

THE STATISTICAL RELIABILITY OF SIGNALS IN SINGLE NEURONS IN CAT AND MONKEY VISUAL CORTEX*

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Abstract—The variability of the discharge of visual cortical neurons in cats and macaque monkeys limits the reliability with which such neurons can relay signals about weak visual stimuli. In general, the variance of a neuron's firing rate is directly proportional to its mean firing rate. The probability that a neuron will fire a criterion number of impulses on a stimulus trial grows monotonically with the contrast of a sinusoidal grating stimulus. Neural probability functions prepared either by computing the probability of criterion response or by integrating receiver operating characteristics to yield the probability of correct choice in a two-alternative forced-choice situation resemble psychometric functions obtained in psychophysical and behavioral experiments on humans and animals, but are shallower in slope. The slopes of neuronal probability functions are slightly higher when they are estimated over short time periods, but even so do not equal the slopes measured psychophysically in human and monkey observers. This discrepancy in slope could be explained if the whole observer responded only when about four neurons were active together.

Visual cortex Response variability Psychometric functions

INTRODUCTION

The detection of weak visual signals by human and animal observers is probabilistic: on some test trials an observer may correctly report the presence of a stimulus, while on others he may fail to see it altogether. The probability that he will correctly detect a stimulus increases with signal strength until at some strength the observer performs correctly on virtually every trial. The function relating this probability to signal strength is the *psychometric function*. It is generally thought that performance on psychophysical tasks is probabilistic—and that the psychometric function is not a step function—because identical physical stimuli elicit neural responses that vary randomly in amplitude from presentation to presentation. Since this variable neural representation of the sensory event alone is accessible to the observer, he must make a *statistical decision* as to whether a particular level of neural activity is more likely to be the response to a stimulus than a random fluctuation in some ongoing background activity (Tanner and Swets, 1954; Green and Swets, 1966).

In the visual system, the responses of single neurons are subject to random variations in amplitude. Successive presentations of identical stimuli do not yield identical responses, and responses are often superimposed upon a fluctuating spontaneous activity. This

variability or "noise" will limit the reliable discrimination of different responses, although it may have the mitigating advantage of ensuring that the average firing rate of a neuron adequately encodes the time-course of a stimulus (Stein, 1970; Knight, 1972). Barlow and Levick (1969) and Barlow *et al.* (1971) studied the way in which response variability limited the reliability of signals relayed by retinal ganglion cells, and in this paper we extend this kind of analysis to the behavior of neurons in the visual cortex of cats and monkeys. The variability of cortical neuron response is known to be considerable (Henry *et al.*, 1973; Tomko and Crapper, 1974; Rose, 1979; Tolhurst *et al.*, 1981; Dean, 1981b). In this paper we analyze the variability of the discharge of cortical cells in a way that allows us to compare their behavior with the behavior of human and animal observers. From this comparison it appears that the variability of cortical responses is rather greater than the variability of whole observers' responses; the difference is, however, sufficiently small to allow us to model an observer's performance on the assumption that he bases perceptual decisions on signals arising from a rather small number of neurons.

These results have been briefly presented elsewhere (Movshon *et al.*, 1982).

METHODS

Our general methods have been described in detail elsewhere (Movshon *et al.*, 1978a, c; Dean, 1981a; Tolhurst *et al.*, 1981).

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Extracellular recordings were made from neurons in the primary visual cortex (area 17) of cats and macaque monkeys (*Macaca nemestrina* and *Macaca fascicularis*), using tungsten-in-glass microelectrodes (Levick, 1972; Merrill and Ainsworth, 1972). After surgery under halothane followed by a short-acting barbiturate or steroid anesthetic [sodium methohexital (Brietal: Lilly), Althesin (Glaxo) or sodium thio-pental (Pentothal: Abbott)], the animal was paralyzed with an infusion of muscle relaxant (cats—gallamine triethiodide, 10–20 mg·kg⁻¹·hr⁻¹; monkeys—pancuronium bromide, 0.1–0.2 mg·kg⁻¹·hr⁻¹), in a dextrose Ringer's solution (3–10 ml·hr⁻¹), and artificially ventilated with a mixture of N₂O, O₂ and CO₂ (typically 78:20:2) supplemented when necessary with an infusion of sodium pentobarbital (Nembutal: Abbott: 0.5–4 mg·kg⁻¹·hr⁻¹). The expired pCO₂, EKG, EEG and rectal temperature were monitored continuously to ensure the adequacy of anesthesia and the soundness of the animal's physiological condition. At the end of the experiments, the animals were killed with an overdose of barbiturate. If histological confirmation of the electrode tracks were desired, the animal was then perfused through the heart with 10% buffered formalin.

The corneas were protected with zero-power contact lenses containing 3 or 4 mm artificial pupils, and supplementary lenses were used when needed to make the retinas conjugate with a screen between 57 and 160 cm distant. All neurons recorded from cats had receptive fields within 5° of the *area centralis*, while those from monkeys had receptive fields within 1.5° of the center of the fovea. The recording sites were verified as lying within area 17 either histologically or by the location and character of the visual receptive fields.

Receptive fields were classified as simple or complex by the criteria of Hubel and Wiesel (1962, 1968) and Gilbert (1977), and corroborated by the form of responses to sinusoidal gratings (Movshon *et al.*, 1978a, b). The neuron's dominant eye was established and the other eye occluded. Visual stimuli were presented on the face of a display oscilloscope subtending between 5 and 15° at the animal's eye, and the neurons were stimulated with moving sinusoidal gratings generated by a PDP 11 computer. After determining the optimal orientation, spatial frequency, extent and direction of movement of the grating, the dependence of each neuron's response upon the contrast of this grating was examined. *Contrast* is defined as the difference between the maximum and minimum luminance of the grating, divided by twice the mean luminance; the mean luminance was held constant for each neuron at a value between 6 and 200 cd/m².

Experimental design

Neurons were tested with gratings of between 10 and 25 contrast levels, including zero. The gratings drifted steadily across the receptive field at 2 or 4 Hz,

and a *trial* was the presentation of the grating for the time it took one cycle to pass any point on the screen; a trial was thus either 250 or 500 msec in duration. Since we wished to measure steady-state responses, individual trials were not presented; rather, each grating was presented for 10 or 20 trials in succession, after a 1 sec period immediately following the onset of the grating in which data were not collected. This was a *set* of trials, and lasted between 2.5 and 10 sec. Sets of trials were presented in *blocks*, in which each contrast level was presented for one set, in random order; a block lasted between 0.5 and 2 min. In a full experiment, between 5 and 10 blocks were run, each with a different random order of presentation, so that the responses to between 50 and 100 trials were collected for each contrast level. A full experiment lasted between 15 and 30 min.

RESULTS

We studied the behavior of 38 neurons from cats (22 simple, 16 complex) and of 15 neurons from monkeys (3 simple and 12 complex).

The response we studied was the number of nerve impulses fired during each trial of an experiment. While it is possible to examine such other aspects of neuronal discharge as the time intervals between successive impulses (e.g. Werner and Mountcastle, 1963), the simplest comparison with psychophysical measurements could be obtained from the counting distributions (Barlow and Levick, 1969). We assume in this comparison that the information available from the train of nerve impulses produced by a single cortical neuron is well represented by the *number* of impulses that the neuron fires in each of a sequence of defined, relatively short intervals, and that the local structure of the spike train can be ignored (cf. Cattaneo *et al.*, 1981).

Amplitude and variance of response

Figure 1 shows, for two neurons, the mean number of impulses generated in response to each trial of a sinusoidal grating at a number of contrasts; the variance of the mean is also shown. Figure 1a shows data for a simple cell recorded from a monkey; Fig. 1b is for a complex cell recorded from a cat. As the grating contrast increased, both the mean and the variance of the number of impulses increased. For low and moderate contrasts, the mean grew approximately linearly with contrast once a low ("threshold") contrast had been exceeded (Tolhurst *et al.*, 1981; Dean, 1981a). The variance was roughly proportional to the average response (Tolhurst *et al.*, 1981; Dean, 1981b).

This proportionality is illustrated in Fig. 2 for a simple cell recorded from a cat. The large solid squares show how the variance of the response to individual trials was related to the mean response. Each point represents the data for one contrast level. The relationship is approximately linear on the double-logarithmic plot; the continuous line is the

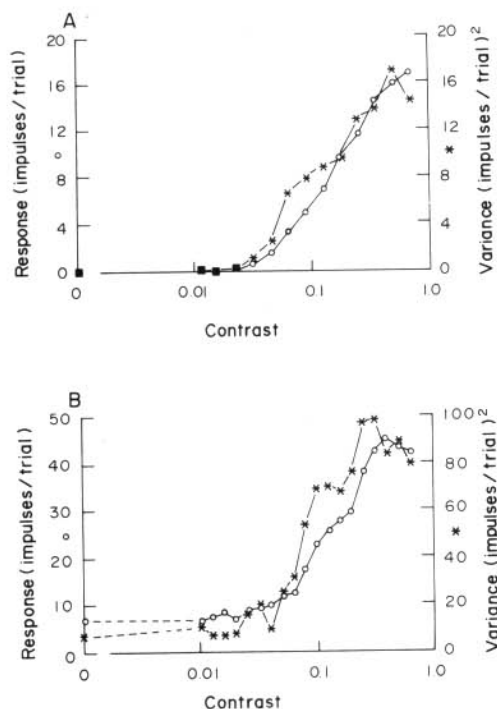


Fig. 1. The mean and variance of the number of impulses fired on each trial by two neurons over a range of stimulus contrasts. In each case the mean response is indicated by circles (left-hand ordinate), and the response variance by stars (right-hand ordinate); the values are based on 100 trials at each contrast level. (A) A simple cell recorded from monkey striate cortex. The spatial frequency was 3.7 c/deg, and the temporal frequency was 4 Hz. (B) A special complex cell recorded from cat striate cortex. The spatial frequency was 1.3 c/deg, and the temporal frequency was 2 Hz.

least-squares regression and has a slope of 1.11 (standard error of estimation = 0.06, $n = 11$, $r = 0.98$), suggesting that the variance was directly proportional to the mean response. The variance was between 2.6 and 3.7 times the mean response; the y -intercept (i.e. the variance when the mean response was 1 impulse per trial) was 2.8.

These data are the means and variances of the responses to 100 trials of the grating at each contrast. Thus each datum summarizes the neuron's behavior over the full duration of the experiment, some 20 min. During this time, it would be likely for the neuron to cycle several times between states of high and low responsiveness (Rose, 1979; Tolhurst *et al.*, 1981). These fluctuations would inflate the ratio of the response variance to the mean response. Now, in this experiment, the grating was presented on 10 separate occasions at each contrast for a set of 10 trials at a time (see Methods). The effects of slow changes in responsiveness may be lessened by considering the mean and the variance of the 10 responses within each discretely presented set. Each datum would then summarize, albeit less accurately, the neuron's behavior over a period of only 5 sec.

The small circles in Fig. 2 show the relationship between the variances and means calculated in this way for each set of 10 trials. Each contrast level is now represented by 10 data points (except when the mean response was less than 0.2; see legend). The small solid circles show the 10 points for one contrast level, and it may be seen that both the mean and variance of the response to the one stimulus changed considerably during the experiment. The slope of a regression line fit to the data from individual trials shown by small circles (dashed line) is 0.99 (SE = 0.05, $r = 0.89$, $n = 103$), and so is little changed. The ratio of variance to mean, however, is reduced by about 50% (as is the y -intercept), to about 1.5. One would expect this analysis to yield a modest decrease in variance, due to the smaller sample sizes involved, but the observed change is about five times larger than this expectation. This shows the importance of the contribution that slow changes in responsiveness can make to the overall estimates of variance calculated from data collected over periods of 15–30 min.

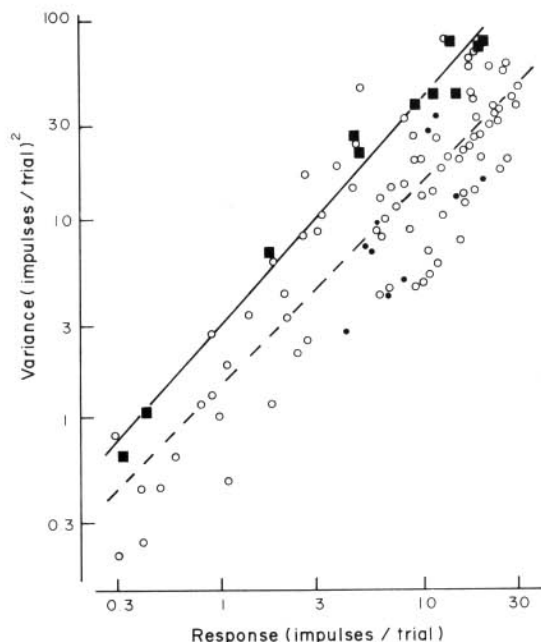


Fig. 2. The relationship between the mean and variance of response for a simple cell recorded from cat striate cortex. The large squares show the relationship between the mean and variance of the response to 100 trials of the grating at each of several contrasts. The continuous line is the regression line for these data. Each small circle shows the relationship between the mean and the variance of response to the 10 trials comprising one set at one contrast. However, if no impulses or only a single impulse were generated in a set of trials, the variance is zero and no information about the underlying process is available. Thus data from seven of the 110 data sets in which less than 2 impulses were generated have not been plotted and were not used for the regression calculation (dashed line). To give an impression of trial-to-trial variability, the small solid circles show the 10 data sets for one of the 11 contrast levels.

Analyses of this kind were performed for 22 neurons recorded from cats, with similar results. The average slope of the relationship between the logarithm of the mean response and the logarithm of its variance was 1.09 (SD = 0.09, $n = 22$), demonstrating the linear nature of the relationship. The results for simple and complex cells did not differ. The average value of the y -intercept of the regression for the full 100 cycles for these 22 neurons was 2.80 (SD = 1.19); this fell to 1.76 (SD = 0.48) when it was calculated from the separate sets of cycles. Not only was the average value reduced by examining the response over short time periods, but the standard deviation of the average ratio was also less ($F = 6.16$; d.f. = 21, 21; $P < 0.001$). This suggests that all neurons tend to have similar instantaneous ratios of response variance to mean response; widely differing values of the long-term ratio may result from different degrees of slow response fluctuation during the experiment.

Probabilistic nature of response

While it is plain that the variability of neuronal discharge must influence visual performance in some way, it is not obvious from data like those shown in Figs 1 and 2 how best to determine the nature and magnitude of this influence. Fig. 3 shows how the neuronal unit data can be related to psychophysical measures of performance.

In the two parts of this figure we plot data for the same two cells whose responses were illustrated in Fig. 1. Here, rather than showing the *mean* response to each contrast, we plot the *probability* that the response on a given trial equalled or exceeded some criterion number of impulses. In Fig. 3A, the criterion responses are 1, 2, 4 and 8 impulses per 250 msec trial; in Fig. 3b, they are 5, 10, 15 and 20 impulses per trial. The probability in all cases rose monotonically from a low value at low contrast levels towards an asymptotic probability near 1.0. The curves drawn through the data have the form

$$P = \delta - (\delta - \gamma) \exp[-(m/\alpha)^\beta] \quad (1)$$

*Maximum-likelihood fitting procedures of this sort are known to be biased when the number of trials contributing to the fit is small; in this case, the most prominent bias would be an overestimate of the value of β (J. Nachmias, personal communication). In order to evaluate the possible bias in our estimates, we performed a number of Monte Carlo simulations of psychometric functions having the form of equation 1, and fit these simulated functions using the maximum-likelihood procedure. For situations like our own (with between 10 and 25 contrast levels each represented by between 50 and 100 trials), the most important factor biasing the estimates of β was the value of γ , the "guessing rate". For a γ value of 0, the mean estimate of β was within 1% of the true value, with a standard deviation of about 3% ($n = 12$). As γ was increased, the estimates of β increased slightly and became more variable: with a γ of 0.5, the mean estimate of β was about 7% larger than the true value, with a standard deviation of about 15% ($n = 12$). Thus even in the worst cases we encountered, the bias was negligible and the standard error of the estimate acceptable for our purposes.

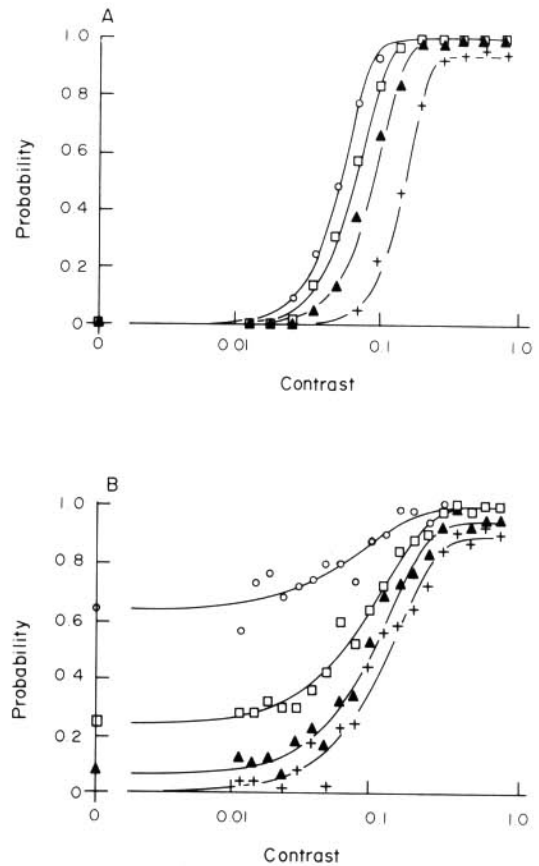


Fig. 3. The probability that at least a criterion number of impulses were fired in a trial by the same two neurons as Fig. 1, again estimated from 100 trials at each contrast level. (A) The simple cell. The response criteria are 1, 2, 4 and 8 impulses per 250 msec trial (circles, squares, triangles and plus). (B) The complex cell. The response criteria are 5, 10, 15 and 20 impulses per 500 msec trial (circles, squares, triangles, plus). The smooth curves are the best-fitting versions of equation 1 (see text).

where P is the probability that the number of impulses in an interval will equal or exceed some criterion value, m is stimulus contrast, α is the contrast at which a criterion probability is reached, β is a parameter governing the slope of the function, γ is the probability of attaining a criterion response in the absence of a stimulus, and δ is the asymptotic value of P as m becomes large. This equation is the integral of the Weibull distribution function, and was introduced as a description of human psychometric functions by Quick (1974). It has certain mathematical advantages (discussed by Quick and by Nachmias, 1981), and provides an acceptable fit to most of our data; we do *not* use it to imply any particular model of response variability. The curves were fitted with an iterative maximum-likelihood estimation procedure (Watson, 1979), with α , β , γ and δ all allowed to vary to find the best fit*. This procedure yields an estimate of goodness of fit which is distributed as χ^2 ; the fit could be rejected with 95% confidence for only six of the 295 data sets examined. Typically, varying the value of the

parameter α by more than about 10%, or the value of β by more than about 20%, caused the value of the error statistic to increase significantly.

An interesting feature of the curves in Fig. 3 is that the slope parameter [β from equation (1)] changed little for the different values of criterion chosen for either cell. For the simple cell, the best values of β for the four criteria shown were 2.6, 2.2, 2.3 and 2.5; for the complex cell, the values were 1.2, 1.3, 1.5 and 1.5. It was generally the case that as the criterion response was increased, β remained roughly constant. This suggests that no simple model of the stochastic process underlying the curves can be generated, since common Poisson or renewal processes (Cox and Lewis, 1966) all share the characteristic that as criterion increases, β should increase markedly.

Signal detection analysis of response

There was an obvious difference between the two neurons whose data are shown in Figs 1 and 3. The simple cell (Figs 1a and 3a) generated no impulses in the absence of a stimulus, while the complex cell (Figs 1b and 3b) had a fairly high level of maintained firing (about 7 impulses \cdot sec⁻¹) in the absence of a stimulus. This difference is strikingly reflected in Fig. 3: for the simple cell, even at the lowest criterion value used (one impulse per trial), the probability of encountering a criterion response on a trial without a stimulus was zero. For the complex cell, however, even a criterion of five impulses per trial was exceeded on about two-thirds of the trials without a stimulus; it was necessary to raise the criterion to roughly 15 impulses per trial in order to obtain a reasonably low probability of response at zero contrast.

If, therefore, an observer were to rely on the activity of a neuron (like the simple cell) with no spontaneous activity, he could confidently report the presence of a stimulus whenever it generated an impulse on a trial. His psychometric function would be identical to the neuron's psychometric function with a criterion of one impulse. This strategy would be inappropriate if the observer were to rely on a neuron with considerable spontaneous activity (like the complex cell): the criterion of one impulse would be exceeded on virtually every trial, whether it contained a stimulus or not. The observer could adopt some arbitrary criterion which would result in fewer positive responses to blank trials; he could, for instance, respond only when the neuron fired at least 15 impulses on a trial. He would then respond on about 7% of trials containing no stimulus, and his psychometric function would be the third function of Fig. 3b.

In situations where they are forced to decide on the presence of a stimulus, human observers, like the complex cell (Fig. 3b), typically respond "yes" on some proportion of the trials that in fact contain no stimulus. It is now common in psychophysics to use the methods of *signal detection theory* (Green and Swets, 1966) to analyze situations of this kind. In a signal-detection paradigm, some factor is manipulated

to cause the subject to alter his *response criterion*—a rating-scale procedure in which the subject reports his confidence that an event occurred is often used. For low criteria or low confidence ratings, an observer will often correctly report the presence of weak stimuli, but will also generate frequent "false-positive" responses. For high criteria or high confidence ratings, the observer will rarely give false positive responses, but detects correspondingly fewer weak stimuli. Precisely analogous behavior would result from relying on the activity of the complex neuron of Fig. 3b.

The appropriate analysis for such data is made from a *receiver operating characteristic* (ROC), which is obtained by plotting, for each choice of criterion or confidence rating, the probability of a correct detection against the probability of a false positive report. Figure 4a shows a family of ROCs derived from the family of psychometric functions shown in Fig. 3b for the complex cell. Each point represents the pair of probabilities associated with one criterion response level at one contrast—we have substituted a range of criterion response magnitudes for the rating scale that is usually used psychophysically. The points on each curve show the data for one contrast (and zero contrast, from which the false-positive rate is obtained). Data for five contrast levels are shown, ranging from a contrast that the cell could not reliably have discriminated from a blank field (0.02, circles), to a contrast that could have been almost perfectly detected (0.32, crosses). As contrast increased, the ROC became more bowed away from the diagonal towards the top left corner of the unit square.

In analyzing ROCs, it is usual to extract the parameter d' , which is an index of the discriminability between the "signal" and "noise" processes underlying performance (Green and Swets, 1966). However, this analysis assumes that the variability of the signal and noise processes is identical, and is Gaussian. Our data show that response variance is by no means independent of response magnitude (Figs 1 and 2); moreover, the distribution of response magnitudes is not Gaussian (Dean, 1981b). We therefore analyzed our ROCs using a more general method which involves computing the *area* under the ROC. This area represents the probability that of a given pair of samples, one from the signal process and one from the noise process, the sample of the signal process will have the larger value (Green and Swets, 1966; Bamber, 1975). This corresponds naturally to the two-alternative forced-choice procedure in psychophysics, in which the observer is required to distinguish between two stimuli, one of which is blank and the other of which contains a stimulus. Recall that the ROC is plotted on a unit square; an ROC following the left and upper boundaries of the square would cover an area of 1.0, implying perfect discrimination; an ROC following the diagonal would cover an area of 0.5, implying chance performance. If we suppose that an observer, basing his decisions on the output of a neuron in a two-

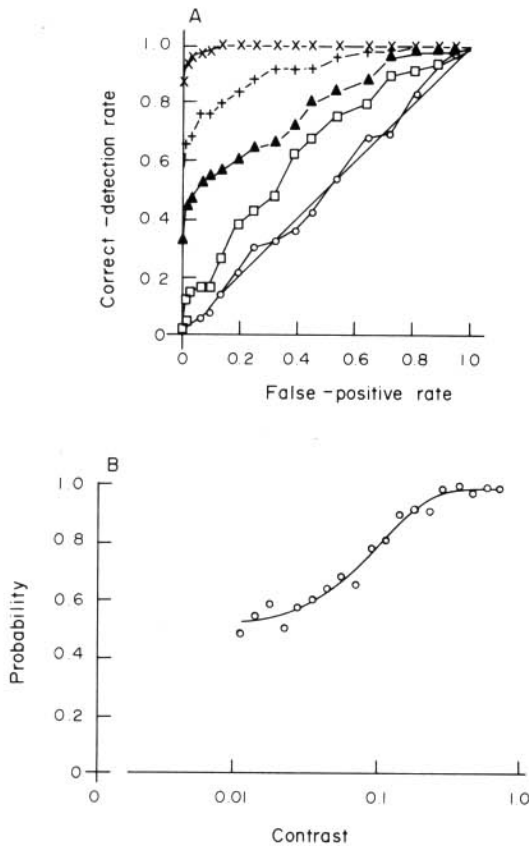


Fig. 4. Receiver operating characteristic (ROC) analysis of the data from the complex cell of Figs 1b and 3b. (A) ROCs derived from the functions of Fig. 3b. For each choice of criterion and each contrast level, the ordinate plots the probability of attaining a criterion response on a stimulus trial and the abscissa plots the probability of obtaining that response on a blank trial. Each ROC is constructed from a range of criteria between 1 and 23 impulses per trial. ROCs are shown for stimulus contrasts of 0.02 (circles), 0.04 (squares), 0.08 (triangles), 0.16 (plus) and 0.32 (crosses). The d' values estimated for these ROCs by the procedure of Bamber (1975) would be 0.04, 0.52, 1.11, 1.96 and 3.75. (B) The probability of correctly discriminating a stimulus trial from a blank trial is plotted against contrast. The probabilities are computed by integrating the ROCs shown in A. The smooth curve is the best fitting version of eqn. 1, with the constraint that $\gamma = 0.5$. The fitted value of β is 1.29.

alternative situation, simply chooses the interval in which a greater number of impulses were fired as containing the stimulus, the area under each ROC in Fig. 4a may be taken as the probability that the observer would correctly distinguish a stimulus of the given contrast from a blank stimulus.

In Fig. 4b, we plot the probability values derived from integrating the ROCs shown in Fig. 4a. At very low contrasts the probability was near 0.5, since the neuron fired equally often on signal and blank trials and the ROCs were near the diagonal. At high contrasts the ROCs approached the boundaries of the unit square, and the probability approached 1. Again the smooth curve is equation (1), but in this case the

parameter γ is fixed at a value of 0.5 (the theoretical value when the signal and blank trials give equal responses).

Brief consideration of the construction of the ROC reveals that, for a neuron lacking spontaneous activity, P_r (the probability derived from the ROC) will be given by

$$P_r = 0.5 + 0.5 P_{yn} \quad (2)$$

where P_{yn} is the probability derived from a "yes-no" analysis at the lowest available criterion; fits to the data of equation (1) will differ only in that γ will change from 0 to 0.5 and δ will change to $(1 + \delta)/2$. So, for neurons whose spontaneous activity was low enough to make the "false-positive" response rate negligible ($n = 22$), we took our estimates of the "threshold" and "slope" parameters α and β from "yes-no" data at a criterion of one impulse per trial. For neurons having significant spontaneous activity ($n = 31$), we based our estimates of these parameters upon probabilities derived from integration of ROCs like those shown in Fig. 4.

Distributions of psychometric function shape

For each of the 53 neurons we studied, we estimated the parameters of the best-fitting version of equation 1: we were particularly interested in the threshold parameter α and the slope parameter β . Figure 5 shows the distribution of values of α and β obtained for our population of neurons. Data for simple and complex cells are plotted separately, and data obtained from monkeys are indicated by stippling.

In Fig. 5a, the distribution of α is shown. The value of this "threshold" parameter is the lowest contrast at which the neuron's response would be greater than its baseline response on 82% of trials. Comparing Fig. 1a with Fig. 3a and, Fig. 1b with Fig. 4b, reveals that values of α for the neurons in question were two to three times larger than the contrast values at which

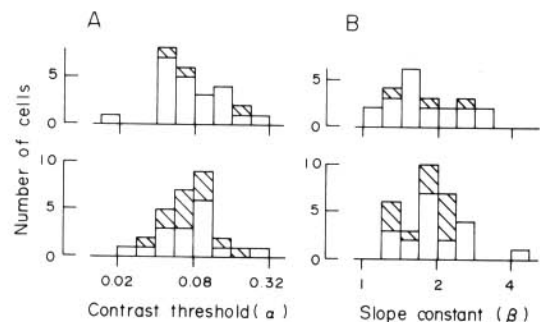


Fig. 5. Distributions of the parameters α and β from equation (1) for the best fits to data from 53 neurons. (A) Distributions of the value of α . The upper histogram represents data from simple cells; the lower histogram represents complex cells. Neurons recorded from monkey striate cortex are stippled. (B) Distributions of the value of β . The upper histogram again represents simple cells, the lower, complex cells, and data from monkey striate neurons are cross-hatched.

the neurons gave reliable *average* responses; this was the case for most other neurons in our sample. Although α would certainly be expected to vary with spatial frequency, this variation was not marked in our sample. This is probably due to the fact that we studied rather few neurons preferring spatial frequencies remote from the frequencies to which either cats or monkeys are most sensitive. The logarithmic mean values of α did not differ between monkeys (0.079) and cats (0.071); nor did simple cells (0.077) differ from complex cells (0.073). The only reliable source of variation in the data was mean luminance: values of α obtained at high luminance (50–200 cd/m², mean = 0.065) were slightly lower than those obtained at low luminance (6 cd/m², mean 0.083) (cf. Hess and Lillywhite, 1980).

It may be seen that while α varied rather widely, the most sensitive neurons in our sample had values of α that approach those observed in psychophysical experiments on animals (see for example DeValois *et al.*, 1974; Pasternak and Merigan, 1981).

Figure 5b shows distributions of the value of β , the slope parameter from equation (1). It may be seen that most values of β fell between 1.25 and 2.5, with a logarithmic mean of 1.82. The mean values of β for neurons from cats (1.83) and monkeys (1.81) were indistinguishable; complex cells (1.96) had a slightly higher mean value of β than simple cells (1.75), although this difference was not statistically significant. As we will consider in the Discussion, the values of β shown here are rather lower than those obtained from human and animal psychophysical observers.

We noticed a tendency for high values of α to be associated with high values of β : these parameters were weakly correlated ($r_{\alpha\beta} = 0.256$, $n = 53$), and this correlation was significant ($t = 1.89$, d.f. = 51, $P < 0.05$).

Short-term and long-term variability of responses

In the course of a series of measurements lasting 15 to 30 min, the responsiveness of cortical neurons seems to fluctuate slowly. As shown by Fig. 2, this

non-stationarity of response contributes markedly to the estimated variability of cortical neuron discharge. The values of the slope constant β shown in Fig. 5b were also based on the full experiment for each neuron, but if the sensitivity were to fluctuate over the trials of an experiment, this would have the effect of reducing the estimate of the slope (cf. Hallett, 1969). To examine the idea that the instantaneous value of the slope constant was higher than the one obtained from full samples, we fitted equation 1 to the set of data for a full experiment, but allowed the threshold parameter α to assume a different value for data from each block of trials (recall that each block contained 10 or 20 trials of each stimulus, and lasted 2–5 min). The slope parameter β (and the asymptotes γ and δ) thus assumed a single value that best described the data from all sets of trials, after the value of α had been optimized for each set. This tests the hypothesis that there exist fluctuations in sensitivity from block to block in an experiment like ours, and that the effect of these fluctuations is to shift the function of equation (1) rigidly along a log contrast axis. If there were no such slow fluctuation, the block-by-block estimate of β should not differ from the estimate obtained over the whole experiment*.

Figure 6 shows the results of this fitting procedure for one neuron, a complex cell recorded from a cat. This neuron had a low spontaneous firing rate, and the probabilities are thus derived from the "yes-no" procedure with a criterion response of one impulse per trial. Figure 6a shows the data averaged over the full 100 trials of the experiment, and two fitted versions of equation (1). The curve of shallower slope shows the fit for the full data set: β was 2.8, and α was 0.099. The curve of steeper slope shows the fit in which a separate value of α was sought for each block of the experiment; β was 6.1, and the logarithmic mean value of α (illustrated) was 0.092. Figure 6b shows superimposed the separate data for four of the ten separate sets of trials presented at each contrast. In each case, probabilities from low and high contrasts where the values were asymptotically stable have been omitted for clarity. The fitted values of α for these sets of data ranged from 0.054 to 0.163. It is clear that the slopes of each data set in Fig. 6b were steeper than that of the overall mean values shown in Fig. 6a, and that the curve of steeper slope in Fig. 6a provides a much better estimate of these individual slopes than does the shallower curve.

In each of the 18 cases for which we performed this analysis, the short-term estimate of β was higher than that obtained over the whole experiment. Figure 7 shows a scatter diagram of these cases: the abscissa represents the value of β obtained over the whole experiment, and the ordinate represents the value of β obtained from the block-by-block analysis. On average, the short-term estimate of β was about 25% higher than the long-term estimate. As would be expected, the data sets yielding the largest increase in β also showed the greatest scatter in α across the trials of the

*We evaluated the possibility that the biases of our maximum-likelihood estimates might increase under these conditions by performing further Monte Carlo simulations of the psychometric functions. We broke our simulated functions with 100 trials per point into 10 data sets, each with 10 trials/point, and fitted them with α free to assume a separate value for each data set. This only slightly increased the estimates of β when γ was small—for a γ of 0, the mean estimate of β was about 3% higher than the true value, with a standard deviation of about 5% ($n = 12$). For no simulated data set with a γ value below 0.1 did we observe an increase in the estimate of β larger than 12%. When γ became large, however, the bias was much more severe—for a γ of 0.5, the mean estimate of β was about 40% higher than the true value, with a standard deviation of about 30% ($n = 12$). We therefore performed the separate-trials analysis only on data for which the value of γ (the "guessing rate", or false-positive rate) was less than 0.1, and did not use data requiring ROC analysis.

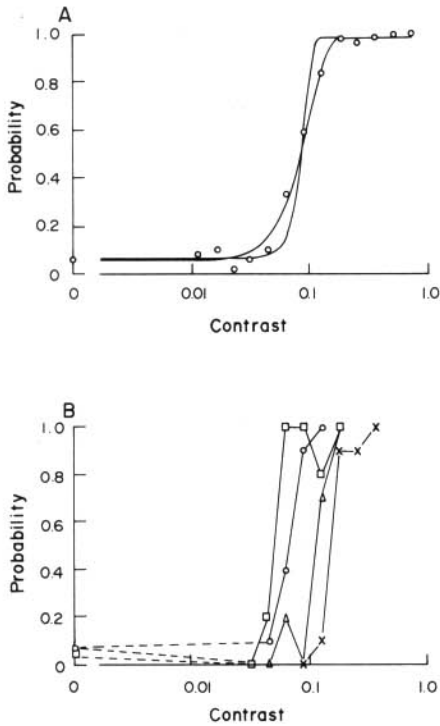


Fig. 6. Analysis of the short-term response variability for a complex cell from a cat. The spatial frequency was 2.2 c/deg and the temporal frequency was 4 Hz. (A) The probabilities based on all 10 blocks (100 trials) of the experiment. Two fitted versions of equation (1) are shown: the shallower curve represents a single fit to the whole data set; the steeper curve represents the mean of the curves fitted as described in the text to each of the 10 sets of trials. (B) The probabilities for four of the 10 blocks considered separately. The data sets shown were fit by values of α of 0.054, 0.076, 0.127 and 0.163 (squares, circles, triangles and crosses, respectively); these include the lowest and highest values obtained in the 10 blocks of the experiment. Each point represents a probability estimate based on ten trials at each contrast. Points at either end of each curve whose values are asymptotically stable have been omitted for clarity.

experiment. For different neurons, the scatter of values of α ranged from 1.5 to 1 to over 3 to 1. We conclude that some slow fluctuation contributed significantly to our estimates of β , and that the instantaneous value of β was in fact somewhat larger than our estimates.

DISCUSSION

In this paper we have examined the variability of response to visual stimuli of neurons in the striate cortex. By constructing "psychometric functions" for individual neurons and using analyses derived from signal detection theory, we have tried to frame our data in a manner as similar to common psychophysical practice as we could. While the data could also provide a basis for a formal statistical model of the processes underlying the response variability, our preliminary attempts in this direction have been un-

successful. Simple Poisson or renewal statistics are inadequate to account for the data for several reasons. First, the ratio of response variance to mean response is typically greater than one. Second, the slopes of the probability functions are invariably greater than 1 (Fig. 5b); moreover, these slopes do not increase with increases in criterion. Two-stage models (cf. Smith and Smith, 1965) show some promise in accounting for these observations, but are still inadequate.

Physiological and psychophysical variability

Our data allow us to examine the relationship between the activity of single cortical neurons and the behavior of human and animal observers in psychophysical situations. To do this we make several assumptions.

One important assumption is that the performance of neurons in anesthetized animals may usefully be compared with that of alert observers. It is generally believed that both neural sensitivity and response variability are affected by general anesthesia. Responsiveness has been reported to be depressed by sleep or anesthesia for neurons in the lateral geniculate nucleus (Maffei and Rizzolatti, 1965; Coenen and Vendrik, 1972) and visual cortex (Ikeda and Wright, 1974; Livingstone and Hubel, 1981). Anecdotal evidence (e.g. Livingstone and Hubel, 1981) also suggests that the statistical character of activity may also be changed, but the quantitative analyses that are available for the spontaneous activity of neurons in cerebral cortex suggest that this effect is slight (Noda and Adey, 1970, 1973; Webb, 1976). We are aware of no data on the variability of visually-driven responses in awake animals, and so we tentatively assume that the instantaneous statistics of neuronal discharge are not grossly altered by anesthesia, even though sensitivity may be reduced. It is also uncertain whether the slow changes in responsiveness we observe are idiosyncratic to anesthetized animals. Periodic sensitivity fluctuations have been reported for alert human observers (Semenoff, 1941; Lee, Finch and Pounds, 1945), and the period and time-course of these fluctuations

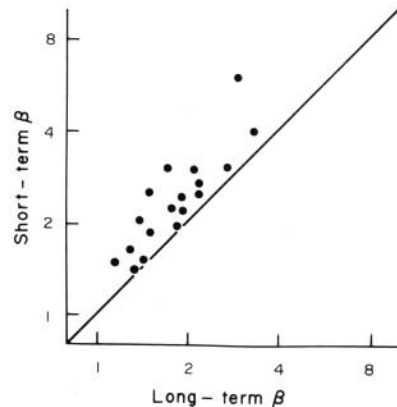


Fig. 7. A scatter diagram of the values of β obtained from long-term (abscissa) and short-term (ordinate) analyses of data for 18 neurons.

are comparable to those we observed in neurons (Figs 6 and 7; Tolhurst *et al.*, 1981). It may therefore be reasonable to suppose that the drifts in neuronal responsiveness reflect a normal rather than a pathological process.

A second assumption is that all variability importantly affecting psychophysical responses occurs at or before the level of the striate cortex. While this rather sweeping assumption might at first seem implausible, it is worth noting that many of the spatial and temporal characteristics of mechanisms thought to mediate contrast detection and discrimination are very similar to the observed spatial and temporal characteristics of visual cortical neurons (see Robson, 1980, for a review). If it is the properties of neural mechanisms like those found in visual cortex that limit visual detection and discrimination performance, then it does not seem unreasonable to suppose that cortical variability should reflect psychophysical variability in these tasks.

Contrast sensitivity

The contrast required to elicit a reliable discharge from any but the most sensitive neurons we observed is probably higher than the contrast threshold of a whole cat or monkey. Unfortunately, the magnitude of the discrepancy is difficult to assess. First, most behavioral studies have used displays of rather low luminance, and luminance importantly affects the contrast sensitivity of both neurons (Hess and Lillywhite, 1980) and cats (Pasternak and Merigan, 1981). Second, as discussed above, anesthesia would be expected to depress the sensitivity of our sample of neurons to some degree. Third, while all the neurons in our sample had receptive fields relatively close to the visual axis, contrast sensitivity falls rapidly (at least in man) as stimuli are presented further into the retinal periphery (Robson and Graham, 1981). Finally, the estimates of α we obtained depend slightly on our (essentially arbitrary) choice of sampling interval. Shorter sampling intervals would increase α , while longer ones would decrease it. There is no objective basis for choosing any particular interval, since we have no way of knowing the interval over which whole observers monitor neural activity when making threshold judgements.

Assuming that there is a genuine sensitivity difference between our neurons and whole animals, the discrepancy would be automatically resolved if more than one neuron were capable of responding to the low contrast stimulus, and if the chance that any particular neuron would respond were independent of the chance that any other neuron would respond. The probability of overall response at any contrast would then be given by

$$P = 1 - \prod_i (1 - p_i) \quad (3)$$

where p_i gives the detection probability for each neuron. A property of the Weibull formulation for the

psychometric function [equation (1)] is that under probability summation with constant β , the psychometric function does not change shape when plotted on a log contrast axis: β remains constant and α decreases by an amount given for n identical neurons by

$$\alpha_n = \alpha \cdot n^{-1/\beta} \quad (4)$$

where α_n is the overall threshold and α is the threshold of each neuron. This is illustrated in Fig. 8a, which shows a psychometric function of the form of equation (1) (with $\beta = 2$), and its transformations under probability summation with values of n of 2, 4, 8 and 16. For this choice of β , the value of α_n is reduced by $\sqrt{2}$ for each doubling of the number of neurons available. If β were higher, the change in α_n would be correspondingly less.

Psychometric function slope

Our estimates of the slope constant β (Fig. 5b) had a mean of 1.84, and ranged from 1.2 to 4.7. This range is rather lower than that obtained from human observers in psychophysical experiments: there, values of β usually fall between 3 and 5 (Quick, 1974; Watson, 1979; Nachmias, 1981). Well-trained monkeys also yield psychometric functions whose slopes fall in this range. W. H. Merigan of the University of Rochester and R. Harwerth of the University of Texas Medical Center made some of their psychometric function data for macaque monkeys available to us. Fitting equation (1) with the same procedure that we used for the neurophysiological data gave estimates of β between 2.4 and 5.7; the logarithmic mean of 11 slopes for monkey psychometric functions was 4.2. Even if we accept that the short-term estimates of β shown in Figs 6 and 7 represent an appropriate psychophysical comparison, our physiological estimates of β do not approach these ranges. Cats typically produce psychometric functions of shallower slope: we fit equation (1) to a collection of published psychometric functions for cats (Bisti and Maffei, 1974; Pasternak and Merigan, 1981)— β lay between 1.2 and 3.2, with a mean of 2.0 for these data. Cats are, however, notoriously difficult animals to train effectively, and it is possible that the shallow slopes of their measured psychometric functions are in part due to poor attention by the animal observers in the testing situation. We observed no systematic difference between the values of β for neurons from cats and monkeys (Fig. 5). We conclude that the slopes of "psychometric functions" measured for single cortical neurons are in general shallower than the slopes of psychometric functions measured in whole human and animal observers, and thus reject the notion that individual cortical neurons are as reliable in their performance as alert observers.

This discrepancy between the values of β for single neurons and whole observers could, however, be resolved if an observer failed to respond if only a single neuron from the available pool were active alone. If, instead, detection were possible only when

several neurons were active together, and the likelihood of their activity was again independent, the overall probability of detecting a particular contrast would be given by "probability multiplication". The predicted detection probabilities here have the form

$$P = \prod_i p_i. \quad (5)$$

While the Weibull function does not retain its analytic form under this manipulation, its shape is not markedly altered. Figure 8b illustrates the same psychometric function as Fig. 8a, and its transformations under probability multiplication with an n of 2, 4, 8 and 16. If equation (1) is fitted to these curves, the resulting β rises rapidly with n , becoming 3.0 for an n of 2, 4.1 for an n of 4, 5.1 for an n of 8 and 6.0 for an n of 16. If β is initially higher, the rise is correspondingly more rapid. The increase in β is of course obtained at the expense of an increase in α (i.e. a decrease in sensitivity), but this increase is not dramatic: α is elevated by about 50% for an n of 5, and by a factor of 2 for an

n of 16. But this increase in α could easily be overcome by probability summation, which in combination with probability multiplication could certainly reconcile our observations on single neurons with the performance of human and monkey observers.

These two combinatorial mechanisms for lowering threshold and for increasing the slope of the psychometric function beyond the values encountered in single neurons rely on an important assumption: the activity of a neuron on a particular trial is unrelated to the activity of other neurons in the available pool. Toyama *et al.* (1981a, b) have recently shown that the discharges of pairs of neurons in the cat's visual cortex can be markedly correlated, especially when they are recorded within 100 to 200 μm of one another. If the activity of the neurons were correlated to some degree, a larger pool of neurons would have to be available to produce the same lowering of threshold, and more neurons would have to be active simultaneously to produce the same steepening of the psychometric function at those shown in Fig. 8.

Neural substrate

We may conclude that, given the assumptions discussed above, psychophysical detection of a reliability similar to that shown by human and macaque observers could be mediated by combining the signals from a small number (between 2 and 8) of cortical neurons having properties like those reported here. The requisite contrast sensitivity would result from probability summation over several such small groups of neurons. While this number seems minute when compared with the number of visual cortical neurons available, a brief reflection makes it seem less startling. Most of the cortical neurons whose receptive fields include a particular patch of the visual field are selective for a number of visual stimulus dimensions, including orientation, spatial frequency, direction of movement, color, binocular disparity and eye dominance. We may suppose that among these neurons there is a sufficient variety of combinations of stimulus preference that any particular combination is closely approached. If this is so, then relatively few neurons can be available whose preferences *precisely* match any *given* stimulus. It is thus not implausible that a mere handful of visual cortical neurons would be involved in detecting any particular visual stimulus.

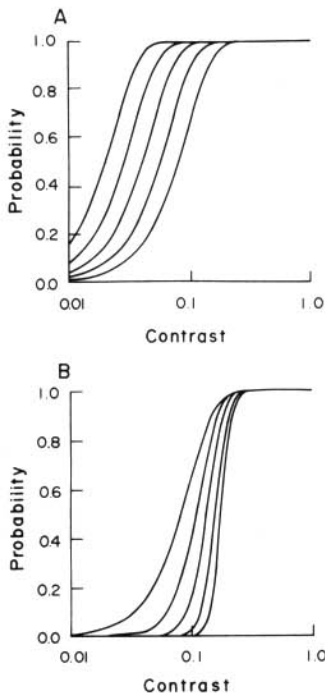


Fig. 8. Two simple models of the way in which signals from single neurons might be combined to yield "overall" psychometric functions. (A) "Probability summation". The overall response occurs if *any* of the neurons respond. The rightmost function represents the modelled psychometric function for one neuron. It is equation (1) with $\alpha = 0.1$, $\beta = 2$, $\gamma = 0$ and $\delta = 1$. The four functions to the left represent (in right-to-left sequence) computed psychometric functions for combinations of 2, 4, 8 and 16 neurons. (B) "probability multiplication". The overall response occurs only if *all* neurons respond. The leftmost function is the same model function as in Fig. 8a. The four functions to the right represent (in left-to-right sequence) psychometric functions for combinations of 2, 4, 8 and 16 neurons.

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REFERENCES

- Bamber D. (1975) The area above the ordinal dominance graph and the area below the receiver operating characteristic graph. *J. Math. Psychol.* **12**, 387–415.
- Barlow H. B. and Levick W. R. (1969) Three factors affecting the reliable detection of light by retinal ganglion cells of the cat. *J. Physiol., Lond.* **200**, 1–24.
- Barlow H. B., Levick W. R. and Yoon M. (1971) Responses to single quanta of light in retinal ganglion cells of the cat. *Vision Res., Suppl.* **3**, 87–101.
- Bisti S. and Maffei L. (1974) Behavioural contrast sensitivity of the cat in various visual meridians. *J. Physiol., Lond.* **241**, 201–210.
- Cattaneo A., Maffei L. and Morrone C. (1981) Patterns in the discharge of simple and complex visual cortical cells. *Proc. R. Soc. Lond., Ser. B* **212**, 279–297.
- Coenen A. M. L. and Vendrik A. J. H. (1972) Determination of the transfer ratio of cat's geniculate neurones through quasi-intracellular recordings and the relation with level of alertness. *Expl Brain Res.* **14**, 227–242.
- Cox D. R. and Lewis P. A. W. (1966) *The Statistical Analysis of Series of Events*. Chapman & Hall, London.
- Dean A. F. (1981a) The relationship between response amplitude and contrast for cat striate cortical neurones. *J. Physiol., Lond.* **318**, 413–427.
- Dean A. F. (1981b) The variability of discharge of simple cells in the cat striate cortex. *Expl Brain Res.* **44**, 437–440.
- De Valois R. L., Morgan H. and Snodderly, D. M. (1974) Psychophysical tests of monkey vision III. Spatial luminance contrast tests of macaque and human observers. *Vision Res.* **14**, 75–81.
- Gilbert C. D. (1977) Laminar differences in receptive field properties in cat primary visual cortex. *J. Physiol., Lond.* **268**, 391–421.
- Green D. M. and Swets J. A. (1966) *Signal Detection Theory and Psychophysics*. Wiley, New York.
- Hallett P. E. (1969) The variations in visual threshold measurement. *J. Physiol., Lond.* **220**, 403–419.
- Henry G. H., Bishop P. O., Tupper R. M. and Dreher B. (1973) Orientation specificity and response variability of cells in the striate cortex. *Vision Res.* **13**, 1771–1779.
- Hess R. F. and Lillywhite P. G. (1980) Effects of luminance on contrast coding in cat visual cortex. *J. Physiol., Lond.* **300**, 56–57P.
- Hubel D. H. and Wiesel T. N. (1962) Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. *J. Physiol., Lond.* **160**, 106–54.
- Hubel D. H. and Wiesel T. N. (1968) Receptive fields and functional architecture of monkey striate cortex. *J. Physiol., Lond.* **195**, 215–243.
- Ikeda H. and Wright M. J. (1974) Sensitivity of neurones in visual cortex (area 17) under different levels of anaesthesia. *Expl Brain Res.* **20**, 417–484.
- Knight B. W. (1972) Dynamics of encoding in a population of neurones. *J. gen. Physiol.* **59**, 734–766.
- Lee R. G., Finch E. M. and Pounds G. A. (1945) Periodic fluctuations in the dark-adapted threshold. *Am. J. Physiol.* **143**, 6–10.
- Levick W. R. (1972) Another tungsten microelectrode. *Med. Biol. Engng* **10**, 510–515.
- Livingstone M. S. and Hubel D. H. (1981) Effects of sleep and arousal in the processing of visual information in the cat. *Nature* **291**, 554–561.
- Maffei L. and Rizzolatti G. T. (1965) Effects of synchronized sleep on the response of lateral geniculate units to flashes of light. *Archs Ital. Biol.* **103**, 609–622.
- Merrill E. G. and Ainsworth A. (1972) Glass-coated platinum-plated microelectrodes. *Med. Biol. Engng* **10**, 662–672.
- Movshon J. A., Thompson I. D. and Tolhurst D. J. (1978a) Spatial summation in the receptive fields of simple cells in the cat striate cortex. *J. Physiol., Lond.* **283**, 53–77.
- Movshon J. A., Thompson I. D. and Tolhurst D. J. (1978b) Receptive field organization of complex cells in the cat striate cortex. *J. Physiol., Lond.* **283**, 79–99.
- Movshon J. A., Thompson I. D. and Tolhurst D. J. (1978c) Spatial and temporal contrast sensitivity of neurones in areas 17 and 18 of the cat's visual cortex. *J. Physiol., Lond.* **283**, 101–120.
- Movshon J. A., Tolhurst D. J. and Dean A. F. (1982) How many neurons are involved in perceptual decisions? *Invest. Ophthalm. visual Sci.* **22** Suppl., 207.
- Nachmias J. (1981) On the psychometric function for contrast detection. *Vision Res.* **21**, 215–223.
- Noda H. and Adey W. R. (1970) Firing variability in cat association cortex during sleep and wakefulness. *Brain Res.* **54**, 243–259.
- Noda H. and Adey W. R. (1973) Neuronal activity in the association cortex of the cat during sleep, wakefulness and anaesthesia. *Brain Res.* **54**, 243–259.
- Pasternak T. and Merigan W. H. (1981) The luminance dependence of spatial vision in the cat. *Vision Res.* **21**, 1333–1339.
- Quick R. F. (1974) A vector magnitude model of contrast detection. *Kybernetik* **16**, 65–67.
- Robson J. G. (1980) Neural images: the physiological basis of spatial vision. In *Visual Coding and Adaptability* (Edited by C. S. Harris). Lawrence Erlbaum, Hillsdale, New Jersey.
- Robson J. G. and Graham N. (1981) Probability summation and regional variation in contrast sensitivity across the visual field. *Vision Res.* **21**, 409–418.
- Rose D. (1979) An analysis of the variability of unit activity in the cat's visual cortex. *Expl Brain Res.* **37**, 595–604.
- Semenoff B. (1941) Sensitivity of the dark adapted eye during prolonged periods of observation. *Nature, Lond.* **147**, 454–455.
- Smith D. R. and Smith G. K. (1965) A statistical analysis of the continual activity of single cortical neurons in the cat unanesthetized isolated forebrain. *Biophys. J.* **5**, 47–74.
- Stein R. B. (1970) The role of spike trains in transmitting and distorting sensory signals. In *The Neurosciences: Second Study Program* (Edited by F. O. Schmitt). Rockefeller Univ. Press, NY.
- Tanner W. P. and Swets J. A. (1954) A decision-making theory of visual detection. *Psychol. Rev.* **61**, 401–409.
- Tolhurst D. J., Movshon J. A. and Thompson I. D. (1981) The dependence of response amplitude and variance of cat visual cortical neurones on stimulus contrast. *Expl Brain Res.* **41**, 414–419.
- Tomko G. J. and Crapper D. R. (1974) Neuronal variability: non-stationary responses to identical visual stimuli. *Brain Res.* **79**, 405–418.
- Toyama K., Kimura M. and Tanaka K. (1981a) Cross-correlation analysis of interneuronal connectivity in cat visual cortex. *J. Neurophysiol.* **46**, 191–201.
- Toyama K., Kimura M. and Tanaka K. (1981b) Organization of cat visual cortex as investigated by cross-correlation technique. *J. Neurophysiol.* **46**, 202–214.
- Watson A. B. (1979) Probability summation over time. *Vision Res.* **19**, 515–522.
- Webb A. C. (1976) The effects of changing levels of arousal on the spontaneous activity of cortical neurones. I. Sleep and wakefulness. *Proc. R. Soc. Lond. Ser. B* **194**, 225–237.
- Werner G. and Montcastle V. B. (1963) The variability of central neural activity in a sensory system, and its implications for the central reflection of sensory events. *J. Neurophysiol.* **26**, 958–977.