The hippocampus and the classically conditioned nictitating membrane response: A real-time attentional-associative model

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The present study introduces an attentional-associative model that incorporates (1) a mechanism capable of establishing associations between conditioned stimuli (CSs) and unconditioned stimuli (USs) and between two CSs; (2) a mechanism that, by combining CS-CS and CS-US associations, is capable of building a "computational cognitive map"; (3) a real-time version of Pearce and Hall's (1980) attentional rule; (4) performance rules that convert learning variables into a topography of the rabbit's nictitating membrane (NM) response; and (5) rules that convert learning variables into neuronal firing. The present study tested the "aggregate prediction" hypothesis as applied to hippocampal function. This hypothesis assumes that (1) the effect of hippocampal lesions (HL) is an impairment in the integration of the aggregate prediction used to compute attentional variables; (2) the effect of the induction of hippocampal long-term potentiation (LTP) is an increase in the value of the aggregate prediction by way of increasing the value of CS-CS associations; and (3) neural activity in the hippocampus is proportional to the instantaneous value of the aggregate prediction. In addition, the present study tested the hypothesis that medial septum activity is proportional to the value of attentional variables. Computer simulations for the HL case were carried out for acquisition under different interstimulus intervals, discrimination reversal, and sensory preconditioning. Computer simulations for the LTP case were carried out for discrimination acquisition. In addition, simulations of hippocampal unit activity during acquisition and extinction, and medial septum unit activity during the acquisition of conditioning, are presented. The aggregate prediction hypothesis proved capable of simulating most, but not all, experimental data regarding hippocampal manipulations in the rabbit's NM response preparation.

Attentional theories of hippocampal function emphasize that the hippocampus participates in the control of the level of processing assigned to each stimulus, thereby controlling what information is to be stored in the brain.

Schmajuk and Moore (1985) proposed a real-time attentional model of hippocampal function based on Pearce and Hall's (P-H) (1980) model of Pavlovian conditioning. This model was designated the S-P-H model. In the framework of the S-P-H model, Schmajuk and Moore suggested that the effects of hippocampal lesions (HL) could be described as an impairment in the integration of the aggregate prediction used to compute attentional variables. This assumption is called the *aggregate prediction* hypothesis. Computer simulations (Schmajuk & Moore, 1985) showed that under the aggregated prediction hypothesis, the S-P-H model is capable of describing

the behavior of HL animals in many classical conditioning paradigms.

In its present form, however, the S-P-H model neither encompasses some paradigms in which the effect of HL has been assessed (e.g., sensory preconditioning) nor provides real-time descriptions of overt behavior in a preparation in which many HL effects have been evaluated—namely, the rabbit's nictitating membrane (NM) response preparation.

On the basis of the preceding considerations, this paper introduces a rendering of the S-P-H model that is capable of sensory preconditioning and that incorporates performance rules that describe the rabbit NM response topography. Using this new version of the S-P-H model, the present study tested the aggregate prediction hypothesis as it relates to hippocampal lesions, hippocampal long-term potentiation (LTP) induction, and hippocampal neuronal activity. In addition, the study explored the correlation between medial septum neuronal activity and attentional variables in the S-P-H model.

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THE S-P-H MODEL

This section describes a version of the S-P-H model that incorporates second-order associations and performance rules that yield real-time descriptions of NM response topography.

The S-P-H model comprises two different types of memory: a trace short-term memory and an associational long-term memory. First-order excitatory and inhibitory associative memories establish predictive relationships between two events (or stimuli): i and k . First-order excitatory and inhibitory associative memories are combined in first-order net associative memories, which express the expectancy that event k is going to follow event i . Second-order associative values result from the combination of different first-order net predictions: if event i predicts event r , and event r predicts event k , then event i predicts event k . Second-order associative values allow the S-P-H model to build up cognitive maps.

In agreement with Pearce and Hall's (1980) view, the S-P-H model assumes that the associability of event i with event k is given by the absolute difference between the aggregate prediction of the intensity of event k and the actual intensity of event k . When this rule is applied, the stimulus that is the best available predictor of event k will enter into an associative relationship with event k , to the detriment of all other stimuli.

Since stimuli i and k can be separated by a finite interval of time, the S-P-H model incorporates the idea that stimuli give rise to short-term-memory traces in the central nervous system that become associated with other stimuli by simultaneously reaching a critical locus of learning.

This section also presents the performance rules that translate learning variables into rabbit NM responses and neural activity. It should be noted that rules that describe changes in trace and associative memories are essential to the model, whereas performance rules are specific for the type of preparation used and may change accordingly.

First-Order Excitatory Associative Values

A first-order excitatory associative value, V_i^k , can be interpreted as the prediction that event k will follow CS_i . Whenever the intensity of event k , λ^k , is greater than that of B^k as defined by Equation 5, the excitatory associative value, V_i^k , between CS_i and event k increases by

$$\Delta V_i^k = \theta S_i \alpha_i^k \lambda^k \tau_i, \quad (1)$$

where θ is the rate of change of V_i^k , S_i is the salience of CS_i , α_i^k represents the associability of CS_i with event k , λ^k represents the intensity of event k , and τ_i represents the trace of CS_i . According to Equation 1, V_i^k increases whenever event k is presented simultaneously with the trace of CS_i , and the associability of CS_i with event k is larger than zero. As in the P-H model, V_i^k never decreases.

Note that in the P-H model, V_i refers to the association of different CS_i with the US, whereas in the S-P-H

model, V_i^k refers to the association of different CS_i s with different events k .

First-Order Inhibitory Associative Values

First-order inhibitory associative values, N_i^k , can be interpreted as being the prediction that event k will *not* follow CS_i . This view agrees with Konorski's (1966) suggestion that a CS could be associated with representations both of a US and of no US. Whenever $\lambda^k < B^k$, the inhibitory associative value between CS_i and event k , N_i^k , increases by

$$\Delta N_i^k = \theta' S_i \alpha_i^k \bar{\lambda}^k \tau_i, \quad (2)$$

where θ' is the rate of change of N_i^k and $\bar{\lambda}^k$ is the intensity of the inhibitory reinforcer. The intensity of $\bar{\lambda}^k$ is $\bar{\lambda}^k = B^k - \lambda^k$. According to Equation 2, N_i^k increases whenever $\bar{\lambda}^k$ larger than zero is presented simultaneously with the trace of CS_i and the associability of CS_i with event k is larger than zero. As in the P-H model, N_i^k never decreases.

First-Order Net Associative Value

The net associative value of CS_i and event k is given by the difference between associative and antiassociative values, and it can be interpreted as the net prediction of event k by CS_i :

$$\dot{V}_i^k = V_i^k - N_i^k. \quad (3)$$

When $i = k$, $\dot{V}_i^k$ defines the net prediction of event i by itself. $\dot{V}_i^k$ can both increase and decrease.

Second-Order Net Associative Value

As presented above, the first-order net prediction of the US by CS_i is represented by the net associative value, $\dot{V}_i^{US}$, and is given by Equation 3. First-order net predictions, however, are unable to describe classical conditioning phenomena such as sensory preconditioning or higher order conditioning.

Consider now the case in which two CSs presented in compound— CS_i and CS_r —predict the US. $\dot{V}_i^{US}$ is the first-order net prediction of the US by CS_i , and $\dot{V}_r^{US}$ is the first-order net prediction of the US by CS_r . It is assumed that CS_i predicts the US directly by $\dot{V}_i^{US}$ and indirectly by predicting CS_r , by $\dot{V}_i^r$. In turn, CS_r predicts the US by $\dot{V}_r^{US}$. The second-order net prediction of the US by CS_i is expressed as the product $\dot{V}_i^r \dot{V}_r^{US}$. The second-order net prediction of event k by CS_i is one when $\dot{V}_i^r$ and $\dot{V}_r^k$ are both one, and zero when either $\dot{V}_i^r$ or $\dot{V}_r^k$ is zero.

B_i^k , the sum of first- and second-order net predictions of event k by CS_i , is

$$B_i^k = (\dot{V}_i^k + \sum_r w_i^r \dot{V}_i^r \dot{V}_r^k) \tau_i. \quad (4)$$

$\dot{V}_i^k$ is the net associative value of CS_i with event k . The sum over index r involves all the CSs with index $r \neq k$. $\dot{V}_i^r$ is the net associative value of CS_i with all CSs with index $r \neq k$. $\dot{V}_r^k$ is the net associative value of all CSs

with event k . τ_i is the trace of CS_i . The mathematical expression for τ_i is given below.

To avoid redundant $CS_i - CS_k$ and $CS_i - CS_i - CS_k$ associations, $w_i^r = 0$ when $i = r$, and $w_i^r > 0$ when $i \neq r$. Coefficient w_i^r also serves to adjust the relative weights of first- and second-order predictions in paradigms such as conditioned inhibition, in which first-order predictions are inhibitory, whereas second-order predictions are excitatory (Rescorla, 1982).

B^k , the aggregate prediction of event k made upon all CSs (including the context) with $\tau_i > 0$ at a given moment, is given by

$$B^k = \sum_i B_i^k. \quad (5)$$

The sum over index i involves all the CSs acting at a given moment.

The integration of different predictions into a larger and new prediction is similar to the process Tolman (1932) called inference. According to Tolman, expectancies can be combined to form new expectancies and then organized in a "cognitive map." Up to the present, models for classical conditioning did not have a mechanism to account for "inference" processes. The introduction of second-order associations allows for the building of "computational cognitive maps" (Moore, 1979) in which CS-CS predictions can be combined with CS-US predictions.

Figure 1 shows a network that, by computing second-order net associative values, is capable of describing sensory preconditioning and secondary reinforcement. Stimuli have dual roles as predictors and events. CS_A , CS_B , and the context (denoted as CX) are predictors of events CS_A , CS_B , CX, and the US. Each node represents the net prediction of an event by a CS. For example, node $\dot{V}_A^{US}$ represents the prediction of the US by CS_A , and node $\dot{V}_B^A$ represents the prediction of CS_A by CS_B . Kohonen (1977) called this type of network a *heteroassociative network*.

Sensory preconditioning is predicted by allowing CS_B to be associated with CS_A in a first phase (denoted by the

Figure 1. Diagram of a network that computes second-order net associative values. A, B, X, and R are "neural-like" elements. CS_B can generate a CR indirectly by activating element A. In turn, element A activates element R. Nodes represent CS-CS and CS-US first-order net associative values. Open nodes: zero values. Solid nodes: positive values.

solid circle, $\dot{V}_B^A$, in Figure 1), and by allowing CS_A to be associated with the US in a second phase (denoted by the solid circle, $\dot{V}_A^{US}$, in Figure 1). When CS_B is presented alone in a test trial, it activates element A through node $\dot{V}_B^A$, and element A activates node $\dot{V}_A^{US}$, generating a conditioned response (CR). Rescorla (1980) found that simultaneous presentations of $CS(A)$ and $CS(B)$ produced higher levels of sensory preconditioning than successive presentations. In agreement with this result, the S-P-H model predicts optimal CS-CS conditioning for simultaneous presentations of two 300-msec CSs.

Secondary reinforcement is predicted by allowing CS_A to be associated with the US in a first phase, and a CS_B to be associated with CS_A in a second phase. Because CS_B is never associated with the US, the model predicts that extinction of the CS_A -US association entails extinction of responding to CS_B . In agreement with this prediction, Rashotte, Griffin, and Sisk (1977) and Rescorla (1978) found that extinction of the CS_A -US association led to a substantial reduction in responding to CS_B . Opposite results, however, were obtained by Rizley and Rescorla (1972) and Holland and Rescorla (1975).

Associability

Pearce, Kaye, and Hall (1984) suggested that CS associability is given by $\alpha_i(n) = \gamma |\lambda(n-1) - \sum_j V_j(n-1)| + (1-\gamma)\alpha_i(n-1)$, where $\alpha_i(n)$ is the CS_i associability on trial n , $\lambda(n-1)$ is the US intensity on trial $n-1$, $\sum_j V_j(n-1)$ is the aggregate prediction of all stimuli present on trial $n-1$, $\alpha_i(n-1)$ is the CS associability on trial $n-1$, and γ is used to compute $\alpha_i(n)$ as a weighted average. The computation of $\alpha_i(n)$ as a weighted average implies a memory for the values of $\alpha_i(n-1)$.

By computing $\alpha_i(n)$ as a weighted average, the P-H model correctly predicts that the intensity of latent inhibition is determined by the number of nonreinforced presentations of the CS, but the model presents problems for describing partial reinforcement (Pearce et al., 1984). To avoid these problems, the present version of the S-P-H model assumes that associability is proportional to the absolute difference between the instantaneous value of the aggregate prediction of the intensity of a given event and the instantaneous value of its actual intensity. Since, in our model, the aggregate prediction of event k is given by B^k , the associability of CS_i with event k at time step t is given by

$$\alpha_i^k(t) = |\lambda^k(t) - B^k(t-1)|. \quad (6)$$

According to Equation 6, the associability of CS_i with event k is proportional to the absolute value of the mismatch between the aggregate prediction of event k and its actual intensity. According to Equations 1 and 2, when α_i^k is zero, neither V_i^k nor N_i^k increase; that is, when ongoing events are perfectly predicted, there are no further changes in stored predictions. Therefore, according to the S-P-H model, the total amount of information to be stored in the brain is proportional to the total degree of uncertainty about ongoing events, as given by $\sum_k \sum_i \alpha_i^k$.

It has been suggested that α_i could be used as a measure of the strength of the orienting response (OR) (Kaye & Pearce, 1984) and of the "controlled" attention toward CS_i (Pearce & Hall, 1980) (but see Hall & Schachtman, 1987). The intensity of "automatic" attention to CS_i is proportional to B_i^{US} . In both cases, the intensity of the responses to CS_i is proportional to B_i^{US} .

Whereas α_i in the P-H model is computed on a trial-to-trial basis and always refers to the associability of CS_i with the US, α_i^k in the S-P-H model is computed in real time and refers to the associability of CS_i with any event k . These changes do not affect the explanations provided by the S-P-H model for most classical conditioning paradigms.

Saliency

In both the P-H and the previous version of the S-P-H model, saliency S_i is a constant. However, in the present rendering of the S-P-H model, S_i is defined by

$$S_i = \delta_i + \alpha_i^i, \quad (7)$$

where δ_i is a constant and α_i^i is the associability of CS_i .

Replacing α_i^i by its value in Equation 6 results in

$$S_i = \delta_i + |\lambda^i - B^i|. \quad (8)$$

Equation 7 implies that when α_i^i equals zero, saliency S_i equals δ_i . According to Equation 8, S_i equals zero when the intensity of CS_i is perfectly predicted by all acting CSs, including itself, at a given time step. Conceptually, this means that saliency S_i decreases as CS_i becomes increasingly associated with the context and with itself (i.e., is more "familiar" to the animal). When CS_i is presented in a novel environment, S_i increases again. According to Equations 1 and 2, larger increments in V_i^* and N_i^* are obtained with novel rather than with familiar CSs.

Equation 7 is used to yield latent inhibition—that is, the effect of CS preexposure in the absence of the US on the subsequent acquisition of the CS-US association. Wagner (1979) proposed a similar mechanism for latent inhibition in the context of the Rescorla-Wagner (1972) model. In both the P-H model and the previous version of the S-P-H model, a mechanism for latent inhibition was provided by computing α_i as a weighted average.

Trace Function

Conditioning of the NM is typically more efficacious when the CS precedes the US than when the two are presented together. Theorists have proposed that stimuli give rise to traces in the central nervous system that somehow impinge simultaneously on critical loci of learning, despite the nonsimultaneous arrangement, as observed at the periphery (Gormezano, Kehoe, & Marshall, 1983).

The S-P-H model assumes that after a 50-msec delay, CS_i generates a trace, τ_i . After the delay, this trace increases over time to a maximum, stays at this level for a period of time, and then gradually decays back to zero.

Formally, and specifically for the rabbit NM preparation, increments in the trace for $50 < t \leq 200$ msec are defined by

$$\Delta \tau_i(t) = k1[CS_i \max - \tau_i(t)], \quad (9)$$

where $CS_i \max$ is the maximum intensity of the trace recruited by CS_i , and $k1$ is a constant, $0 < k1 \leq 1$. Parameter $k1$ is selected so that when applying Equations 1, 2, 9, and 10, the interstimulus interval (ISI) for NM optimal conditioning is 200 msec. For any CS duration, the amplitude of the trace rises during the first 200 msec after CS_i onset. Independently of the CS duration, $\tau_i(t)$ remains equal to $CS_i \max$ for 200 msec.

If CS_i is present at 200 msec after its onset, $\tau_i(t)$ does not decay until CS_i offset. If CS_i is not present at 200 msec after its onset, decrements in $\tau_i(t)$ are given by

$$\Delta \tau_i(t) = k1[-\tau_i(t)]. \quad (10)$$

Performance Rules

Performance rules were selected to translate variables in the model into the topography of the NM response and simulated unit activity.

Response topography. Acquisition of the NM conditioned response proceeds with an orderly sequence of changes: the percentage of NM responses generated in each session increases, the CR latency decreases, and the CR amplitude increases. The CR latency moves progressively forward in the CS-US interval with training (Smith, 1968). At the beginning of training, the first CRs are initiated just before the unconditioned response (UR), but CR onset moves to progressively earlier portions of the CS-US interval, with an asymptotic latency occurring at about the midpoint of the CS-US ISI. As CR onset latency decreases, the maximal response amplitude (CR peak) tends to be located around the time of the US occurrence. In summary, the NM response topography is characterized by (1) the latency to CR onset, (2) the shape during the CS period, (3) the shape during the US period, and (4) the decay to baseline.

Latency to CR onset. If t_i denotes the time step at which CS_i onset occurs, then the time of CR onset, denoted t_{CR} , is the earliest time t such that

$$\sum_{t=t_i} \sum_j B_j^{US}(t) \geq L1. \quad (11)$$

The sum over index j involves B_j^{US} of all CSs with $\tau_j > 0$, excluding the context. The sum over index t involves all time steps on which $\tau_j > 0$, starting at the time step when the amplitude of the NM response, as defined by Equations 12 and 13, equals zero (see below). $L1$ is a threshold greater than zero. Equation 11 implies that as B_j^{US} increases over trials, $L1$ is reached at earlier times, t_{CR} , and therefore CR onset latency moves progressively toward an asymptote determined by $L1$. In general, CR onset latency decreases as B_j^{US} increases. For $t < t_{CR}$, NM response amplitude is zero.

CS period. For time steps $t > t_{CR}$ (i.e., after the time of CR onset), the amplitude of the NM response, $NMR(t)$, is changed by

$$\Delta NMR(t) = k2[\sum_j B_j^{US}(t) - NMR(t)]. \quad (12)$$

The sum over the index j involves B_j^{US} of all CSs with $\tau_j > 0$, including the context. $k2$ is a constant ($0 < k2 \leq 1$) that reflects the mechanical properties of the NM system. Equation 12 implies that as B_j^{US} s increase over trials, the amplitude of the NM response also increases.

US period. During the US period, when $\sum_j B_j^{US}(t) > \lambda^{US}(t)$, $NMR(t)$ still increases according to Equation 12. However, when $\sum_j B_j^{US}(t) < \lambda^{US}(t)$, $NMR(t)$ increases by

$$\Delta NMR(t) = k2[\lambda^{US}(t) - NMR(t)]. \quad (13)$$

Equation 13 implies that when the intensity of the US is greater than $\sum_j B_j^{US}(t)$, the US intensity determines the amplitude of the NM response.

Decay to baseline. When $\sum_j B_j^{US}(t)$ and $\lambda^{US}(t)$ equal zero, $NMR(t)$ decays to baseline by

$$\Delta NMR(t) = k2[-NMR(t)]. \quad (14)$$

With the addition of the described performance rules, the S-P-H model provides real-time descriptions of NM topography, defining CR onset latency, CR amplitude during CS and US periods, CR peak amplitude, and latency to CR peak amplitude. With these performance rules, the S-P-H model also describes between-trial changes in NM CR amplitude as a realistic S-shaped acquisition function. An alternative approach to real-time descriptions of NM topography during classical conditioning was proposed by Moore et al. (1986).

Performance rules are accurate when they are used to define the time of the CR peak for ISIs longer than 200 msec. For ISIs longer than 200 msec, Equation 11 generates NM CRs with peaks that appear at approximately the time when the US was presented. Because the trace decreases after 200 msec and the CS is terminated, the model predicts that B_j^{US} will decrease when ISI is increased. Because longer ISIs imply smaller B_j^{US} s, longer ISIs also imply a longer latency before $\sum_j B_j^{US}(t)$, according to Equation 11, exceeds the threshold $L1$. Therefore, the CR latency is longer and the CR peak appears at approximately the time of US presentation.

Performance rules are inaccurate when they are used to define the time of the CR peak for ISIs shorter than 200 msec. For these ISI values, Equation 11 generates NM CR peaks after the US presentation. This is so because the trace increases from 0 to 200 msec, and therefore B_j^{US} is directly proportional to ISI in the 0–200 msec temporal range. Because shorter ISIs imply smaller B_j^{US} s, they imply a longer latency, according to Equation 11, for $\sum_j B_j^{US}(t)$ to exceed threshold $L1$; therefore, CR begins later in the ISI and the CR peak appears later than

the time of the US presentation. Because most simulations use ISIs equal to or greater than 200 msec, time inaccuracies are not present in most of the results presented in this paper.

Neuronal activity. Neural activity was simulated under the assumption that neurons code the instantaneous magnitude of different model variables. For example, the instantaneous value of $B^{US}(t)$ was translated into neuronal firing by application of the following rules. If at time t , $\sum_i B_i^{US}(t) < L2$, no spike is generated. If at time t , $\sum_i B_i^{US}(t) \geq L2$, a spike is generated and the sum is reset to zero.

Table 1 summarizes the intervening variables and parameters used in the S-P-H model. The S-P-H model has nine learning variables and eight parameters.

HYPOTHESES

In this section, we introduce the aggregate prediction hypothesis as applied to HL, LTP induction, and hippocampal neuronal activity, as well as the “associability” hypothesis as applied to medial septum neuronal activity. These hypotheses are independent of the description of the S-H-P model as a model for classical conditioning.

The Aggregate Prediction Hypothesis Applied to HL, LTP Induction, and Hippocampal Neuronal Activity

Schmajuk (1984; Schmajuk & Moore, 1985, p. 281) suggested that the effect of HL can be described as an impairment in the computation of CS-US associability values. This impairment results from the lack of integration of new and old predictions about an event arising from all CSs present at a given time. In mathematical terms, instead of computing CS_{*i*} associability by $\alpha_i(t) = \gamma|\lambda^{US}(t) - \sum_j \dot{V}_j^{US}(t-1)| + (1-\gamma)\alpha_i(t-1)$, $\alpha_i(t)$ for the HL case was given by $\alpha_i(t) = |\lambda^{US}(t) - \dot{V}_i^{US}(t-1)|$. Because individual predictions replace the aggregate prediction in the computation of $\alpha_i(t)$ for the HL case, this assumption is called the *aggregate prediction* hypothesis.

As in Schmajuk (1984) and Schmajuk and Moore (1985), this paper also tests the aggregate prediction hypothesis for HL. In the present version of the S-P-H model, B^{US} , the aggregate prediction of the US, can be derived from Equations 4 and 5:

$$B^{US} = \sum_i (\dot{V}_i^{US} + \sum_r w_r \dot{V}_i \dot{V}_r^{US}) \tau_i. \quad (15)$$

Since the integration of predictions, according to Equation 15, is achieved through the sum of the individual net predictions ($\sum_i$) and through second-order associations ($\dot{V}_i \dot{V}_r^{US}$), the lack of integration of predictions implies that both computations are absent in the HL case.

When $\sum_i$ is not computed and $\dot{V}_i$ becomes zero in Equation 15, associability for the HL case becomes

$$\alpha_i^{US}(t) = |\lambda^{US}(t) - \dot{V}_i^{US}(t-1) \tau_i(t-1)|. \quad (16)$$

Table 1
S-P-H Model: Intervening Variables and Parameters

Symbol	Variable	Psychological Interpretation
V_i^k	First-order excitatory association of CS_i with event k	The long-term memory of the direct prediction that event k will follow CS_i .
N_i^k	First-order inhibitory association of CS_i with event k	The long-term memory of the direct prediction that event k will not follow CS_i .
$\dot{V}_i^k$	Net first-order association of CS_i with event k	The net direct prediction that event k will or will not follow CS_i .
B_i^k	First-order plus second-order net association of CS_i with event k	The sum of direct and indirect net predictions that event k will or will not follow CS_i .
B^k	Aggregate net association of all CS s present with event k	The prediction of event k based on all CS s present at a given moment.
α_i^k	Associability of CS_i with event k	The mismatch between the actual intensity of event k and its predicted intensity based on all CS s present at a given moment.
S_i	Salience of CS_i	The mismatch between the actual intensity of CS_i and its predicted intensity based on all CS s present at a given moment, plus a constant.
λ^k	Intensity of event k	The perceived intensity of event k .
τ_i	Trace of CS_i	The short-term memory of CS_i .
NMR	Amplitude of the NMR	The prediction of the intensity of the US based on all CS s present at a given moment.

Symbol	Parameter	Value
θ	Rate of change of V_i^k	0.03
θ'	Rate of change of N_i^k	0.015
w_i^k	Weight of second-order associations	2.0
δ_i	Constant part of S_i	0.5
$k1$	Trace constant	0.1
$k2$	NMR mechanical constant	0.5
$L1$	Threshold for CR onset	0.5
$L2$	Threshold for neural activity	0.5

Equation 16 is equivalent to that used by Schmajuk and Moore (1985) for the HL case. In the S-P-H model, blocking and overshadowing are achieved when the associability of the to-be-blocked CS is reduced due to the association of the blocker with the US. Since, according to Equation 16, the associability of the to-be-blocked CS is independent of the association accrued by the blocker CS, the use of Equation 16 implies impairments in blocking and overshadowing. In the S-P-H model, inhibitory association is achieved when the associability of $CS-$ is increased due to the excitatory association of the $CS+$. Since, according to Equation 16, the associability of $CS-$

is independent of the association accrued by $CS+$, the associability of $CS-$ remains zero, and $CS-$ cannot gain inhibitory association. Consequently, Equation 16 implies impairments in inhibitory conditioning paradigms, such as conditioned inhibition and differential conditioning.

Because Equation 16 allows the context to accrue more association with the US than when Equation 6 is applied, responding in HL animals depends relatively more on the association gained by the context and relatively less on the association gained by the CS. Consequently, changes in the characteristics of the nominal CS do not affect responding in HL animals as much as they do in normal

animals. Therefore, the generalization gradient is sharper in normal animals than in HL animals.

As mentioned above, Kaye and Pearce (1984) suggested that the strength of the OR was proportional to α_i . Under this assumption, since α_i^{US} for the HL case (Equation 16) is greater than α_i^{US} for the normal case (Equation 6), the use of Equation 16 also implies that HL animals display stronger ORs than do normal animals.

When Σ_i is not computed and $\dot{V}_i$ becomes zero in Equation 15, the intensity of the inhibitory reinforcer, $\bar{\lambda}^{US}$, becomes

$$\bar{\lambda}^{US} = \dot{V}_i^{US} \tau_i - \lambda^{US}. \quad (17)$$

Equation 17 is equivalent to that used by Schmajuk and Moore (1985) for the HL case.

When Σ_i is not computed and $\dot{V}_i$ becomes zero in Equation 15, salience S_i is given by

$$S_i = \delta_i + \lambda^i. \quad (18)$$

Equation 18 means that salience does not decrease over trials, or, equivalently, that the CS does not become increasingly "familiar" over time. The use of Equation 18 implies impairments in latent inhibition.

Because all $\dot{V}_i$ s equal zero, B_i^{US} , which was defined in Equation 4, is given by

$$B_i^{US} = \dot{V}_i^{US} \tau_i. \quad (19)$$

In general, the use of Equation 19 implies impairments in cognitive mapping. Specifically, in the case of classical conditioning, the use of Equation 19 implies impairments in sensory preconditioning, secondary reinforcement, compound conditioning, and serial compound conditioning.

Performance rules translate B_i^{US} values into NM responses, thereby accounting for changes in NM response topography after HL. Since, according to Equation 16, overshadowing is absent after HL, B_i^{US} is generally greater in the HL than in the normal case. Because a larger B_i^{US} implies a shorter CR onset latency according to Equation 11, the use of Equation 19 implies shorter onset latencies after HL.

Whereas the aggregate prediction hypothesis considers the effect of HL to be an impairment in the integration of multiple predictions, the present paper assumes that this integration increases when LTP is induced. Since this integration is achieved through the sum of the individual net predictions (Σ_i) and through second-order associations ($\dot{V}_i \dot{V}_r^{US}$) in Equation 15, the aggregate prediction hypothesis proposes that all $\dot{V}_i$ s increase whenever LTP is induced.

Since the aggregate prediction hypothesis accounts for HL and LTP effects by affecting the computation of B_i^{US} , for consistency we assume that some hippocampal neurons code this aggregate prediction, that is, that the activity of some hippocampal neurons is proportional to the instantaneous value of B_i^{US} .

The "Associability" Hypothesis Regarding Medial Septum Neuronal Activity

As mentioned before, α_i can be used as a measure of the strength of both the OR and the "voluntary" attention toward CS_i . From a different perspective, Vanderwolf, Kramis, Gillespie, and Bland (1975) suggested that "voluntary" behavior was correlated with hippocampal theta. In addition, Anchel and Lindsley (1972) found that the strength of the OR was correlated with hippocampal theta. Therefore, voluntary behavior, theta activity, and strong ORs would be correlated with large values of α_i^t , whereas nontheta activity, automatic behavior, and weak ORs would be correlated with small values of α_i^t .

Berger and Thompson (1978b) suggested that neural activity in the medial septum represented an arousal signal that controlled hippocampal theta. As discussed in the previous paragraph, theta activity is correlated with α_i^t . Therefore, the present study assumes that the frequency of medial septum neuronal firing is proportional to the instantaneous magnitude of $\Sigma_k \Sigma_i \alpha_i^t$ —that is, the sum of CS-CS and CS-US associabilities of all CSs present at a given time. As mentioned above, $\Sigma_k \Sigma_i \alpha_i^t$ is proportional to the total degree of uncertainty about ongoing events in the external world, and it determines the total amount of information to be stored in the brain.

SIMULATIONS

Method

The simulations that described NM topography for normal, HL, and LTP cases were carried out with the S-P-H model. This section defines and justifies the values of the different parameters adopted for the simulations. *Parameter values were kept constant for all simulations.*

For the simulations, the model was converted to discrete time, which allowed for the generation of values of the relevant descriptive variables at discrete time instants, which we denote as $t = 1, 2, 3, \dots$. For convenience, we assume that the basic time step is one abstract unit, which can be related to various intervals of real time as required. In our simulations, we assumed that one time step or bin was equivalent to a duration of 10 msec. Each trial consisted of 120 bins, which was equivalent to 1,200 msec. Only 600 msec are represented in the figures that display NM response topography.

All simulations assumed 200-msec CSs, the last 50 msec of which overlapped the US. CS onset was at 200 msec. Since asymptotic conditioned NM responding is reached in approximately 200 trials (Gormezano et al., 1983), 1 simulated trial is approximately equivalent to 20 experimental trials.

The right upper panel of all figures that display simulation results shows the net associative values at the end of each trial. The right lower panel shows the product of associabilities multiplied by salience at the moment the US was presented on reinforced trials, as a function of trials. The left panel shows NM response topography as a function of time and of trials.

The initial values of V s and N s were normally zero. In the case of LTP, all V_{CS}^{CS} s were set to be equal to one. The initial values of associability were always set to be equal to zero.

The parameter values for the variations of associative values were selected $\theta = .03$ and $\theta' = .015$. For computations of B_i^t , $w_i' = 2$ when $i \neq r$. The value of w_i' was selected so as to allow the model to display secondary reinforcement before conditioned inhibition in a secondary reinforcement paradigm. The constant part of S_i , δ_i , was set equal to 0.5 for every CS.

The S-P-H is very robust with respect to changes in its parameters. Previous simulations with the model (Schmajuk, 1986; Schmajuk & Moore, 1985) yielded qualitatively the same results, even in a completely different range of parameters ($\theta = .1$ and $\theta' = .01$), a different trace constant ($k = .067$), a different number of simulated bins (12 or 60), and slightly different rules for computing α_i^t .

NM Response Topography

For the computation of τ , $k1$ was set to $k1 = .1$, which was the appropriate value for an optimal ISI of 200 msec. For computations of the NM CR onset, $L1$ was set equal to .5 so the CR onset latencies would reach asymptote at approximately the midpoint of the ISI. For the NM response topography, $k2 = .5$, which ensured that the NM response reached the value of $\Sigma_j B_j^{US}$ within the CS period.

Neuronal Activity

To obtain realistic neural frequencies, threshold $L2$ was set equal to .5.

Results

This section presents relevant experimental data and contrasts the data with the results of computer simulations that describe the NM topography of normal and HL rabbits. The following procedures were simulated for the normal and the HL case: delay conditioning, conditioning under different ISIs, discrimination reversal, and sensory preconditioning. In addition, hippocampal neuronal unit activity during acquisition and extinction, medial septum unit activity during acquisition, and discrimination acquisition after LTP induction were simulated for the normal case.

Acquisition of Delay Classical Conditioning

Experimental data. Several studies have described the effect of HL on acquisition rates. Using a delay conditioning paradigm, Schmalz and Theios (1972) found that the acquisition of the conditioned NM response in HL rabbits was faster than normal with a 250-msec CS, a 50-msec shock US, and a 250-msec ISI. In contrast with these data, Solomon and Moore (1975) and Solomon (1977) found no difference in the rate of acquisition between normal and HL rabbits in forward-delay conditioning of the NM response with a 450-msec CS, a 50-msec shock US, and a 450-msec ISI. In summary, *acquisition rates* become accelerated or remain unaffected by HL.

Several studies have described the effect of HL on NM topography during acquisition. Solomon and Moore (1975) and Solomon (1977) found that CR topography did not differ in normal and HL rabbits in forward-delay conditioning of the NM response with a 450-msec CS, a 50-msec shock US, and a 450-msec ISI. Port and Patterson (1984), using a 500-msec CS, a 50-msec shock US, and a 450-msec ISI, found that CR latency was shorter in rabbits with fimbrial lesions (i.e., hippocampal output) than in rabbits with cortical or sham lesions, mainly during the first day of acquisition. In summary, *CR onset latencies* in a delay conditioning paradigm become shorter or remain unaffected after HL.

Powell and Buchanan (1980) reported an increased OR (measured as an increased bradycardia) over conditioning trials in HL rabbits relative to controls.

Simulation results. Figure 2 shows simulations of 10 trials in a delay conditioning paradigm. The model describes an S-shaped acquisition function, and shows the abrupt shifts in responsiveness that occurred during acquisition. As Figure 2 illustrates, CR amplitude for the normal case shows a small increment during the first two trials, followed by a sudden increment on Trial 3, and a relatively slow increment between Trials 3 and 10.

In agreement with Schmalz and Theios (1972), the simulation results show a faster than normal acquisition rate in the HL case. Simulations for the normal case show that both context and CS associabilities decreased over trials, with the CS overshadowing the context. In the HL case, both the CSs and the contextual associabilities were larger than in the normal case; therefore, both the CS and the context were able to acquire larger associative values at a faster rate than in the normal case.

Figure 2. Delay conditioning. L: HL case. N: normal case. A: CS(A). X: context. Left panels: Simulated NM response topography in 10 reinforced trials. Upper-right panels: Net associative values (VT) at the end of each trial as a function of trials. Lower-right panels: Associability (ALPHA) at 350 msec as a function of trials.

Also, in agreement with Port and Patterson (1984), the simulated CR latency was shorter for the HL than for the normal case.

As mentioned above, Kaye and Pearce (1984) suggested that the strength of the OR was proportional to α_i . Figure 2 shows greater α_i^{US} for the HL than for the normal case, a result in agreement with Powell and Buchanan's (1980) data.

ISI Effects

Experimental data. Systematic manipulations of the ISI affect CR topography in normal animals. At ISIs of zero, CRs are negligible; at ISIs of around 200 msec, CRs increase dramatically; and for longer ISIs, CRs gradually decrease (Schneiderman, 1966; Smith, 1968).

Port, Mikhail, and Patterson (1985) examined the effects of HL on the acquisition rates of the NM response in groups of rabbits trained with short (150 msec), optimal (300 msec), or long (600 msec) ISIs. For all groups, CS and shock US durations were 850 and 50 msec, respectively. The acquisition rates become accelerated, and the HL animals produced more CRs than the normal animals in the short- and long-ISI HL groups, but not in the optimal-ISI HL group. However, as mentioned before, Schmaltz and Theios (1972) reported faster acquisition rates after HL with an optimal (250 msec) ISI. In summary, CR acquisition rates become accelerated with short, optimal, and long ISIs, but they sometimes remain unaffected with optimal ISIs.

Port et al. (1985) also reported that HL rabbits showed a shorter CR onset latency with a short ISI than did the controls, but normal CR onset latency with optimal and long ISIs. More recently, however, James, Hardiman, and Yeo (1987) reported that HL rabbits trained with a 250-msec white noise CS, a 50-msec shock US, and a long (750-msec) ISI showed shorter onset latencies than controls. As mentioned before, Port and Patterson (1984), using a 500-msec CS, a 50-msec shock US, and an optimal 450-msec ISI, found that CR latency was shorter in rabbits with fimbrial lesions. In summary, CR onset latencies may become shorter with short, optimal, and long ISIs, but they sometimes remain unaffected with optimal and long ISIs.

Different results have been reported regarding NM response topography in HL animals when different types of US were used. Solomon, Vander Schaaf, Thompson, and Weisz (1986) reported that CR onset latencies were shorter in HL rabbits than in normal rabbits trained in a trace-conditioning paradigm with a 250-msec tone CS, a 500-msec ISI, and a 100-msec airpuff US. Port, Romano, Steinmetz, Mikhail, and Patterson (1986) observed similar effects in HL rabbits trained in a trace-conditioning paradigm with a 250-msec tone CS, a 750-msec ISI, and a 100-msec airpuff US. In summary, CR onset latencies with long ISIs become consistently shorter with airpuff US.

Simulation results. The acquisition of classical conditioning was simulated with a 50-msec CS, and 0-, 200-,

Figure 3. Simulated CR amplitude and CR onset latency as a function of ISI for normal and HL cases after 10 simulated trials with a 50-msec CS, a 50-msec US, and 0-, 100-, 200-, 300-, and 400-msec ISIs.

300-, and 400-msec ISIs. The shock US was 50 msec in duration.

Figure 3 (upper panel) summarizes the simulated results for CR amplitude for the normal and HL cases with ISIs of 0, 100, 200, 300, and 400 msec. The simulated data resemble the "inverted-U" ISI function obtained by Smith (1968), Schneiderman (1966), and Schneiderman and Gormezano (1964) in normal rabbits, in which a peak occurred at the 150-msec ISI. The simulated data show accelerated acquisition rates and larger CR amplitudes for all groups. The simulation results agree with data showing accelerated acquisition rates in short-, optimal-, and long-ISI HL groups. The S-P-H model describes some conditioning with simultaneous CS-US presentations, a prediction that awaits experimental testing.

Figure 3 (lower panel) summarizes the results after 10 simulated trials for CR onset latency for the normal and HL cases with ISIs of 100, 200, 300, and 400 msec. The CR onset latencies are shorter for the HL case than for the normal case for short-, optimal-, and long-ISI groups. The results agree with HL experimental data obtained with shock and airpuff US.

Discrimination Reversal

Experimental data. The effect of HL on discrimination reversal has been studied in rabbit NM and eyelid preparations. Buchanan and Powell (1980) examined the effect of HL on acquisition and reversal of eyeblink discrimination in rabbits. HL slightly impaired the acquisi-

tion of discrimination and severely disrupted its reversal by increasing responding to CS-. Berger and Orr (1983) contrasted HL and control rabbits in two-tone differential conditioning and reversal of the rabbit NM response using an 850-msec CS, a 100-msec airpuff US, a 750-msec ISI, and an average 30-sec ITI. Although HL did not affect initial differential conditioning, these animals were incapable of suppressing CRs to the original CS+ after the CS+ assumed the role of CS-. This was true even after extended training. Similar results were recently reported by Weikart and Berger (1986) in a tone-light discrimination reversal-learning paradigm, which suggests that deficits in two-tone reversal learning after HL are not due to increased within-modality generalization to the tone CS that serves as CS+ and CS-. Port, Romano, and Patterson (1986), who used a tone 200-msec CS+, a tone 800-msec CS-, a 50-msec shock US, a 1-sec ISI, and a 30-sec ITI, found that HL impaired the reversal learning of a stimulus-duration discrimination paradigm.

The effect of HL on NM topography in a discrimination-reversal paradigm has also been studied. Orr and Berger (1985) used an 850-msec CS, a 100-msec airpuff US, a 750-msec ISI, and an average 30-sec ITI, and reported that HL affected CR topography in a discrimination-reversal task, but not during discrimination acquisition. On the last trials of reversal, the HL animals showed a greater peak NM amplitude and a greater area under the NM response curve during the CS period for both the CS+ and the CS-.

Simulation results. Figure 4 shows simulations of a discrimination-reversal paradigm. In the differential conditioning phase, five reinforced trials with one CS (A) were alternated with five nonreinforced trials with a second CS (B). During reversal, the original nonreinforced CS (B) was reinforced for five trials; these trials were alternated with five trials in which CS(A)—the reinforced CS in the first phase—was presented without the US.

After differential conditioning in the normal case, $\dot{V}_A^{US}$ was higher than $\dot{V}_B^{US}$, which had become inhibitory. After reversal in the normal case, $\dot{V}_B^{US}$ increased to approximately the same level achieved by $\dot{V}_A^{US}$ during differential conditioning. At the same time, $\dot{V}_A^{US}$ decreased as a consequence of the nonreinforced trials, and $\dot{V}_X^{US}$ became inhibitory. After differential conditioning in the HL case, $\dot{V}_A^{US}$ was higher than $\dot{V}_B^{US}$, but $\dot{V}_B^{US}$ did not become inhibitory. After reversal in the HL case, $\dot{V}_B^{US}$ increased to approximately the same level achieved by $\dot{V}_A^{US}$ during differential conditioning. At the same time, $\dot{V}_A^{US}$ decreased as a consequence of the nonreinforced trials, but since $\dot{V}_X^{US}$ did not become inhibitory, a higher level of responding was achieved.

Given the reported high levels of conditioned responding to both reinforced and nonreinforced CSs after extended reversal training in HL animals, it would appear that the S-P-H model renders a realistic portrayal of these data. Furthermore, in agreement with Orr and Berger's (1985) results, normal and HL simulations show differences in the NM amplitude and in the area under the NM

Figure 4. Discrimination reversal. L: HL case. N: normal case. A: CS(A). B: CS(B). X: context. Left panels: Simulated NM response topography in A- and B- trials after discrimination acquisition with five CS(A) reinforced trials alternated with five CS(B) nonreinforced trials followed discrimination reversal with five CS(B) reinforced trials alternated with five CS(A) nonreinforced trials. Upper-right panels: Net associative values (VT) at the end of each trial as a function of trials. Lower-right panels: Associability (ALPHA) at 350 msec as a function of trials.

response curve during the CS period on the last trials of reversal, with either the CS+ or the CS-.

Sensory Preconditioning

Experimental data. In sensory preconditioning, CS(A) and CS(B) are presented together in the absence of the US. Later pairing of CS(A) with the US results in conditioned responding to CS(B).

Port and Patterson (1984) preconditioned control rabbits and rabbits with fimbrial lesions with simultaneous presentations of a tone CS and a light CS in the absence of the US. Preconditioning was followed by presentations of the light CS in the presence of the US. This procedure yielded excitatory conditioning to the tone in normal animals, but not in rabbits with fimbrial lesions.

Simulation results. Figure 5 shows simulations of a sensory preconditioning paradigm. In the first phase, there

Figure 5. Sensory preconditioning. L: HL case. N: normal case. A: CS(A). B: CS(B). X: context. Left panels: Simulated NM response topography in A- and B- trials after 10 CS(A) and CS(B) nonreinforced trials and 10 CS(A) reinforced trials. Upper-right panels: Net associative values (VT) at the end of each trial as a function of trials. Lower-right panels: Associability (ALPHA) at 350 msec as a function of trials.

were 10 nonreinforced trials with a compound CS(A and B). During the second phase, one of the nonreinforced CSs (A) was reinforced for 10 trials. A test trial assessed the CR to CS(B), which was never paired with the US. The simulations show that context associability decreased during preconditioning in the normal case, but not in the HL case. In the nonreinforced test trial in the normal case, CS(B) acquired inhibitory associative value because it was presented in a context with excitatory associative value. CS(B) generated a CR only in the normal case.

Port and Patterson (1984) found that fimbrial lesions eliminated the responses to CS(B), a result in accordance with the simulations.

LTP Effects

Experimental data. Berger (1984) found that entorhinal cortex stimulation that produced LTP increased the rate of acquisition of a two-tone classical discrimination

of the rabbit NM response. LTP increased responding to CS+ and, to a lesser degree, to CS-. Berger suggested that LTP might have enhanced the rate of conditioning by enhancing the rate at which hippocampal unit activity increased during acquisition.

Simulation results. Figure 6 shows CR amplitude for CS+ and CS- after 10 simulated trials in a discrimination paradigm for LTP and control cases. The simulations show faster acquisition and larger CR amplitude in the treated group than in the control group because of the increased $\dot{V}_{CS}^{US}$ associations. These increased associations increased the values of B_{CS-}^{US} and B_{CS+}^{US} , resulting in stronger responding to CS+ and to CS- in the LTP group and, therefore, in little change in the discrimination between CS+ and CS-. These results are in disagreement with experimental data obtained by Berger (1984).

Hippocampal Neuronal Activity During Acquisition and Extinction of Classical Conditioning

Experimental data. Hippocampal activity during classical conditioning of the NM response is positively correlated with the topography of the NM response. During acquisition, increments in hippocampal unit activity *precede* the acquisition of NM CR by over 100 trials (Berger, Alger, & Thompson, 1976). More specifically, Berger and Thompson (1978a) and Berger, Rinaldi, Weisz, and Thompson (1983) found that pyramidal and dentate granule cells in the dorsal hippocampus increased their frequency of firing over conditioning trials with a pattern that correlates with the amplitude-time course of the rabbit NM response. Lesions of the dentate and interpositus cerebellar nuclei ipsilateral to the trained eye caused abolition of both the NM CR and the conditioned increases in hippocampal CA1 neural activity evoked by the CS (Clark, McCormick, Lavond, & Thompson, 1984).

Berger and Thompson (1982) found that, during extinction, pyramidal and granule cells in the dorsal hippocampus decreased their frequency of firing in correlation with behavioral extinction during the US period, but in *advance* of behavioral extinction during the CS period.

Figure 6. Effect of long-term potentiation on discrimination acquisition. Simulated CR amplitude after five CS+ and five CS- trials for experimental and control groups.

Simulation results. Figure 7 shows simulations of single-unit recordings obtained from the hippocampus after 10 trials of classical conditioning. It was assumed that the frequency of pyramidal firing was proportional to B^{US} . In agreement with experimental data, the simulated unit activity shows a pattern that correlates with the amplitude-time course of the rabbit NM response.

The upper panel of Figure 8 shows that the predicted unit activity preceded the behavioral response during acquisition. This was so because a sufficiently large value of $\Sigma_j B_j^{US}$ is necessary before the behavioral threshold (see Equation 11) is surpassed and behavior is elicited. The lower panel of Figure 8 shows that simulated unit activity decreased simultaneously with CR amplitude during extinction. Therefore, the model rendered realistic simulations of single-unit recordings obtained from pyramidal cells during acquisition (Berger et al., 1983) but not during extinction of classical conditioning (Berger & Thompson, 1982).

Medial Septum Neuronal Activity During Acquisition of Classical Conditioning

Experimental data. Berger and Thompson (1978b) recorded neuronal unit activity from the medial septum during classical conditioning of the rabbit NM. They found that neuronal activity in the medial septum during the acquisition of classical conditioning decreased over trials during both the CS and the US periods. Unpaired controls showed the same pattern of activity, and no statistically significant difference was found between groups.

Simulation results. A simulated paired group received 10 CS-US presentations, and a simulated unpaired group received 20 alternated CS-alone and US-alone trials. Figure 9 shows simulated medial septum unit recordings made during the acquisition of classical conditioning. Simulated unit activity decreased during both the CS and the US period within every trial, and across trials during acquisition. On Trial 10, activity during the US period

Figure 7. Simulated NM response topography and hippocampal single-unit activity after 10 reinforced trials.

Figure 8. Simulated CR amplitude and hippocampal unit activity at the time of US presentation during acquisition and extinction of delay conditioning.

was higher than activity during the CS period, and activity was higher in the unpaired group than in the paired group during the US period, but activity was higher in the paired group than in the unpaired group during the CS period.

During the CS period, simulated neural activity reflects the sum $|\lambda^x - B^x| + |\lambda^{CS} - B^{CS}| + |-B^{US}|$. As the CS-US association increases over trials, so does the value of $|-B^{US}|$. This increase is compensated, however, by the decreasing values of $|\lambda^x - B^x| + |\lambda^{CS} - B^{CS}|$. During the US period, simulated neural activity reflects the sum of $|\lambda^x - B^x| + |\lambda^{CS} - B^{CS}| + |\lambda^{US} - B^{US}|$. As the CS-US association increases over trials, the value of $|\lambda^{US} - B^{US}|$ decreases.

In summary, simulated medial septum activity during the acquisition of classical conditioning decreased over trials during both the CS and the US periods in both paired and unpaired control groups. These results are in agreement with single-unit recordings obtained from medial septum cells during acquisition by Berger and Thompson (1978b).

DISCUSSION

The present article shows that the S-P-H model is able to provide real-time descriptions of the rabbit NM response topography in many complex classical conditioning paradigms.

Figure 9. Simulated medial septum unit activity during CS and US periods during acquisition of delay conditioning for paired and unpaired groups.

One important feature of the present version of the S-P-H model is that it incorporates a heteroassociative network that allows the building of "computational, cognitive maps." In the case of classical conditioning, cognitive maps are applied to sensory preconditioning and secondary reinforcement. In the context of instrumental learning, cognitive maps have been associated with spatial learning (O'Keefe & Nadel, 1978). Notably, it has been proposed that heteroassociative networks represent the neuronal arrangement of hippocampal CA3 and CA1, and that these networks participate in the learning of conjunctions of environmental information, as well as in spatial mapping (McNaughton & Morris, 1987; Rolls, 1987).

In the present paper, it was assumed that the hippocampus was involved in the computation of the aggregate prediction of ongoing events. This internal prediction was compared with information from the external world in order to determine the amount of processing to be assigned to external stimuli. It was assumed that the aggregate prediction was disrupted by HL, enhanced by LTP induction, and represented in hippocampal neuronal activity. Activity in the medial septum was assumed to be proportional to the degree of uncertainty about ongoing events and to the amount of processing and storage of external information. Results obtained through the application of these hypotheses to the S-P-H model are discussed below.

HL Effects

The aggregate prediction hypothesis regards the effect of HL as an impairment in the integration of multiple predictions into the aggregate prediction B^{US} . Table 2 summarizes the results of the simulation experiments for the HL case obtained in the present paper together with results obtained in a previous study (Schmajuk, 1986). Under the aggregate prediction hypothesis, the model successfully described HL effects on delay conditioning, conditioning with short, optimal, and long ISIs with a shock US, conditioning with long ISIs and an airpuff US, extinction, latent inhibition, generalization, blocking, discrimination reversal, and sensory preconditioning.

In addition, the model predicts that paradigms involving cognitive mapping (such as secondary reinforcement, compound conditioning, and serial compound conditioning), differential conditioning, positive and negative patterning, conditional responding, and overshadowing are impaired by HL, and that partial reinforcement and simultaneous conditioning are facilitated by HL. These predictions await experimental testing in the rabbit's NM response preparation.

The S-P-H model has problems in describing conditioned inhibition and in describing mutual overshadowing for the HL case. The failure of the model to explain HL effects in an overshadowing paradigm was limited to the case in which both CSs had similar saliences: the S-P-H model correctly described HL effects on overshadowing when CSs of different saliences were used (Schmajuk & Moore, 1985). In summary, simulation results show that the aggregate prediction hypothesis predicts a large number of experimental data, although the hypothesis fails to predict some HL effects.

An alternative assumption that yields improved HL descriptions is that α_{CS}^{CS} equals zero but α_{CS}^{US} remains unaffected. If α_{CS}^{CS} equals zero, anterograde but not retrograde CS-CS amnesia is predicted; that is, V_{CS}^{CS} equals zero for CSs paired after HL, but V_{CS}^{CS} remains unchanged for CSs paired before HL. Impairments in α_{CS}^{CS} imply impairment in latent inhibition and sensory preconditioning. As a consequence of the CS-CS anterograde associative deficits, α_i^{US} is also modified, and is given by

$$\alpha_i^{US}(t) = |\lambda^{US}(t) - \sum_j \dot{V}_j^{US}(t-1)\tau_j(t-1)|. \quad (20)$$

Because $\sum_j \dot{V}_j^{US}\tau_j$ is smaller than B^{US} , α_i^{US} for the HL case computed with Equation 20 is larger than α_i^{US} for the normal case given by Equation 6. Therefore, the use of Equation 20 implies impairments in blocking and overshadowing. Schmajuk (1987) showed that the use of Equation 20 yields correct predictions for HL effects on conditioned inhibition.

LTP Effects

The aggregate prediction hypothesis assumes that LTP induction increases the integration of multiple predictions

Table 2
Simulations of the S-P-H Model Compared With the Experimental Results
of Classical Conditioning of the NM Response

Paradigm	Observed	Simulated
HIPPOCAMPAL LESION EFFECT		
Delay Conditioning	normal/shorter latency normal/faster acquisition	shorter latency faster acquisition
ISI Effects (Shock US)		
Zero ISI	?	+
Short ISI	shorter latency faster acquisition	shorter latency faster acquisition
Optimal ISI	normal/shorter latency normal/faster acquisition	normal latency faster acquisition
Long ISI	normal/shorter latency normal/faster acquisition	shorter latency faster acquisition
ISI Effects (Airpuff US)		
Long ISI	shorter latency faster acquisition	shorter latency faster acquisition
Orienting Response	+	+
Conditioned Inhibition	0	-*
Extinction	0	0
Latent Inhibition	-	-
Generalization	+	+
Blocking	-	-
Mutual Overshadowing	0	-*
Discrimination Reversal	-	-
	greater NM peak greater CS+ area greater CS- area	greater NM peak greater CS+ area greater CS- area
Sensory Preconditioning	-	-
LONG-TERM POTENTIATION EFFECT		
Discrimination Acquisition	+	0*
HIPPOCAMPAL NEURAL ACTIVITY		
Acquisition	increases precedes behavior models NM response	increases precedes behavior models NM response
Extinction	decreases precedes behavior	decreases simultaneous with behavior*
MEDIAL SEPTUM NEURAL ACTIVITY		
Acquisition	decreases	decreases

Note—Symbols: - = deficit, + = facilitation, 0 = no effect, ? = no available data. *The model fails to accurately describe the experimental result.

into the aggregate prediction B^{US} by way of increasing CS-CS associations. Computer simulations show that under this hypothesis, the S-P-H model does not correctly describe the effect of LTP induction on the acquisition of a classical discrimination. If the effect of LTP induction is not adequately described as an increase in CS-CS associative values, then perhaps CS-CS associations are stored in regions of the brain other than the hippocampus in the form of LTP. Therefore, heteroassociative networks that represent the neuronal arrangement of hippocampal CA3 and CA1 would store information other than CS-CS associations.

Hippocampal Neuronal Activity

The aggregate prediction hypothesis assumes that neural activity in the hippocampus is proportional to the instantaneous value of the aggregate prediction, B^{US} . We

have shown that activity in pyramidal cells in the dorsal hippocampus is correctly described as proportional to B^{US} during acquisition but not during extinction of classical conditioning.

Medial Septum Neuronal Activity

The associability hypothesis proposes that neuronal activity in the medial septum is proportional to $\sum_k \sum_t \alpha_t^k$ (i.e., to the degree of uncertainty about ongoing events in the external world and the amount of information to be stored in the brain). As shown above, the S-P-H model adequately describes medial septal unit activity over acquisition trials.

Simulation results suggest that neural activity in the medial septum is proportional to the sum of different $\alpha_t^k = |\lambda^k - B^k|$ —that is, comparisons between actual and predicted events. These results do not imply, however,

that actual and predicted events are compared in the medial septum. It is possible that these comparisons are performed in other brain regions and conveyed to the medial septum. For example, Vinogradova (1975) argued that the CA3 region is involved in comparing actual and predicted events; when novelty is detected, an orienting response is elicited and cortical activity increases in order to store new information. Similarly, Gray (1982) proposed that actual and predicted events were compared in the subiculum: when there is a match, then behavior is maintained; when there is a mismatch, then the current behavior is inhibited, attention is increased, and new information is stored in the temporal lobe.

CONCLUSION

The present study shows that the S-P-H model is able to describe the CR topography of the rabbit NM response in real time in a large number of classical conditioning paradigms. Although the aggregate prediction hypothesis provides interesting insights into diverse aspects of hippocampal function, they are unable to describe some effects of hippocampal manipulations. It is apparent, however, that the S-P-H model provides a powerful tool to test other hypotheses regarding hippocampal function.

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