonholing, conversely changes the probability that a particular category i is selected without affecting the conditional probability that element x is selected given that category i is selected.

A neural interpretation of TVA is given in (Bundesen, Habekost, & Kyllingsbæk, 2005). Basically here pigeonholing (selection of features) is considered an increase in the rate of firing of neurons while filtering (selection of objects is considered an increased mobilization of neurons.

Corresponding to the interpretation in NTVA the fraction $w_x/\sum w_z$ in equation (1), which is the relative attentional weight of object x compared to the weight of all objects z in the visual field S, can be directly interpreted as the relative fraction of neurons allocated to process a given object x, compared to the total number of neurons processing just any object z belonging to the visual field S.

Each and every characterization generally takes the form *object x belongs to category i*.

Denoting the set of all features as R the total processing capacity, can be considered a constant C, which equals the sum of all encoding rates v; see (Bundesen, 1990).

$$C = \sum_{x \in S} \sum_{i \in R} v(x,i) \tag{3}$$

Shibuya and Bundesen (1988) assume that rates of encoding for targets, v_T and for distractors, v_D can be calculated according to the formulas:

$$v_T = \frac{C}{T + \alpha D} \qquad v_D = \frac{\alpha C}{T + \alpha D} = \alpha\, v_T \tag{4}$$

Here α characterizes the ratio of discrimination between distractors and targets.

The effective exposure duration τ is smaller than the actual exposure duration t by an amount t_0 corresponding to the temporal threshold before conscious processing begins. However the effective exposure duration can not be negative so computationally it is set to:

$$\tau = \max(0, t - t_0) \tag{5}$$

In our model we adopt the parameters C, α and t_0 and further, following Bundesen, we make use of equations (4)-(6).

The Neural Network model of VSTM

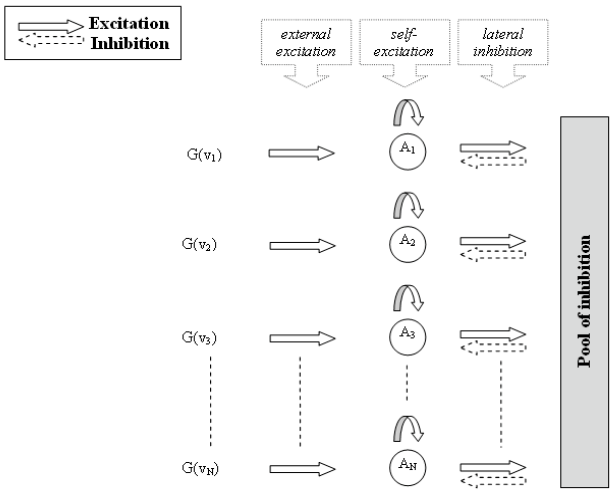

Figure 2: The Neural Network model of VSTM. The total number of neuron assemblies is *N* and each assembly is represented by a level of activation *A*

An object can enter VSTM once it receives external excitation, *G* taking the shape of Poisson distributed spike trains, arriving with the rate parameter *v*. (See Figure 2).

A neural assembly that has obtained a positive level of activation will automatically seek to re-excite itself, so that it can stay in VSTM, at the same time trying to inhibit activation in other neuron assemblies representing other objects, i.e. working to suppress other object from co-temporally being stored in VSTM.

The initial condition for the simulations is that all neuron assemblies start with an activation of zero, i.e. no objects are initially stored in VSTM. As a consequence neither re-excitation nor lateral inhibition exists, before the assemblies are externally activated.

Implementation

The activation A_x of neuron assembly x (representing object x) is given by the first order differential equation:

$$\frac{dA_x}{dt} = -A_x + \alpha^* F(A_x) - \beta^* \sum_{z \neq x} F(A_z) + \gamma^* G(v_x) \quad (6)$$

The above equation characterizes a leaky accumulator model. There is passive decay of the activation towards the rest level, with a time constant chosen as 1, reflecting the time scale that physiologically is observed with synaptic currents (Usher & Cohen, 1998).

F is a squashing function that keeps the activation within bounds:

$$F(A) = 0, \quad for\ A \leq 0$$
$$F(A) = \frac{A}{1+A}, \quad for\ A > 0 \quad (7)$$

As a consequence of the squashing function F, the parameter α^* is the limiting value of maximal self-excitation that assemblies can up-hold and the parameter β^* is the limiting maximal value of inhibition that can be sent from one assembly to another.

Also the model assume we can not have negative self-excitation, i.e. self-inhibition and further the model does not implement any terms that could account for excitation laterally between the assemblies. The latter effect could for instance be included if one wanted to account for semantically related objects and their effect on the number of reported objects.

The attentional significance that object *i* is present in the visual field *R* is represented by the encoding rate v_i. In our model we follow the approach from (Bundesen, 1990) and interpret this rate as the firing rate of a Poisson spike generator *G*. Hence γ^* characterizes the amplitude of the Poisson distributed input spikes arriving to the neuron assembly *x*.

The model was implemented in MATLAB's Simulink toolbox. At least in the operated parameter domain we judge the stiffness of the system to be negligible so for simplicity we numerically apply Euler integration with integration step size $dt = 0.01$.[1]

Model Performance

The Dataset

The data covers the performance of a single subject, participating in an extensive series of whole and partial report experiments. The subject was instructed to report targets, i.e. digits while ignoring distractors, i.e. letters displayed on an imaginary circle around a small fixation cross at the center of the screen. Experimental trials covered twelve different combinations of total number of 2 – 6 targets, *T*, and 0 – 6 distractors, *D*. Further, exposure durations *t* were varied systematically at 10, 20, 30, 40, 50, 70, 100, 150 and 200 ms. Each experimental condition was repeated 60 times but trials were mixed so that the subject had no a-priori knowledge of the experimental condition. Moreover trials were grouped into blocks to minimize the element of fatigue. Each presented character was immediately followed by a mask lasting for 500 ms. Further information can be found in (Shibuya & Bundesen, 1988).

[1] We verified that we used an appropriately small step size in our update formula in order not to consider the influence from having more than one spike per time interval, the probability for more than one spike was calculated to 0.37 %.

Performance of the Neural Network model

Figure 3 shows accumulated score distributions. The score is defined as the number of targets reported correctly. The upper most curve represents the accumulated score of j = 1, i.e. the probability of reporting 1 or more targets correctly. Other curves represent accumulated probabilities for reporting at least 2, 3, 4 or even 5 targets.

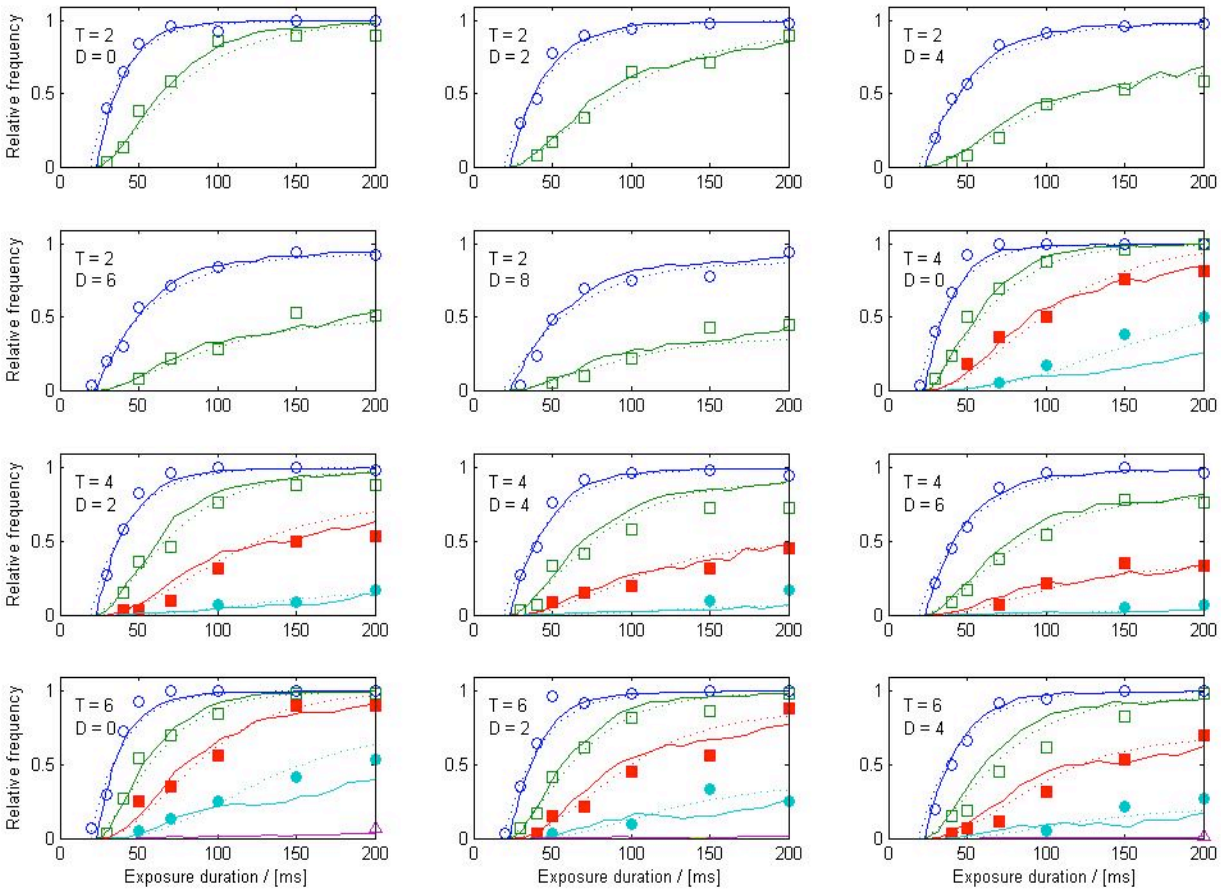

Figure 3: Accumulated score distribution for subject MP in (Shibuya & Bundesen, 1988). Empirically found values are plotted with symbols as markers. The dotted lines represent the fit by Shibuya & Bundesen (1988). Solid lines represent the performance of our neural network model.

Shibuya and Bundesen (1988) proposed a mixture model, mixing probabilities obtained with using a statistical model that assumed memorial capacities of either $K = 3$ or $K = 4$ respectively.

There is a relatively close fit between the proposed mixture model and the empirical data. We see however that data points obtained with exposure duration around 50 ms are generally under fitted and more noticeably the model does not account for cases where more than 4 targets are reported, as is actually the case in two out of three of the lower most plots.

What we observe with the previous model can be considered a trade-off between two conflicting demands. The first demand is to fit the initial part of the curves, i.e. the larger the processing capacity C the steeper the curves will rise, on the other hand the second demand, which is to keep the score distribution reasonably low for long exposure durations, require that the processing capacity C is not set too high. Hence the setting of C is set subject to a compromise.

Addressing the performance of our neural network model we think it clearly meets the standard of Shibuya and Bundesen's model. Moreover, and in contrast to Shibuya and Bundesen's model, our new model readily demonstrates its capability of predicting extreme cases, where more than 4 objects are reported.

Discussion

Our new dynamic model of visual attention and VSTM is able to account for the complete set of data from whole and partial report experiments. Where the previous account by Shibuya and Bundesen (1988) treated extreme scores as

outliers, the new model encompasses these as natural consequences of the internal dynamics. Further, the model explains VSTM capacity and consolidation as the result of a dynamic process rather than as a static store, which capacity is independent of processing capacity and the attentional set of the subject.

In future studies, we wish to explore the model's ability to explain the dynamic consolidation in VSTM found in temporally extended paradigms such as the attentional blink paradigm and studies of attentional dwell time; e.g. (Ward, Duncan, & Shapiro, 1996). Here, consolidation in VSTM is strongly dependent on competition between items already encoded into VSTM and visual items presented at a later point in time. This competitive process follows naturally from the dynamic architecture of the present model.

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