



# Changes in perceptual sensitivity related to spatial cues depends on subcortical activity

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**Spatial cues allow animals to selectively attend to relevant visual stimuli while ignoring distracters. This process depends on a distributed neuronal network, and an important current challenge is to understand the functional contributions made by individual brain regions within this network and how these contributions interact. Recent findings point to a possible anatomical segregation, with cortical and subcortical brain regions contributing to different functional components of selective attention. Cortical areas, especially visual cortex, may be responsible for implementing changes in perceptual sensitivity by changing the signal-to-noise ratio, whereas other regions, such as the superior colliculus, may be involved in processes that influence selection between competing stimuli without regulating perceptual sensitivity. Such a segregation of function would predict that when activity in the superior colliculus is suppressed by reversible inactivation, animals should still show changes in perceptual sensitivity mediated by the intact cortical circuits. Contrary to this prediction, here we report that inactivation of the primate superior colliculus eliminates the changes in perceptual sensitivity made possible by spatial cues. These findings demonstrate changes in perceptual sensitivity depend not only on neuronal activity in cortex but also require interaction with signals from the superior colliculus.**

attention | perception | sensitivity | superior colliculus | cortex

Spatial cues are known to improve perceptual sensitivity on visual discrimination and detection tasks, and these behavioral effects seem to originate from changes in neural activity across several brain regions (1). In monkey visual cortex, spatial cues change the statistics of neuronal activity, and these changes are thought to reflect an increase in signal-to-noise synonymous with the spatially restricted changes in perceptual sensitivity characteristic of selective attention (2–4). The frontal and parietal cortex are also strongly implicated in the control of spatial attention (2, 3). Electrical microstimulation of neurons in frontal cortex of monkeys leads to shifts in selective attention mimicking the effects of visual cues (5); conversely, suppression of neural activity in frontal or parietal cortex leads to deficits in performance on attention-demanding tasks (6–8).

These and similar observations have led to an explanatory framework in which the fidelity of sensory processing in visual cortex is regulated by a network of frontal and parietal cortical areas (9–12). This framework predicts that suppression of activity in one or more of these areas should impair the ability of an animal to use cues to improve its perceptual sensitivity. This prediction has not been directly tested in animals, although clinical cases (13) and experiments in humans using transcranial magnetic stimulation (14, 15) corroborate the idea that these cortical areas are important for the orienting of attention and the use of spatial cues.

In addition to this network of cortical areas, selective attention also involves subcortical brain regions, including the superior colliculus (SC) and thalamus (16, 17). Thalamic nuclei such as the pulvinar seem to be an important extension of the cortical network, regulating signal transmission across cortical areas (18). In contrast, the SC seems to lie functionally downstream of, or

parallel to, the visual cortex. The SC plays a causal role in the control of selective attention, as shown by the effects of electrical microstimulation (19, 20) and the neglect-like deficits caused by reversible inactivation (21). However, during the deficits in selective attention induced by SC inactivation, neurons in visual cortex still display cue-related changes in activity normally associated with improvements in perceptual sensitivity (22); this indicates that SC activity is not necessary for regulating sensory signals in visual cortex but instead is necessary for regulation of a subsequent stage of processing, in cortex or elsewhere.

Recent studies have generated a specific suggestion about what this subsequent stage of processing might be. Luo and Maunsell (23) adopted a classic signal detection framework (24) and showed that attention-related modulation in visual cortical area V4 was related to changes in perceptual sensitivity, but not to changes in selection criterion; in their discussion, they suggest the complementary possibility that criterion shifts are mediated by subcortical structures such as the SC. This suggestion is consistent with other physiological results implicating the SC in criterion changes (25) and stimulus selection (26), and with recent models of attention that draw distinctions between changes in perceptual sensitivity and changes in choice bias (27). If the SC were associated with criterion shifts and not perceptual sensitivity, then when activity in the SC is suppressed by reversible inactivation animals should still show changes in perceptual sensitivity, because this aspect of their behavior would be mediated by cortical circuits left intact during the SC inactivation. The experiments reported in this paper directly test this hypothesis.

## Significance

**Our paper addresses an important question about the brain circuits for visual spatial attention: what are the mechanisms that make it possible to focus on some visual objects and ignore others? Recent work suggests that cortical and subcortical areas might make distinct contributions to attention: some cortical areas may be responsible for changes in perceptual sensitivity whereas other cortical and subcortical areas may control how subjects select between visual objects. Contrary to this suggestion, our results demonstrate that activity from a subcortical structure in the primate, the superior colliculus, is also necessary to produce changes in perceptual sensitivity in an attention-cueing paradigm. Thus, attention-related changes in perceptual sensitivity are not accomplished by cortical areas alone but also depend on subcortical signals.**

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location was drawn randomly from four possible diagonal directions; consequently, response direction was independent of the cue location.

In the uncued condition, the task proceeded in the same sequence but no cue was presented, and the coherent motion pulse could occur in any of the four motion patches.

This cued versus uncued design not only allowed us to balance the frequency of the different trial types, making more efficient use of the limited number of trials available during inactivation, but also maintained compatibility with the “cues versus foil” design that we used in a previous study (21).

In the single condition, the timing was again similar, but only a single motion patch was presented. Other task details were the same as used previously (21).

**SC Inactivation.** As described previously (34), we injected muscimol (0.5  $\mu\text{L}$ , 5  $\mu\text{g}/\mu\text{L}$ ), a GABA agonist, into the intermediate and deep layers of the SC using an injection cannula with an electrode threaded down its barrel. We localized the cannula tip within the intermediate and deep layers of the SC before injection using three criteria (21). First, we advanced the cannula to a depth (1.5–3 mm below the SC surface) corresponding to the intermediate and deep layers. Second, we recorded activity during saccades consistent with known responses in the SC, thus confirming the depth in the SC. The location of the units’ movement fields also indicated our placement within the SC’s retinotopic map. Third, we evoked saccades with microstimulation. The current required to evoke saccades (typically 10 mA in the intermediate and deep layers) provided an additional indication of depth, and the direction and amplitude of the evoked saccades indicated the position within the map. Muscimol injection produced changes in saccade metrics consistent with targeting the intermediate and deep layers of the SC (Fig. S4), namely, that saccades directed into the affected quadrant were hypometric with decreased peak velocity and increased error in their endpoints. Nevertheless, we cannot be certain that our effects are due solely to inactivation of neurons in these layers of the SC, because some drug may have diffused vertically through the layers or tracked up the shaft of the injection cannula to affect neurons in the overlying superficial layers. We performed a total of eight SC inactivation experiments (four for subject M and four for subject F) and pooled the data across those sessions separately for each subject. To properly pool data based on inactivation location and cued location we reflected responses along the horizontal and vertical axes. As a result, the relationship between the choice directions and cued locations were consistent and the relationship between choice directions within the same hemisphere was preserved. We reflected inactivation data such that the inactivated region was in the upper right quadrant with respect to the choice directions. We reflected control data so that the discriminandum was in the upper right quadrant.

**Bayesian Decision Model.** We separately characterized perceptual sensitivity and response bias from the behavioral choice data with a multiple alternative version of a traditional SDT model. SDT-based models are often used to describe both detection and two-alternative forced-choice tasks (24). Extensions of this framework to multiple alternatives have been described in detail previously (27, 35). Our model is derived in a manner similar to that of Sridharan et al. (27) and we therefore superficially recapitulate its derivation.

The model accounts for the discrimination as a decision process based on latent (or only indirectly observable) evidence variables. Each of the four response options is associated with an evidence variable. The evidence variables together form a multivariate evidence vector, and the decision is made based on where the vector falls within a decision space. As in the traditional SDT model (24), the perceptual sensitivity of the observer is derived from the separability of the evidence distributions when the signal is present and when the signal is absent. The model makes no assumptions about the specific mechanisms that give rise to these evidence distributions except for the usual assumption that these distributions are Gaussian. Similarly, response bias is reflected by the decision criterion, but instead of a single scalar value as in the SDT model, criteria are conceptualized as planes separating the different regions of the decision space (27).

First we describe the representation of perceptual sensitivity. We index the response options as  $i, i \in \{1, 2, 3, 4\}$  and refer to the evidence for the corresponding response option as  $\psi_i$ . Evidence for a response direction is related to the stimulus configuration in terms of the motion coherence, which we denote as  $x, x \in [0, 0.5]$ , and the direction of the motion, which we denote as  $r, r \in \{1, 2, 3, 4\}$ . We take noise to be normally distributed with zero mean and unit variance:  $\varepsilon_i \sim N(0, 1)$ . Therefore, the signal model is

$$\psi_i = \begin{cases} 2 \cdot d \cdot x + \varepsilon_i, & \text{if } i = r \\ \varepsilon_i, & \text{if } i \neq r \end{cases} \quad [1]$$

The perceptual sensitivity is  $d$  because it is the expected difference between the evidence at maximum coherence and at no coherence:  $E\{\psi_i | x = 0.5, i = r\} - E\{\psi_i | x = 0\} = E\{d + \varepsilon_i\} - E\{\varepsilon_i\} = d$ .

Second, we describe the representation of response bias. We model response bias as related to the expected value of the response options. According to Bayesian decision theory, the optimal decision is that which minimizes the total expected risk (rather than the decision with the maximum evidence). The total expected risk ( $R_{ij}$ ) for response  $i$  is the sum of the conditional risks for choosing option  $i$  when the correct response may be  $j$ . It is specified in terms of the loss function ( $L_{ij}$ , the loss associated with choosing option  $i$  when the correct response is option  $j$ ) and posterior probability:  $R_{ij} = L_{ij}p(j|\psi)$ . The total expected loss for option  $i$  is the sum over all conditional losses:  $R_{ij} = \sum_{j \neq i} L_{ij}p(j|\psi)$ . As Sridharan et al. (27) observed, all decision regions share at least a point as a boundary within the decision space, meaning that planes of equal risk, or risk “isosurfaces,” separate each decision region from every other decision region. Within each region, the conditional loss for the corresponding choice is less than that of each of the alternatives. Therefore, the response option that minimizes total expected loss also has lower conditional risk than all alternatives.

Because conditional risk is equal on decision boundaries, the plane separating the region corresponding to response option  $i$  from that corresponding to response option  $j$  can be defined by the ratio of conditional risks. If response option  $i$  is preferred over response option  $j$ , then the following inequality holds:

$$\frac{R_{ij}}{R_{ji}} = \frac{L_{ij}p(j|\psi)}{L_{ji}p(i|\psi)} = \frac{L_{ij}p(\psi|j)p(j)}{L_{ji}p(\psi|i)p(i)} < 1.$$

Without much loss of generality, we assume that the cost of any given response option is independent of the possible alternatives. As a result, we can express the inequality in terms of the expected value of a response,  $V_i$ :

$$\frac{p(\psi|j)}{p(\psi|i)} < \frac{L_i p(i)}{L_j p(j)} = \frac{V_i}{V_j} \quad [2]$$

Thus, the decision boundary is the plane in evidence space for which the likelihood ratio is equal to a ratio of expected value for each response. Furthermore, because we have assumed that the evidence variable is normally distributed, we can more easily work with the relationship as the log-likelihood ratio:

$$\ln \frac{p(\psi|j)}{p(\psi|i)} = d \cdot (\psi_j - \psi_i) < \ln V_i - \ln V_j = B_i - B_j \quad [3]$$

Here we define bias for response  $i$ ,  $B_i = \ln V_i$ , as the log of the expected value of that response. Response option  $i$  is preferred to option  $j$  if the following rule is satisfied:

$$d \cdot \psi_i + B_j > d \cdot \psi_j + B_i \quad [4]$$

This decision rule allows us to fully specify the region of evidence space for which the corresponding response,  $Y$ , is  $i$ :

$$Y = i \text{ if } \psi \in \left\{ \psi | d \cdot \psi_i + B_j > d \cdot \psi_j + B_i \forall j \neq i \right\}. \quad [5]$$

Finally, we can find the probability of response given a motion direction by finding the probability of the event described in Eq. 5:

$$p(Y = i | r) = \Pr \left\{ d \cdot \psi_i + B_j > d \cdot \psi_j + B_i \forall j \neq i \right\}.$$

Substituting the signal model in Eq. 1 for the evidence variables gives the event in terms of the Gaussian distributed noise variables:

$$p(Y = i | r, x) = \Pr \left\{ d \cdot (2 \cdot d \cdot x \cdot \delta(i - r) + \varepsilon_i) + B_j > d \cdot (2 \cdot d \cdot x \cdot \delta(j - r) + \varepsilon_j) + B_i \forall j \neq i \right\}.$$

Here  $\delta(\cdot)$  is the Kronecker delta function, which is zero everywhere except where its argument is zero, in which case it is one. Calculating the probability of response requires first finding the conditional probability of response given a particular value of the noise variable,  $\varepsilon_i$ :

$$p(Y=i|r, x, \varepsilon_i = e_i) = \text{pr} \left\{ \varepsilon_j < 2 \cdot d \cdot x \cdot \delta(i-r) - 2 \cdot d \cdot x \cdot \delta(j-r) + e_i + \frac{1}{d} \cdot (B_j - B_i) \forall j \neq i \right\}. \quad [6]$$

However, the right-hand side of Eq. 6 can be expressed as the product of cumulative normal distributions:

$$p(Y=i|r, x, \varepsilon_i = e_i) = \prod_{j, j \neq i} \Phi \left\{ 2 \cdot d \cdot x \cdot \delta(i-r) - 2 \cdot d \cdot x \cdot \delta(j-r) + e_i + \frac{1}{d} \cdot (B_j - B_i) \right\}.$$

With this result we are prepared to find the probability of response given a stimulus configuration in terms of perceptual sensitivity and response bias:

$$p(Y=i|r, x) = \int_{-\infty}^{\infty} \prod_{j, j \neq i} \Phi \left\{ 2 \cdot d \cdot x \cdot \delta(i-r) - 2 \cdot d \cdot x \cdot \delta(j-r) + e_i + \frac{1}{d} \cdot (B_j - B_i) \right\} \cdot \mathcal{N}(e_i) \cdot de_i.$$

Because response probabilities depend on the difference in bias terms, all four terms cannot be specified independently. We therefore chose one of the response directions to be a reference (analogous to the pivot in multinomial logistic regression). The bias terms are then defined with respect to this direction. For convenience, we chose the direction always pointing away from the motion stimulus or from the inactivated region (response option indexed as 3). Therefore, bias is reparameterized as  $B_1^* = B_1 - B_3$ , and  $B_3^* = 0$ . Proportion correct is then

$$p(Y=r|r, x) = \int_{-\infty}^{\infty} \prod_{j, j \neq i} \Phi \left\{ 2 \cdot d \cdot x + e_r + \frac{1}{d} \cdot (B_j^* - B_r^*) \right\} \cdot \mathcal{N}(e_r) \cdot de_r. \quad [7]$$

Examination of Eq. 7 reveals that as either sensitivity or motion coherence increases, choice behavior becomes less dependent on response bias, as expected. Conversely, as bias toward a response option increases, the likelihood of choosing that option increases regardless of motion coherence or direction. Furthermore, Eq. 7 is reminiscent of the probit model in that the argument to the cumulative normal function is a linear combination of

signal strength and bias; in fact, were there only two options, Eq. 7 would reduce to this model.

We estimated the perceptual sensitivity and response bias terms using maximum likelihood estimation. Because Eq. 7 has no closed form solution, for the purposes of estimating parameters we used Monte Carlo integration with a sample size of  $N = 1 \times 10^6$ . Given a Monte Carlo sample  $X_k, k = 1, \dots, N$  and  $X_k \sim \mathcal{N}(0, 1)$ , we approximate Eq. 7 as

$$p(Y=r|r, x) \approx \hat{p}_{rx} = \frac{1}{N} \sum_{k=1}^N \prod_{j, j \neq i} \Phi \left\{ 2 \cdot d \cdot x + X_k + \frac{1}{d} (B_j^* - B_r^*) \right\}.$$

We formed the log-likelihood function based on the number of correct responses ( $C_{rx}$ ) and trials ( $N_{rx}$ ) for each of the four directions ( $r$ ) and each of the coherences used ( $x$ ) for binomially distributed data:

$$\mathcal{L} = \sum_x \sum_r C_{rx} \cdot \ln \hat{p}_{rx} + (N_{rx} - C_{rx}) \cdot \ln(1 - \hat{p}_{rx}).$$

We minimized the negative log likelihood function using the constrained minimization function in MATLAB (we constrained the sensitivity to be always positive). In addition, we performed hypothesis testing on the alternative models using a likelihood ratio test based on this log-likelihood function. We calculated independent 95% confidence intervals as the limits of a distribution of the parameters generated with Monte Carlo Markov Chain simulation ( $N = 1 \times 10^6$ ).

We demonstrate application of this model to both control and inactivation data for the single patch condition in Fig. S5. The model captures the asymmetries in task performance based on response direction that are a product of response bias. Parameter estimates and confidence intervals for both subjects in all conditions are given in Tables S1 and S2.

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