The filament (shown in Fig. 3A as a linear structure for simplicity) is more likely to be compacted in a solenoid in which the DNA is more likely to be paired for partitioning. Evidence for paired intermediates in the partitioning of plasmid R1 and involving its cognate ParB analog has recently been obtained (21). The filament (shown in Fig. 3A as a linear structure for simplicity) is more likely to be compacted in a solenoid in which the DNA is more likely to be paired for partitioning. Evidence for paired intermediates in the partitioning of plasmid R1 and involving its cognate ParB analog has recently been obtained (21).

References and Notes
inition task exhibited short-latency stimulus-evoked (phasic) responses to target (CS+) stimuli but not to distractor (CS−) stimuli or other task events (2). The latencies of these LC responses were substantially shorter than, and temporally correlated with, the latencies of corresponding behavioral responses, indicating that LC activity may affect task responding. However, the mechanisms that govern LC activity or its effect on behavior have remained unclear.

LC neurons were recorded in four Cynomolgus monkeys performing a visual discrimination task (2). This task required the monkey to respond to infrequent visual target stimuli but not to frequent distractors (3). In many of our recordings, LC neurons changed levels of tonic discharge several times (Fig. 1A), in association with alterations in task performance. We divided behavioral performance into epochs of “good” and “poor” performance, on the basis of the frequency of false alarm (FA) errors produced [as described previously (2, 4)]. Signal detection sensitivity (d’) was substantially higher in epochs of good compared with those of poor performance, so the difference between these cannot be explained by a simple change in response criterion (4). Furthermore, although mean lever response times (RTs) were not systematically different between the two levels of performance, there was a significant narrowing of the distribution of lever release latencies during the good epochs (4) (Fig. 1B).

As shown in Fig. 1A, epochs of poor performance were associated with significantly higher tonic LC activity than were epochs of good performance (3.0 ± 0.3 spikes/s compared with 2.0 ± 0.2 spikes per second P < 0.001; FA frequencies were 7.6 ± 0.9% compared with 1.0 ± 0.2% of trials; P < 0.01; n = 30 cells; paired t tests). Similar results were obtained in an additional 37 multicell LC recordings. Thus, in addition to our previous finding of a close relationship between phasic LC discharge and behavioral responses (2), we also found a close relationship between the level of LC tonic activity and behavioral performance. We refer to the lower level of tonic LC activity during epochs of good performance as “intermediate,” to distinguish it from the low (near zero) level typically associated with drowsiness or sleep (2, 5).

We also found that sensory-evoked LC responses varied with the level of tonic LC activity and task performance. The phasic responses that LC neurons exhibit selectively for target stimuli in this task occurred almost exclusively during epochs of intermediate tonic LC activity and good task performance (Fig. 1, C to F). For the 30 single-cell recordings described above, response magnitudes to target stimuli during epochs of good performance were significantly greater than during epochs of poor performance (2.7 ± 0.4 compared with 0.8 ± 0.2; P < 0.001; paired t test). Thus, increased tonic LC discharge was associated with decreased responsivity of LC neurons to target stimuli as well as decreased task performance. This three-way association of tonic LC activity, LC phasic responses to target stimuli, and level of task performance was observed consistently across our recordings.

These results suggest that there is a precise relation between LC activity and behavioral performance. To elucidate the mechanisms that might underlie this relation, we developed a computational model of LC function and its effect on performance in this task.

The model is a hybrid, with two primary components: an LC network and a stimulus discrimination (behavioral) network (Fig. 2A). The LC network is relatively fine-grained and designed to simulate physiological mechanisms underlying LC function, whereas the behavioral network is the simplest capable of simulating performance in the visual discrimination task. Although the use of such a hybrid model that combines components at different levels of abstraction may be unusual, this is justified by the correspondence between each component of the model and the

---

Fig. 1. Representative data from a typical LC neuron recorded in a monkey during performance of the visual discrimination task. (A) The rate of discharge for an LC cell (top curve) and the number of FAs (bottom curve), both integrated for a sliding window of 20 s. (B) Normalized distributions for behavioral response latencies (lever releases) during “good” epochs (solid line) compared with “poor” epochs (dashed line) averaged for sessions in three monkeys. Similar distributions were obtained for the individual monkeys, and the distributions were consistently more narrow during good epochs. (C to F) Poststimulus time histograms (PSTHs) for LC activity during the visual discrimination task. (C and D) Response for targets. (E and F) Response for distractors. (C and E) "Good" behavioral epochs. (D and F) "Poor" behavioral epochs (FA rate typically > 7%). Stimuli occur at time zero. All histograms are normalized to a standard of 100 trials. Similar results were obtained in another 29 single-cell recordings and 37 multicell recordings.

---

M. Usher, Department of Psychology, University of Kent, Canterbury, UK. J. D. Cohen, Department of Psychology, Princeton University, Princeton, NJ 08540, USA and Department of Psychiatry, University of Pittsburgh, Pittsburgh, PA 15213, USA. D. Servan-Schreiber, Department of Psychiatry, University of Pittsburgh, Pittsburgh, PA 15213, USA. J. Rajkowski and G. Aston-Jones, Department of Psychiatry, University of Pennsylvania, VAMC (151), University and Woodland Avenues, Philadelphia, PA 19104, USA.

*To whom correspondence should be addressed. E-mail: gaj@mail.med.upenn.edu
that is responsible for a spontaneous firing rate of about 1 spike/s [as observed in vivo (2)].

The behavioral component of the model is a simple connectionist network, consisting of two input units (one for target and one for distractor stimuli), two corresponding decision units, and one response unit (Fig. 2A). Connections between units in different processing layers are excitatory (reflecting information flow), connections within a layer are inhibitory (competition), and the activity of units is subject to small random variations (noise) (12). Each input unit has a strong weight to the corresponding decision unit and a weaker projection to the other decision unit. The target decision unit has a positively weighted connection to the response unit and to the LC network (13). Finally, consistent with previous simulation work, we assume that NE release has the effect of increasing the gain of the activation function for units in the decision and response layers (see below and (14, 15)).

A task trial was simulated by activating the input unit corresponding to the current stimulus, which resulted in the spread of activation to the competing units in the decision layer and then to the response unit and LC. Characteristic dynamic responses of different units in the behavioral network after presentation of each type of stimulus (in the absence of modulation by LC) are displayed in Fig. 2B.

The simulated pattern of LC firing with and without electrotonic coupling, after target and distractor stimuli, is shown in Fig. 3. Target stimuli evoke a transient, synchronized LC response as a result of input from the target decision unit to LC cells. The target-evoked response is terminated by NE-mediated collateral inhibition within the LC. Electrotonic coupling among LC neurons has two main effects. First, coupling causes a stronger response of the LC population to target inputs, as a result of the reinforcement of spike-induced depolarizations in each individual neuron by similar, simultaneous depolarizations in other LC cells within the population. Second, coupling reduces the spontaneous (tonic) firing rate of LC cells by mutually shunting the effect of uncorrelated noise on each cell’s membrane potential (16). These simulation results closely resemble the patterns of monkey LC discharge observed during epochs of intermediate (versus high) tonic activity and good (versus poor) behavioral performance (Figs. 1 and 3).

As noted above, the output of the target decision unit provides input to the LC net-

**Fig. 2.** (A) Architecture of the model of task performance. Arrows represent excitatory links and small circles represent inhibition. There is a moderate positive bias on the response unit, which captures the observation that monkeys in this task make many FAs but very few misses (2). (B) Dynamic trajectories of the target, distractor, and response assemblies (as indicated), in response to targets (top) or distractors (bottom). Stimulus presentation is at time zero. Solid lines, target unit; dashed lines, distractor unit; dotted lines, response unit. In response to each stimulus, there is partial activation of both target and distractor decision units due to their overlapping connections with the input. However, because of mutual competition, after about 100 ms, the decision unit corresponding to the activated stimulus typically prevails, and the competing unit is suppressed. When the target unit prevails, the activity of the response unit is driven above threshold, and a response is recorded. FAs occur because of noise in the response unit, which interacts with transient activation of the target decision unit by a distractor stimulus to produce a response. A threshold is set for activation of the response unit (0.6).

**Fig. 3.** (A to D) PSTHs for the simulated data. (A and B) Response to targets. (C and D) Response to distractors. (A and C) Coupling among LC neurons. (B and D) No coupling among LC neurons. PSTHs are normalized for 100 trials, as for the empirical data (see Fig. 1). (E) Response time distributions for model responses (response unit activations) after targets. Solid line, distribution during simulated coupling among LC neurons; dashed line, distribution during no coupling among LC neurons. The difference of about 150 ms between the latencies of empirical (Fig. 1B) and simulated behavioral responses (E) is consistent with a residual sensory or motor latency.
work, whereas LC activity modulates the gain of units in the decision and response layers of the behavioral network. Unlike in previous models, where the effect of catecholamines on cognitive performance was modeled as a fixed gain parameter throughout a simulation (15), here the value of the gain was determined dynamically by the output of the LC network. Thus, the synchronized, transient responses to target stimuli during epochs of high coupling (Figs. 1, C to F, and 3, A to D) resulted in a temporally modulated process. The effect of LC on the performance of the behavioral network can be seen by comparing the activation of the response unit under conditions of high and low coupling among LC neurons. Increased coupling among LC neurons produced a reduction in FAs (from 12 to 2%), without an increase in misses, and a significant narrowing of the RT distribution, without a change in the mean (Fig. 3E). Thus, a change in coupling among LC neurons in the model reproduces the changes in LC activity, behavioral performance, and the relation between these that is observed empirically.

Changes in electrotonic coupling produce the associated changes in behavior for several reasons. First, increased coupling reduces tonic LC activity, reducing NE release in the behavioral network and thereby lowering the responsivity of those units. For the response unit, this is equivalent to raising its threshold (15), which reduces the number of FAs and anticipatory responses. Ordinarily, raising the response threshold would also increase the number of misses and lengthen mean RT. However, increased coupling enhances evoked LC responses to target stimuli. The enhanced LC response produces a transient reduction in threshold specifically and shortly after target stimuli, which compensates for the overall increase in response threshold and potentiates the processing of target stimuli. This averts an increase in misses or RT (17). This temporal modulation of processing, with maximal gain occurring shortly after a target stimulus, is consistent with an attentional window reported in the cognitive literature (18) and also with recently proposed mechanisms for attentional modulation based on neural synchrony (19). Moreover, this mechanism has the combined effect of eliminating anticipations and of speeding up slow responses, explaining the observed narrowing of the RT distribution during the good behavioral epochs (Figs. 1B and 3E). Thus, a change in a single parameter (an increase in coupling within LC) can account for the reduction in tonic LC activity, the enhanced target-evoked phasic responses, and the association of this pattern of LC activity with a reduction of FAs and a tightening of the RT distribution in behavioral performance.

The model makes the prediction that improved performance is associated with increased electrotonic coupling and therefore should also be associated with greater synchrony in the spontaneous firing of LC neurons (Fig. 4B) (20). We tested this prediction by comparing cross correlograms generated for pairs of simultaneously recorded LC neurons during epochs of good and poor performance. Consistent with our prediction, we found that 18 of 23 pairs of recorded neurons exhibited a central peak in cross correlograms during epochs of good performance that was not present for the same neurons during poor performance (Fig. 4, A and B). Quantitative analyses of correlograms for these 23 pairs of cells indicated that the central peak during good performance was significantly greater than during poor performance.

Our simulation results suggest that electrotonic coupling may be an important mechanism underlying patterns of LC activity and may play a role in regulating behavioral performance. Strong evidence for coupling within the LC of neonatal rats has been reported (21). Although electrotonic coupling appears to decrease postnatally, recent studies indicate that coupling may persist in the LC of the adult rat (22, 23). However, the presence of such coupling in the adult primate has not yet been empirically demonstrated. The model we have developed, together with the data regarding synchronization of LC activity, support this possibility and indicate that modulation of electrotonic coupling may produce potent effects on behavioral performance (24).

One important question concerns the adaptive advantage of the changes in behavior that are produced by changes in LC activity. In our model, intermediate tonic LC activity (due to increased coupling) facilitates a state of selective responding. This state is beneficial in a stable environment such as in our experimental task, where the source of reward is predictable and the behaviors relevant for acquiring it are known and consistent. However, what are the advantages of high tonic LC activity, which is associated with impaired performance in our experimental task? One possible answer is that heightened selectivity may at times be disadvantageous, such as in an uncertain or stressful environment, in which unexpected but imperative stimuli occur (for example, prey suddenly facing a predator), or when previously reinforced responses lose their reward value (for example, satiety). Such circumstances require reevaluation of the sensory environment and abandonment of current behaviors in the search for more adaptive ones. This ability may also be critical for normal developmental and learning processes, as suggested by recent findings indicating that the best predictor of success in acquiring a new skill is not the speed with which the correct behavior is first discovered but the number of alternatives that are initially explored (25). According to our model, high tonic LC activity (as a result of low coupling) can provide a mechanism for sampling new stimuli and behaviors by reducing attentional selectivity and increasing behavioral responsiveness to unexpected or novel stimuli.

These considerations suggest that a tension exists between optimizing performance in a stable environment and favoring more flexible behavior in a changing or unfamiliar environment or when current rewards lose their value. This is a fundamental trade-off, which has been recognized in computational theories of reinforcement learning that distinguish between states that favor “exploitation” and “exploration” (26).
of existing behavioral routines versus “explo-
ration” of new ones (26). The mechanisms responsible for shifting between such states have not been specified. Our model indicates that changes in the mode of LC functioning (produced by alterations of electrotonic coupl-
ing) may provide a neural mechanism for mediating such shifts. This hypothesis also helps to integrate previously proposed roles for LC function (27). Future research is needed to directly test this hypothesis (28) and to characterize the neural system or systems providing input to the LC that are responsible for monitoring the current behavioral context and altering coupling among LC neurons when shifts of state are appropriate. It will also be important to determine the relation of the LC-NE neuromodulatory system to oth-
ers, such as the dopamine system, that are thought to regulate behavior based on expecta-
tions about future events (29).

References and Notes
3. Training and experimental recording sessions took place in an acoustically insulated, electrically shielded metal chamber (IAC, Bronx, NY). Monkeys were trained to depress a lever and to stably evoke a fixation stimulus on a video monitor, at which point this stimulus was replaced by a target or nontarget stimulus (horizontally or vertically oriented rectangles). The animal was required to selectively release the lever in response to the target stimulus (20% of trials). Responses to the other stimulus were not reinforced but instead generated a 3-s time-out. Training continued until animals performed at a level of at least 85% correct. See (2) for more details.
4. Typically, epochs of poor performance contained more than seven times the frequency of FA errors as epochs of good performance. The hit rates varied only slightly between these periods, remaining either constant or declining slightly during poor perfor-
4. mance intervals. For the three monkeys analyzed, the d' values in poor compared with good periods in-
creased from 2.9 to 5.1, 3.7 to 4.7, and 3.7 to 5.1. The response criterion b also increased during the good periods, from 0.36 to 2.92, and 0.06 to 1.11, respectively. For these monkeys, the standard devia-
5. tions of RTs were 55, 55, and 46 ms, respectively, during poor intervals and 33, 33, and 35 ms, respectively, during epochs of good performance (P < 0.001; Levene test of variances).
8. Each LC cell integrates its input current (see below) and fires when its voltage at time t, \(V(t)\), reaches threshold \(V_T\), after which it is artificially reset to rest (\(V = 0\)) and remains refractory until its voltage begins to rise again. We chose a refractory period of 10 ms, to mimic the afterhyperpolarization that follows individual LC spikes, \(V(T + 1) = \lambda \cdot V(T) + b\), where \(\lambda\) is related to the membrane integration constant, and \(b\) is an additive input current that depends additively on the activity of the target cell assem-
9. bly \(x\), the total amount of NE, and the hypothe-
sized gap-junctional current \(g_c\) (see below) and is also affected additively by the Gaussian noise. The gap-
junctional current \(g_c = \sum (V_j - V) / V_j\) on each LC unit is proportional to the sum of the ohmic currents contributed by the other LC units (which depend
10. increases in voltage for spiking neurons, \(V_c\) is taken as \(V_c \approx V - V_T\)).
12. Lateral inhibition occurs with a rise time of about 25 ms after LC cell firing and a decay of 250 ms [S. L. Foote, B. E. Bloom, Physiol. Rev. 63, 844 (1983)]. This collateral NE release regulates the firing rate of the LC population: After each target-
evoked, synchronized response of the population (see below), a slightly delayed inhibitory effect appears (as reflected in the PSTH histograms; Figs. 1C and 3A).
13. Electrotonic coupling is consistent with observa-
tions of gap junctions among LC neurons in neo-
pal rats (21) and with recent evidence for coupl-
ing among LC neurons in the adult rat (22, 23). We assume that coupling produces a weak ohmic conductance among LC neurons, which results in a maximum of about 2.5% of the input current received by the cell, corresponding to the amount of current found in gap junctions identified in neonatal LC neurons. (22).
14. This network is not intended to be a detailed simulation of specific neuronal circuits at the cell-
ular level. Rather, it is intended to simulate task perfor-
mance that is consistent with those of biological information processing [see, for example, J. L. McClelland, in Attention and Performance, vol. XIV (MIT Press, Cambridge, MA, 1993), pp. 635–688; D. E. Rumelhart and J. L. McClelland, Parallel Distributed Processing (MIT Press, Cambridge, MA, 1986)]. For example, the behavior of cell assemblies thought to represent task-relevant stimuli and responses in the cortex is simulated as simple processing units with continu-
ously-valued activation levels, on the assumption that information is represented in the cortex as the average spike rate over time intervals ([D. Amft, Modeling Brain Function (Cambridge Univ. Press, Cambridge, 1989)]. Recurrent self-connections simulate excitatory connections between cells that belong to a particular assembly.
15. The weak weight from each input unit to the opposite decision unit captures our assumption that the stimuli used in the task have overlapping features and therefore each partially activates the representation of the other. The weights from the distractor decision unit to the response unit and LC network are zero (and therefore not implemented). This value corresponds to our as-
sumption that the distracter has not been overattended to respond to the target but not the distractor, there have been selective strengthening of projections from the target decision unit to the response unit and LC module, but not vice versa.
16. The gain parameter g is an amplification factor that multiplies the net input to each unit, i, in its transfer function \(\alpha_j(V_i) = V_i(0^+ + \exp[-g \times \text{netinput}(i)])\) where \(\text{netinput}(i)\) is computed from the activations at the previous iteration step as
\[
\text{netinput}(i) = 1 - \sum_{j} \text{activity}_j \times \text{weight}_{ji} + (1 - \text{netinput}(i))
\]
for all units j that project to unit i with weight, and processing rate \(\alpha\). The gain parameter is determined by the summed outputs of units in the LC network, with a lag time of about 55 to 90 ms between a change in mean LC unit activity and the consequent change in the gain parameter of units in the behav-
17. ioral network (not reported to exist in LC neurons) or simulta-
18. neously increasing excitation or inhibition 
19. ney evoke the amplification effect but do not lead to the reduction of tonic activity or increased synchrony. Note, however, that if response occurs immediately, it would also potentiate processing in the distracter unit, which is transiently activated by the target stimulus (see Fig. 2B). This lead to an increase in misses (through competition with the target unit) as well as an increase in FAs. However, the target-
evoked LC response occurs about 100 ms after target presentation, which is after the time interval of tran-
sient activation of the distracter unit.
19. LC phasic responses to targets (which modulate the gain of decision and response units in the model) are characterized by a concentration of spikes 80 to 150 ms after stimulus presentation, which is compensated by postactivation inactivity, so that only the temporal alignment, but not the total number of spikes, differs after target stimuli. Such synchronous activity in one part of a system can enhance transmission into a subsequent pro-
tico-cortical interactions to interactions between sub-
cortical structures and the cortex.
20. Previous experimental studies have linked electroton-
ic coupling with an increase in synchrony of firing [for example, R. Llinas, R. Baker, C. J. Sotelo, J. Neuro-
Light-Gap Disturbances, Recruitment Limitation, and Tree Diversity in a Neotropical Forest

S. P. Hubbell,* R. B. Foster, S. T. O’Brien,† K. E. Harms, R. Condit, B. Wechsler, S. J. Wright, S. Loo de Lao

Light gap disturbances have been postulated to play a major role in maintaining tree diversity in species-rich tropical forests. This hypothesis was tested in more than 1200 gaps in a tropical forest in Panama over a 13-year period. Gaps increased seedling establishment and sapling densities, but this effect was nonspecific and broad-spectrum, and species richness per stem was identical in gaps and in nongap control sites. Spatial and temporal variation in the gap disturbance regime did not explain variation in species richness. The species composition of gaps was unpredictable even for pioneer tree species. Strong recruitment limitation appears to decouple the gap disturbance regime from control of tree diversity in this tropical forest.

When a tree dies in a closed-canopy forest, it creates a “light gap,” a local disturbance that sets in motion a mini-successional sequence called gap-phase regeneration, which culminates in the replacement of the original canopy tree by one or more new trees (1). A widely accepted generalization in community ecology is that localized disturbances, such as treefall gaps, promote the coexistence of species having different resource use strategies and dispersal and competitive abilities—a hypothesis known as the intermediate disturbance hypothesis (2). A well-documented physiological and life-history trade-off exists in pioneers versus shade-tolerant mature forest trees in their degree of dependence on light and light gaps for germination, growth, and survival (3). At issue here is whether such life history trade-offs exist or whether pioneers have an absolute requirement for gaps. The question is whether spatial and temporal variation in the gap disturbance regime is actually predictive of stand-to-stand variation in tree species richness and composition in particular tropical forests. If not, then the role of light gap disturbances in maintaining local tree diversity may need to be re-evaluated.

We tested the intermediate disturbance hypothesis in a 50-ha plot of old-growth tropical moist forest on Barro Colorado Island (BCI), Panama (4). All woody plants (excluding lianas) with a stem diameter of ≥1 cm dbh (diameter at breast height) have been tagged, measured, mapped, and identified to the species level (>300,000 stems comprising 314 species). Complete censuses have been conducted in 1982, 1985, 1990, and 1995 (5). From 1983 to 1996, we measured canopy height and gaps annually on a complete 5-m grid of 20,301 sample points (1, 6). From these data and the distribution of each species, we classified species into three regeneration niche guilds: strongly gap-dependent pioneer species, shade-tolerant species, and intermediate species (7). Through 1995, we monitored changes in 1983 sapling communities (stems 1 to 3.9 cm dbh) in all 1983 gap sites (canopy height ≥5 m) and nongap control areas. Control areas comprised the 28.1% of the 50-ha plot that remained in undisturbed high canopy (>20 m) mature forest for the entire 13-year period. Because stem density increases in gap areas, we normalized species richness by dividing by number of stems. We compared species richness per stem in all 20 m by 20 m quadrats containing a gap in 1983 with nonoverlapping quadrats from control areas. We also tested for a relationship between the frequency of canopy disturbance and the 1995 species richness in the sapling community (8). Using a gap-focused method, we tested for an effect of gap size on species richness (9). In 1985, 1990, and 1995, we analyzed the sapling communities in same-aged (2-year-old) gaps created in 1983, 1988, and 1993. We analyzed the species richness and composition of sapling assemblages as a function of gap size for the three regeneration niche guilds. The disturbance regime in the BCI forest produces frequent but small light gaps from the death of one to several canopy trees (Fig. 1A). There are no records of severe disturbances such as hurricanes ever striking central Panama or BCI. Gaps varied over a 46-fold size range from 25 m² to the largest gap of 1150 m². Light gaps markedly increased sapling stem densities relative to nongap, mature forest control sites (P < 0.001). Gaps of 25 m² were legitimately included in the analysis, because pioneer species successfully germinated, survived, and grew in them (Table 1). As predicted by the intermediate disturbance hypothesis, quadrats containing light gaps had substantially more species than did quadrats in nongap, mature forest sites (P < 0.001, Komolgorov-Smirnov test) (Fig. 2A).