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Capacity of perirhinal cortex network for recognising frequently repeating stimuli

Rafal Bogacz[a,*], Malcolm W. Brown[b]

[a] *Department of Computer Science, University of Bristol, Woodland Road, Bristol BS8 1UB, UK*
[b] *MRC Centre for Synaptic Plasticity, Department of Anatomy, University of Bristol, Bristol BS8 1TD, UK*

Abstract

Much evidence indicates that discrimination of the familiarity of visual stimuli is dependent on the perirhinal cortex of the temporal lobe. A stimulus can become familiar to animals or humans either when a stimulus is seen once but is behaviourally significant, or when a stimulus is not significant but repeats many times. This paper shows that a previously developed network model of familiarity discrimination in the perirhinal cortex is also able to judge familiarity for these different types of stimuli. The network continues to achieve high capacity and discriminative accuracy. © 2002 Published by Elsevier Science B.V.

Keywords: Recognition memory; Novelty detection; Perirhinal cortex; Familiarity discrimination

1. Introduction

Work in amnesic patients and in monkeys has established that discrimination of the relative familiarity or novelty of visual stimuli is dependent on part of the brain's temporal lobe, the perirhinal cortex [1,4,5]. We have previously developed a biologically plausible model of the familiarity discrimination network in the perirhinal cortex [3]. We calculated the capacity of the familiarity discrimination network, which we define as the maximum number of presented stimuli for which a network can discriminate familiarity with an accuracy of 99%. The capacity of the model establishes that the perirhinal cortex alone may discriminate the familiarity of many more stimuli than current neural network models indicate could be recalled (recollected) by all the remaining areas of the cerebral cortex [3].

* Corresponding author.
E-mail address: rbogacz@princeton.edu (R. Bogacz).

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Our own experience suggests that a stimulus can become familiar to us in more than one way, for example: (i) when a stimulus is seen once but is behaviourally significant (e.g. a person with whom we had an important conversation), and (ii) when a stimulus is not significant but repeats many times (e.g. a person who happens to travel everyday on the same bus as ourselves). In other words in case (i), stimuli are presented only once, but since they are important, the goal of the network is to discriminate whether a given stimulus has been encountered previously or not. The previous work [3] established the capacity of familiarity discrimination networks for the case (i).

This paper calculates the capacity for case (ii), when the goal of the network is to recognise frequently repeating stimuli. In case (ii), stimuli are presented a number of times among other stimuli, and the goal of the network is to discriminate frequently repeating stimuli from others. It is assumed that insignificant stimuli produce weaker weight modifications, so that a single presentation is not sufficient for such a stimulus to be classified as familiar when it next occurs, but repeated presentations do cause sufficient cumulated weight modifications for correct classification to be made eventually.

In the previous work we have shown that familiarity discrimination may be performed very efficiently by evaluating Hopfield energy [2]. Using this method, a network of N neurons may discriminate familiarity for case (i) with accuracy 99% for $0.023N^2$ stimuli [2]. We further demonstrated that this algorithm may be implemented by a biologically plausible network that mimics responses of perirhinal neurons [3]. In this paper, for simplicity of analysis and calculation, we consider capacity of the Hopfield network for case (ii), but the presented results may be readily extended to the biologically plausible network [3].

2. Model

Let us consider a Hopfield network [6] with N neurons. Let the activity of neuron i be denoted as x_i. The network is presented with a sequence of binary patterns of N bits. Essentially, each pattern represents the encoding of the presented stimulus into inputs to the network. Bit j of a pattern presented μ time steps ago is denoted by ξ_j^μ and may be equal to -1 or $+1$ (corresponding to inactive and active states of a neuron). In the considered task, P stimuli repeat L times at an interval of K time steps as shown in Fig. 1.

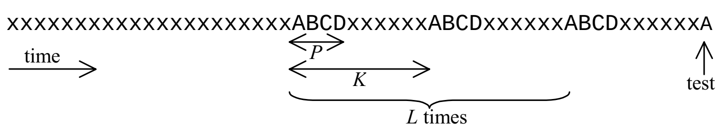

Fig. 1. The task of recognising frequently repeating stimuli. P stimuli denoted by capital letters repeat every K steps for a total of L times (here: $P = 4$, $L = 3$, $K = 10$). x denotes another stimuli (each x is a different stimulus represented by a random pattern).

The task of the network is to discriminate between repeating stimuli (denoted by capital letters in Fig. 1), and novel stimuli (denoted by x in Fig. 1). For simplicity we assume that if a repeating stimulus is presented at test, its previous presentation occurred exactly K time steps ago (as shown for stimulus A in Fig. 1). This task is artificial—stimuli do not repeat so regularly in the real world—but this simplification allows analysis of the capacity of the network.

Initially, all synaptic weights are set to 0. In order to perform the task, for each presented stimulus, the weights are modified according to the Hebb rule:

$$w_{ij} \leftarrow \alpha w_{ij} + \frac{1}{N} x_i x_j, \tag{1}$$

where α is a constant, which prevents the weights from growing without limit; its optimal value depends on K and L (see Appendix A). The Hopfield energy is defined as [6]:

$$E(\bar{x}) = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j w_{ij}. \tag{2}$$

The discrimination whether a given stimulus represented by pattern x has been repeatedly seen or is novel, may be done by setting the activities of the Hopfield network's units to be those given by pattern x and evaluating the energy immediately after this. In this abstract algorithm the neurons do not perform any computation (i.e. there is no relaxation); the familiarity discrimination is done by an external agency which sets up the activations of the neurons and calculates the network's energy for a given pattern.

As shown in Appendix A, the average value of the energy is lower for repeating patterns than for novel patterns. Hence by taking the middle value as the threshold discrimination can be achieved: if the energy is below the threshold, the pattern is classified as repeating, otherwise it is novel.

3. Capacity

Appendix A shows that the network may discriminate whether a pattern is novel or repeating with an accuracy of 99% for the following number of repeating patterns:

$$P_{\max} = 0.023N^2 - \frac{3K}{2L}. \tag{3}$$

The results of the simulations in Fig. 2 match this theoretical prediction of capacity. Simulations ("irregular" series in Fig. 2) were also performed for a more realistic scenario illustrated in Fig. 3. In this case, half of the stimuli repeat L times within the last KL presentations; the other half (bold letters in Fig. 3) are presented once only, but the magnitudes of their weight modifications are L times larger (in Eq. (1) term $(1/N)x_i x_j$ is replaced by $(L/N)x_i x_j$) to correspond to, for example, greater attention being paid during presentation of these stimuli.

Results ("irregular", Fig. 2) show that for this case, the capacity is lower but fitting data of Fig. 2 by multilinear regression indicates that this capacity may be approximated

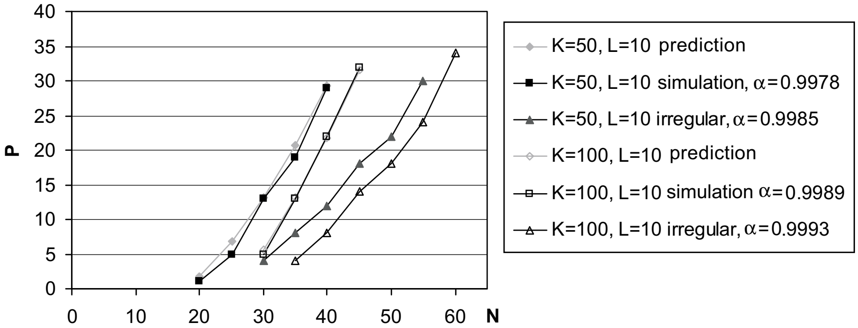

Fig. 2. Comparison of simulated capacity for recognising frequently repeating stimuli with theoretical predictions. For different values of K, L, N and P, accuracy of network classification was tested on 2000 patterns (1000 repeating and 1000 novel patterns). In each case, the simulated capacity is taken as the maximum number of stored patterns P, for which the error rate is $\leqslant 1\%$.

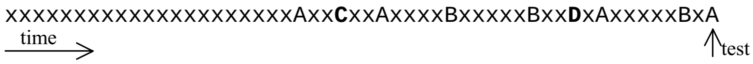

Fig. 3. Example of a more realistic testing scenario. The network should store the occurrences of $P = 4$ stimuli. Half of them (denoted by bold letters: **C**, **D**) occur once only but they produce larger weight modifications. The other half (denoted by letters: A, B) repeat $L = 3$ times and the average number of intervening stimuli between their two successive presentation is equal to $K = 10$.

by 0.013 times the number of synapses in the network minus a constant depending on K and L. For this case the optimal value of α is slightly larger than in the regular case. These results also show that both ways of acquiring familiarity (by a single significant exposure and by multiple presentations) may be efficiently implemented within a single network.

4. Discussion

The calculations of this paper show that for repeating stimuli in a sequence, the number of stimuli which the network can accurately recognise is proportional to the number of synapses in the network decreased by a constant that depends on the pattern of repetition of the stimuli (see Eq. (3)). Therefore, the capacity in this case is not much smaller than in case of recognising single presentations of important stimuli even though the task of recognising frequently repeating stimuli seems more difficult, because the network is exposed to a much larger number of patterns.

Both ways of acquiring familiarity are useful for living organisms, and both may be implemented in a single network in which the magnitude of weight modification is larger for behaviourally more significant stimuli.

Appendix A. Derivation of capacity

Let us calculate the value of minus double the Hopfield energy after presentation of a repeating pattern A (see Fig. 1).

$$-2E(A) = \sum_{\substack{i=1\\j=1}}^{N} A_i A_j w_j = \frac{1}{N} \sum_{\substack{i=1\\j=1}}^{N} A_i A_j \sum_{\mu=1}^{\infty} \alpha^{\mu-1} \xi_i^{\mu} \xi_j^{\mu}. \tag{A.1}$$

Among patterns ξ^{μ}, some are the previous presentations of A, others represent presentations of other repeating patterns (like B in Fig. 1) and, finally, the remainder are non-repeating patterns (like $\times$ in Fig. 1). Hence, split the summation from Eq. (A.1) into three corresponding sums.

$$-2E(A) \approx \frac{1}{N} \left(\sum_{\substack{i=1\\j=1}}^{N} \sum_{\mu=1}^{L} \alpha^{K\mu} A_i^2 A_j^2 + \sum_{\gamma=2}^{P} \sum_{\mu=1}^{L} \alpha^{K\mu} \sum_{\substack{i=1\\j=1}}^{N} A_i \xi_i^{K-\gamma} A_j \xi_j^{K-\gamma} \right.$$

$$\left. + \sum_{\mu=1}^{\infty} \alpha^{\mu-1} \sum_{\substack{i=1\\j=1}}^{N} A_i \xi_i^{\mu} A_j \xi_j^{\mu} \right). \tag{A.2}$$

Since $A_j \in \{-1, 1\}$ then $A_j^2 = 1$. From the equation for the sum of a geometric series:

$$\sum_{\mu=1}^{L} \alpha^{K\mu} = \alpha^K \frac{1-\alpha^{KL}}{1-\alpha^K}. \tag{A.3}$$

Denote the above sum by s. The summation $\sum_{i=1,j=1}^{N} A_i \xi_i^{\mu} A_j \xi_j^{\mu}$ in Eq. (A.2) may be treated as a random variable with a binomial distribution of mean 0 and standard deviation $2N$ [2]. Hence it may be approximated by the normal distribution $\theta(0, 2N)$. Eq. (A.2) becomes

$$-2E(A) \approx \frac{1}{N} \left(N^2 s + \sum_{\gamma=2}^{P} s\theta(0, 2N) + \sum_{\mu=1}^{\infty} \alpha^{\mu-1} \theta(0, 2N) \right)$$

$$\approx Ns + \theta(0, s\sqrt{2P}) + \sqrt{2}\theta \left(0, \sqrt{\sum_{\mu=0}^{\infty} \alpha^{2\mu}} \right)$$

$$= Ns + \theta \left(0, \sqrt{s^2 2P + \frac{2}{1-\alpha^2}} \right). \tag{A.4}$$

After presentation of a novel pattern, the average value of $-2E$ is 0 but the variance remains the same. Therefore, by taking as a threshold the middle value $Ns/2$, the $-2E$ will be usually above the threshold for repeating patterns and below for novel. The probability of correct classification is equal to

$$\Pr\left(\theta\left(0, \sqrt{s^2 2P + \frac{2}{1-\alpha^2}}\right) < \frac{Ns}{2}\right)$$

$$= \Pr\left(\theta(0,1) < \frac{N}{2\sqrt{2}\sqrt{P + \frac{1}{(1-\alpha^2)s^2}}}\right). \tag{A.5}$$

In order to maximise the probability of correct classification, one has to find $\alpha_{\max}$ that maximises $\Omega = (1-\alpha^2)s^2$. Such an $\alpha_{\max}$ was not found analytically, but numerical simulations show that it may be approximated by $\alpha_{\max} \approx (1/3)^{1/KL}$ and for $\alpha_{\max}$, $\Omega \approx 2L/3K$. Hence the maximal number of repeating patterns $P_{\max}$, for which network's accuracy is 99% may be found by solving the following equation:

$$\Pr\left(\theta(0,1) < \frac{N}{2\sqrt{2}\sqrt{P_{\max} + \frac{3K}{2L}}}\right) = 0.99. \tag{A.6}$$

By checking the value of the inverted standard normal cumulative distribution for 0.99 and solving Eq. (A.6), one gets Eq. (3).

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