



Model of co-operation between recency, familiarity and novelty neurons in the perirhinal cortex

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Abstract

Much evidence indicates that discrimination of the familiarity of visual stimuli is dependent on the perirhinal cortex of the temporal lobe. Within the monkey's perirhinal cortex, ~25% of neurons respond strongly to the sight of novel objects but respond only weakly or briefly when these objects are seen again. These neurons can be divided into three populations based on their patterns of responsiveness. Specific temporal dependencies exist among the activities of the three populations of neurons, suggesting the existence of specific connections between them. This report concerns computer modelling that indicates how such connections may be used to increase reliability in the determination of whether or not a stimulus is being seen for the first time. © 2001 Elsevier Science B.V. All rights reserved.

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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 [1,2,5–7]. Thus, damage to the perirhinal cortex results in impairments in recognition memory tasks that rely on discrimination of the relative familiarity of objects. Within the monkey's perirhinal cortex, ~25% of neurons respond strongly to the sight of novel objects but respond only weakly or briefly when these objects are seen again [9] (Fig. 1). These neurons can be divided

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into three types: novelty neurons that respond strongly only to the first presentations of novel stimuli (N1 in Fig. 1); recency neurons that respond strongly to stimuli which were not presented recently (N1 and F1); and familiarity neurons that respond strongly to unfamiliar stimuli (N1 and N2) [9]. Furthermore, simultaneous neuronal recordings reveal that action potentials of novelty neurons are commonly followed at short latency (~ 3 ms) by action potentials of recency and familiarity neurons [8,5]. When action potentials of novelty neurons follow those of familiarity and recency neurons they do so only at relatively long latency (> 10 ms) [5,8] (Fig. 2). This may indicate the existence of direct projections from novelty neurons to familiarity and recency neurons and polysynaptic connections from recency and familiarity neurons to novelty neurons. No short-latency interactions have been found between recency and familiarity neurons. This study investigates the function of interactions between novelty, recency and familiarity neurons, using computer modelling.

This work is an extension of our model of familiarity discrimination in the perirhinal cortex, where only novelty neurons were considered [4,3]. Connections in that model result in novelty neurons being active for novel and inactive for familiar patterns. The decisions made by the network are accompanied by confidence levels—the higher the confidence about the novelty of the stimulus, the higher is the population activity of the novelty neurons.

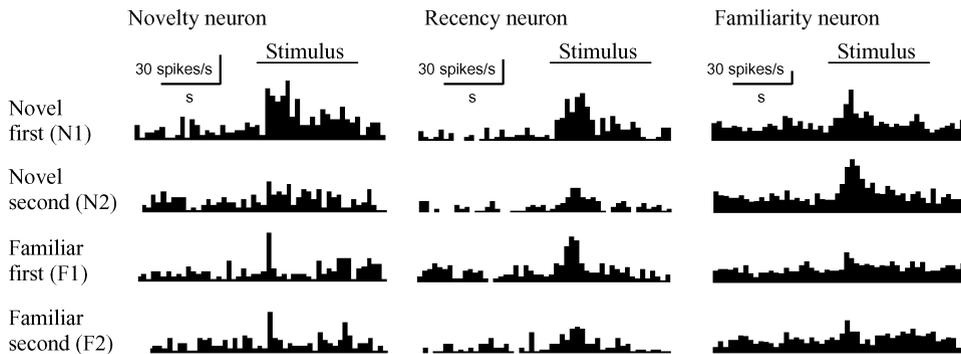


Fig. 1. Responses of novelty, recency and familiarity neurons recorded from monkey perirhinal cortex [9]. Each display shows a cumulated peristimulus-time histogram of the occurrence times of the neuron's action potentials during the presentation of 10 different pictures. The responses were recorded during presentations of four types of stimuli: Novel-first (N1)—stimuli seen by the monkey for the first time; Novel-second (N2)—unfamiliar stimuli presented for the second time during the recording session; Familiar first (F1)—stimuli familiar (well known) to the monkey presented for the first time during the day of recording; Familiar second (F2)—familiar stimuli presented for the second time during the session.



Fig. 2. Temporal dependencies between activity of recency, familiarity and novelty neurons [8,5].

2. The extended model

The existence of novelty, recency and familiarity neurons in the perirhinal cortex allows a network to determine not only if a stimulus is presented for the first time, but also if it was presented recently [5]. According to our model, the neurons of each type create subsystems each of which has the network architecture described in [4] for novelty neurons. The different behaviours of the neurons in the different subsystems may be reproduced by introducing specialised synaptic properties for recency neurons (synapses that have a short-term memory and are reset after a short period of time) and familiarity neurons (synapses that have a delayed or slowly developing plasticity), based on the experimentally observed responses of these neurons [9].

Recency and familiarity neurons can discriminate among all four stimulus classes of Fig. 1, without the need for novelty neurons. However, it is particularly important to identify the first presentation of a novel stimulus (N1)—it might signal danger—and hence to minimise errors in this decision. The model establishes that having novelty neurons can further decrease the probability of such errors. Thus it could be advantageous for there to be two systems, the recency-familiarity system and the novelty system, each capable of identifying case N1. To avoid making inconsistent decisions and to decrease the probability of error, these two systems must co-operate in making the final decision as to whether a stimulus is of type N1.

If the two systems give inconsistent answers, the final decision is taken as that of the more confident system. The decision may be reached as follows. The confidence of the novelty system that a stimulus is of type N1 is represented by the population activity of the novelty neurons; the confidence of the recency-familiarity system is given by the smaller of the population activities for the recency neurons and the familiarity neurons. If the novelty system is highly confident, it uses direct connections from novelty neurons to recency and familiarity neurons to increase the population activity of recency and familiarity neurons and so change their activity to that appropriate for a stimulus of type N1. Otherwise, it is necessary to have *comparator* neurons which calculate the confidence level of the joint recency–familiarity system, i.e., determine the smaller of the population activities for recency neurons and familiarity neurons. These additional neurons project to the novelty neurons and allow the recency–familiarity system to change the overall activity in the novelty system. The interactions between the subsystems may be implemented by the connections shown in Fig. 3, which are consistent with those suggested by experimentally observed interactions (Fig. 2).

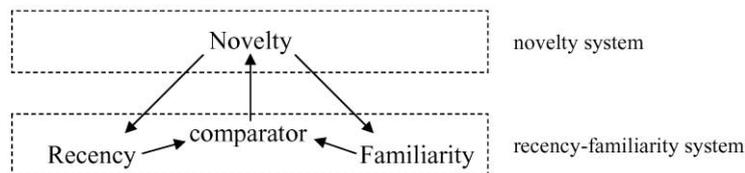


Fig. 3. Connections between recency, familiarity and novelty neurons in the model.

3. Simulations

Simulations were performed at two levels of abstraction. First, to calculate precisely network error, the three sub-systems were simulated separately (following [4]), and the final decision of the combined system was made by evaluating a function D , reflecting interactions between the subsystems (weighted sum of the confidences of both systems),

$$D = C^N + \min\left(\frac{C^F}{N^F}, \frac{C^R}{N^R}\right) RF_{\text{weight}}(N^F + N^R),$$

where C^N , C^F , C^R are the decision confidences of novelty, familiarity and recency subsystems (taken from the population activities of the neurons in the subsystems); N^F , N^R are the numbers of familiarity and recency neurons, and RF_{weight} is an empirically established constant equal to 0.8. D has higher values for patterns of type N1 and lower for others. Hence, by taking as a threshold a middle value, D may be used to decide whether a stimulus is of type N1. Results of sample simulations using D (Table 1) show that for a given number of neurons: (i) the network consisting of only novelty neurons (Table 1, (a)) the error rate is low—but this network cannot distinguish highly familiar from recently presented stimuli, and (ii) the combined network (c) which can discriminate amongst all four types of stimuli has a lower error rate than the recency–familiarity network (b).

Second, that co-operation between the subsystems works to this effect has been established in simulations using a more realistic spiking-neuron version of the model.

4. Conclusion

The model shows that specific connections between recency, familiarity and novelty neurons, as suggested by experimental observations in the perirhinal cortex, may be

Table 1

Error (%) in discriminating whether stimuli are of type N1. Three networks were tested each consisting of 60 neurons with 100 synapses per neuron: (a) 60 novelty neurons (this network cannot distinguish between 3 of the 4 stimulus categories of Fig. 1); (b) 30 recency and 30 familiarity neurons; (c) 20 of each type of neuron. The tabulated errors are averaged over 10 tests. Before each test, synaptic weights were reset and 300 patterns were written to the network (i.e., weights were modified as described in [4]). The written patterns consisted of: 100 patterns of type N2—written to novelty and recency subsystems, 100 patterns of type F1—written to novelty and familiarity subsystems, and 100 patterns of type F2—written to all subsystems. During each test the network error in discriminating whether stimuli are of type N1 was calculated after presentation of all the previously written patterns (which the network was supposed to classify as not N1) and an additional 300 random patterns different from the written ones (which should be classified as N1)

		Error (%)
(a) Novelty neurons only	$N^N = 60, N^R = N^F = 0$	1.6
(b) Recency–familiarity neurons only	$N^N = 0, N^R = N^F = 30$	3.5
(c) All types of neurons	$N^N = N^R = N^F = 20$	2.4

efficiently used to increase the reliability of discriminating whether stimuli are being seen for the first time.

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Christophe Giraud-Carrier received the B.S., M.S., and Ph.D. in computer science at Brigham Young University in 1991, 1993, and 1994, respectively. He is currently a Senior Lecturer in computer science at the University of Bristol, UK. His main research interests are in machine learning and focus on induction in highly-structured domains, constructive incremental learning methods, meta-learning, and hybrid systems. Dr. Giraud-Carrier is founder and co-ordinator of the Machine Learning Research Group at Bristol. His work is funded by the British Research Councils, the European Union and industry.