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Rapid Communication

Efficiency and internal noise for detection of suprathreshold patterns measured using simple reaction time

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Abstract

Studies of the detection of simple visual patterns at threshold contrast have found that human performance is limited by the addition of internal noise and by the sub-optimal sampling efficiency of the visual system. Many common visual tasks require the detection of a signal having a contrast well above threshold, and we sought to measure the internal noise and sampling efficiency for such signals using simple reaction time (RT). Observers were presented with suprathreshold Gabors in dynamic Gaussian white noise and were required to hit a button as soon as each was detected. By comparing the RT variances from humans to those of an ideal observer, visuomotor internal noise and sampling efficiency were measured. The internal noise remains constant and the sampling efficiency increases as the signal contrast increases.

Keywords: Efficiency; Internal noise; Ideal observer; Reaction time

1. Introduction

Many daily tasks require a rapid response to a highly visible signal. For example, when a pedestrian steps out in front of a car, the driver must quickly apply the brake. In daylight the pedestrian will have a very high contrast–far above detection threshold. A great deal is known about the detection of simple patterns having very low contrasts. By adding visual noise (pixels with random contrasts) to such near-threshold patterns it has been found that visual detection is limited by two factors: sampling efficiency and internal noise (Legge, Kersten, & Burgess, 1987; Nagaraja, 1964). Human observers do not use all the energy contained in the stimulus—they have low sampling efficiency. They also act as though their visual systems add extra noise to the stimulus.

In the studies of human visual efficiency just discussed, the stimulus contrast was at the detection threshold. In most everyday situations, however, the visual patterns available to the observer are well above threshold. At these high contrast levels human detection performance as measured by the signal detection theory index d' becomes unmeasurably high. If we wish to measure the efficiency of human visual detection at high contrasts, some new method must be used. We will measure visual efficiency for detection of suprathreshold patterns using reaction time (RT). Before going any further it is necessary to formulate an ideal observer model, since efficiency is defined by reference to an ideal.

2. Ideal observer

In a simple RT experiment the observer receives a visual signal that is flashed at some random time τ_0 (see Fig. 1). The waveform received by the observer, $r(t)$, is the sum of the signal $s(t-\tau_0)$ and superimposed white Gaussian noise $n(t)$. If the observer is to respond at the time of the signal flash, he must form an estimate of the signal's time of arrival. Woodward (1953) showed that the ideal way to do this is to cross-correlate the noisy stimulus with all possible time-shifted versions of the signal:

$$q(\tau) = \int_0^T r(t)s(t-\tau)\,\mathrm{d}t.$$

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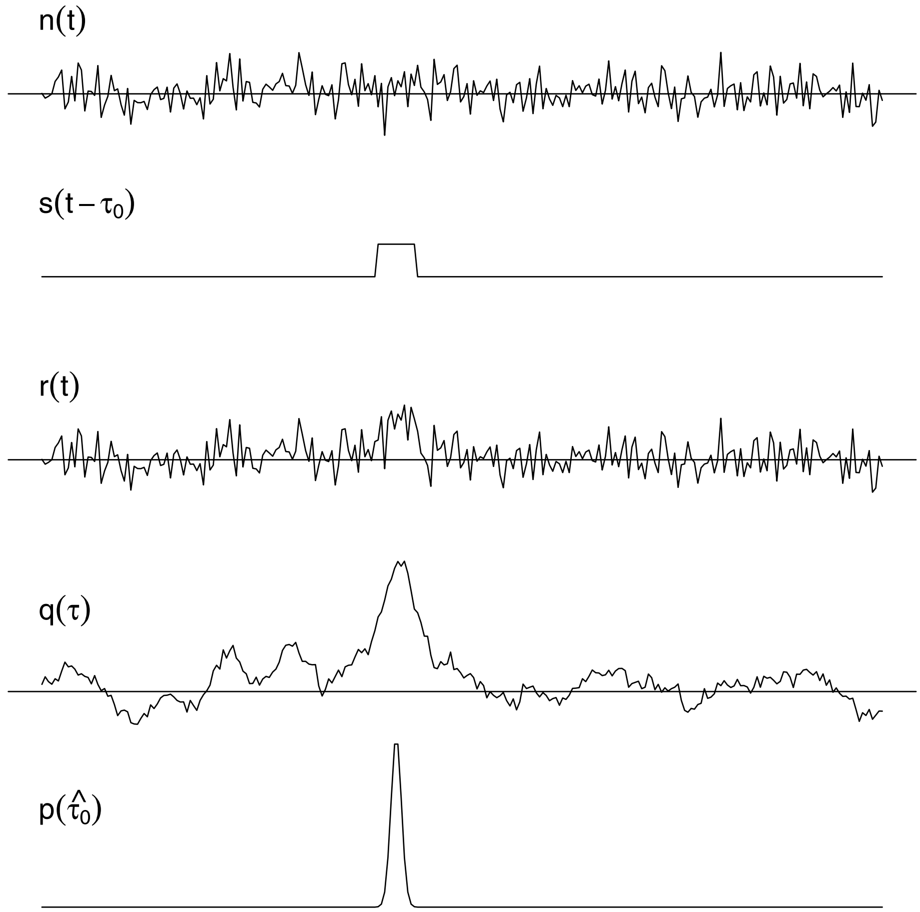

Fig. 1. The observer receives $r(t)$, a pulsed Gabor $s(t-\tau_0)$ embedded in Gaussian noise $n(t)$. The ideal observer cross-correlates $r(t)$ with $s(t-\tau)$ to get the cross-correlation function $q(\tau)$. The time at which the peak in $q(\tau)$ occurs is the observer's estimate of the signal's time of arrival $\hat{\tau}_0$. The distribution of this estimate is $p(\hat{\tau}_0)$.

The time at which the peak of this cross-correlation function $q(\tau)$ occurs is the estimated time of arrival $\hat{\tau}_0$. In the reaction time experiment however the observer operates in real time and so will hit the button when $q(\tau)$ exceeds some criterion instead of finding the global peak. Due to the noise, the estimated time of arrival $\hat{\tau}_0$ will vary randomly from trial to trial according to the distribution $p(\hat{\tau}_0)$.

If such a cross-correlator mechanism is used in the simple RT experiment, the variability in RT is caused by variability in $\hat{\tau}_0$. For the ideal observer, this variability is

$$\sigma_{\mathrm{RT}}^2 = \frac{D^2\sigma_{\mathrm{e}}^2}{E} \tag{1}$$

where σ_{RT}^2 is the RT variance, D is the pulse duration, σ_{e}^2 is the variance of the external noise, and E is the signal energy (integrated squared contrast). The derivation of the variance of the time-of-arrival estimate is based on an assumption of a high signal-to-noise ratio (Woodward, 1953, pp. 104–105). Indeed if the signal-to-noise ratio becomes too low then the distribution of the estimate becomes a mixture of a Gaussian density centred on the true time-of-arrival and a uniform density. Woodward (1953, pp. 105–108) terms this situation "ambiguity". We have performed simulations which confirm that Eq. 1 is a good description of how the variance of the time-of-arrival estimate changes as the noise variance increases provided the signal-to-noise ratio is not too low.

Previous psychophysical detection experiments (Legge et al., 1987; Nagaraja, 1964) have found that human observers add internal noise with variance σ_{i}^2 and have sub-unity sampling efficiency k, leading to the prediction

$$\sigma_{\mathrm{RT}}^2 = \frac{D^2(\sigma_{\mathrm{e}}^2 + \sigma_{\mathrm{i}}^2)}{kE}. \tag{2}$$

According to the cross-correlator model, the RT variance for detecting a signal of fixed energy should increase linearly as the external noise variance increases. We will measure the sampling efficiency and internal noise by fitting Eq. (2) to the RT data.

Simple RT has been studied for a long time and many models exist (Luce, 1986). It is not our aim to compare various models of simple RT. Our aim is to measure internal noise and efficiency, and this can be done only by using a ideal observer model. An added benefit is that the same cross-correlator framework can be used understand both simple RT and conventional detection experiments measuring threshold or d'.

3. Methods

The stimuli were displayed on a CRT having a 120 Hz frame rate. Custom hardware mixed the RGB signals (Pelli & Zhang, 1991) which permitted the display of 256 grey levels from a palette of 4096. The observers viewed the display from a chinrest 81 cm away and fixated a small black dot at the centre of the screen. A warning beep occurred 0.5 s before a 3 s trial interval in which the signal could appear. Throughout this interval dynamic white Gaussian spatiotemporal noise was presented at a rate of 120 Hz by randomly permuting a palette filled with Gaussian luminance values. A potential drawback of this method is that all pixels on a frame having a particular luminance change their luminance at the same time when the palette is shuffled. This introduces spatial correlations that are not present in true white noise. These correlations were not apparent to our real observers. It should be noted that in the presence of correlated noise the ideal observer will "prewhiten" the noise (Whalen, 1971, pp. 176–179).

The total display area was 15×15 deg. The Gabor patch signal (embedded in noise) was delivered at a uniformly distributed random time within the interval. The Gabor patch was horizontal with a spatial frequency of 0.4 c/deg, a diameter (5 SDs) of 15 deg, and a duration of 1/120 s. The mean luminance was 30 cd/m^2. In the first experiment, the signal contrast was equal to twice the threshold value: 0.10 for WS and 0.06 for KF. The contrast threshold was measured using identical stimuli as in the RT experiment except using 50% blank trials. d' was measured for an external noise level of zero and several signal contrast levels using method of constant stimuli. The contrast threshold (at $d' = 1$) with standard error was 0.034 ± 0.004 for KF, 0.05 ± 0.01 for WS, and 0.052 ± 0.005 for JC. The signal energy was computed numerically for the actual stimuli by squaring and summing the contrast of each pixel.

4. Results

Human observers viewed a noisy display similar to a detuned TV set. A Gabor patch was briefly flashed at a random time within a 3 s observation interval. The observer's task was to press a button as quickly as possible after each flash. The variance of the observer's RT was measured as a function of the variance of the dynamic Gaussian white noise.

Fig. 2 shows quantile plots of the RTs for for two observers. The slopes of the quantile plots become shallower, indicating an increase in RT variance, as the external noise variance increases. The quantile plots also become more shifted to the right, indicating that increasing the noise level has the same slowing effect on RT as reducing the contrast. The RT variance increases linearly as the external noise variance increases (Fig. 3) as predicted by the cross-correlator model (Eq. 2). Thus at least some of the RT variability is due to noise at the input. Noise is also added internally; the measured internal noise variance with standard error was 0.020 ± 0.003 for observer KF and 0.030 ± 0.016 for WS. The internal noise is shown as the absolute value of the x-intercept in Fig. 2. In a comparable study measuring detection threshold of a Gabor patch in dynamic noise Legge et al. (1987), found an internal noise spectral density of about 0.2 μdeg^2 s which when converted into a variance is 0.03, a value close to that found here.

An ideal observer's RT variance increases with the noise variance. The steeper the slope in Fig. 3, the lower the sampling efficiency k. The measured sampling efficiencies with standard errors were $3.3e-6 \pm 5.2e-7$ for KF and $8.2e-6 \pm 2.8e-6$ for WS. Legge et al. (1987) found a sampling efficiency of about 4% for the detection of a Gabor patch in dynamic noise, and another study (Eckstein, Whiting, & Thomas, 1996) found overall efficiencies between 1% and 12%. There are many possible reasons for the lower efficiencies measured here. The size of the patch in our experiment (15 deg wide) was much larger than that used in the other studies (about 1.5–2 deg). It is known that humans are less efficient in detecting large patches (Kersten, 1987). We used the large patch because RT improves as the spatial frequency declines and a large patch is needed to present low frequencies. A second factor is that our stimulus duration was very short (8.3 ms) compared to that used in the other studies (240–4000 ms). A third factor is that our stimuli had a high degree of temporal uncertainty attached to them, whereas in the other studies there was no temporal uncertainty. The final factor that we will mention is probably the most important. The other studies measured contrast threshold or d' in the threshold region, whereas we measured RT for suprathreshold stimuli. The efficiencies we report are for the whole eye–brain–hand system. It is reasonable to propose that a large part of the variability in RT arises from the motor system rather than the visual system. Thus a large part of the inefficiency can be attributed to the motor system.

The key advantage of RT is that it allows us to measure the visuomotor sampling efficiency and internal noise for detection of suprathreshold signals. The RT variances for several suprathreshold contrast levels are shown in Fig. 4. The figure shows the fit of a model which has a fixed internal noise level for all signal

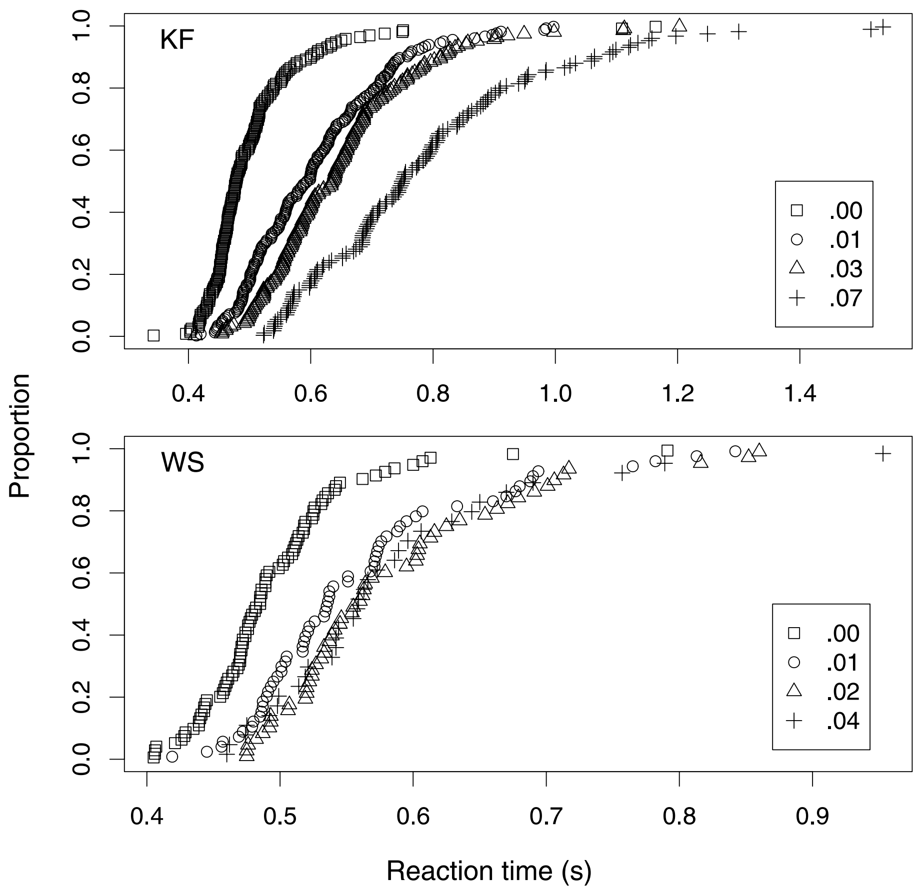

Fig. 2. Quantile plots (empirical cumulative distributions) of RT for both observers for the external noise variances shown in the legend.

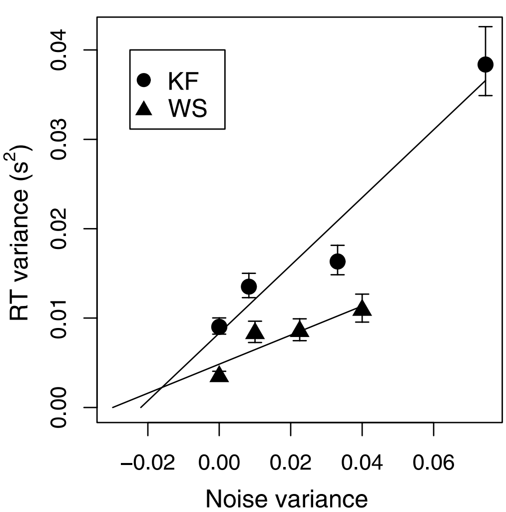

Fig. 3. Reaction time variance as a function of dynamic Gaussian white noise variance for observers KF and WS. Standard errors are shown.

contrasts. Using likelihood ratio tests (Faraway, 2000, pp. 19–24), we successively tested the fit of a single x-intercept model against two-intercept models which added a separate internal noise level for each signal contrast. Adding an extra intercept never produced a statistically significant improvement in fit. Therefore we conclude that the internal noise level remains constant as the signal contrast increases. The measured internal noise variance with standard error for KF is 0.025 ± 0.002 and for JC it is 0.005 ± 0.003.

It can be seen in Fig. 4 that the RT variance decreases as the signal contrast increases. This is what is expected from a cross-correlator detector. Harwerth and Levi (1978) found the same result for the detection of noiseless gratings.

The sampling efficiencies for the different signal contrasts are plotted in Fig. 5. The efficiency increases as the signal contrast rises. This may be due to the observer developing a more accurate template for the higher contrast signals (Burgess, 1990).

The ideal cross-correlator's estimate of the signal's time of arrival is the time at which the peak cross-correlation between the noisy received stimulus and the expected signal occurs. However in the RT experiment the observer cannot wait until the end of the observation interval, form the estimate, and then go back in time to respond at the estimated time of arrival. Instead we proposed that the observer sets a criterion level of $q(\tau)$ and responds when the criterion is reached. We have just

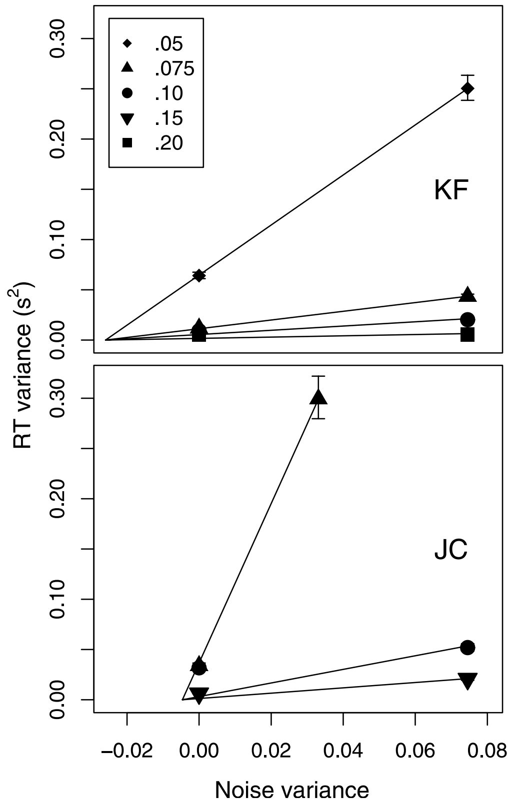

Fig. 4. Reaction time variance as a function of external noise variance and signal contrast for observers KF and JC. Signal contrasts are shown in the legend. Standard errors are shown.

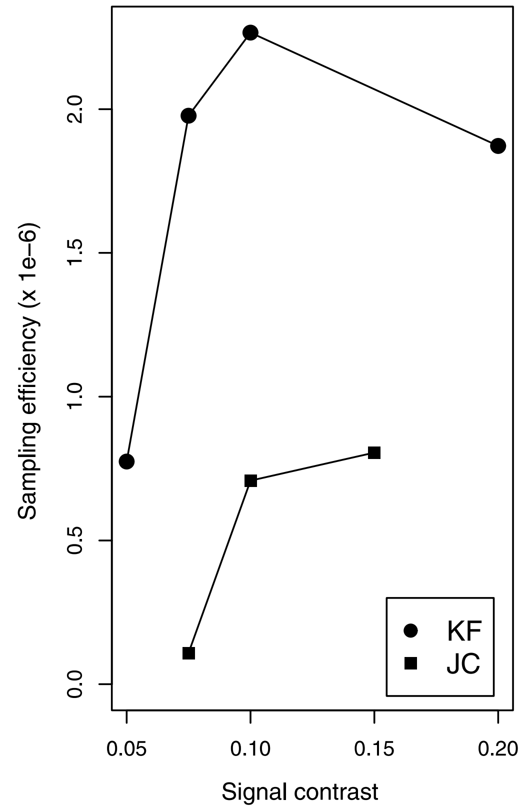

Fig. 5. The sampling efficiencies as computed from the data in Fig. 4 plotted as a function of signal contrast for observers KF and JC.

concluded that the sampling efficiency increases as the signal level increases. Can the results be instead due to the observers shifting their criteria with signal level?

We have done simulations which show that the RT variance will decrease as the criterion is made stricter. So a changing criterion could potentially be the underlying cause of the observed reduction of RT variance as the signal level increases. The presence of fluctuations in the criterion can be detected by examining the proportion of misses. A miss is recorded when no response occurs during a trial. According to theory, a miss will happen if the peak of $q(\tau)$ during a trial is less than the criterion. Using simulations, we found that the peak level of $q(\tau)$ is normally distributed and that the mean of this distribution is proportional to signal contrast. Therefore if a fixed criterion is used p(miss) will be a normal ogive with respect to signal contrast. Fig. 6 shows p(miss) as a function of signal contrast for both observers for an external noise variance of 0.0745. The curves are maximum likelihood fits to the data. The estimated standard deviation (slope) of the ogive is 0.029 ± 0.004 for KF and 0.027 ± 0.004 (standard errors are given). Thus both observers have very similar sensitivities. The data are consistent with the use of a fixed criterion across signal levels. KF has a laxer criterion (0.048 ± 0.003) than does JC (0.092 ± 0.004).

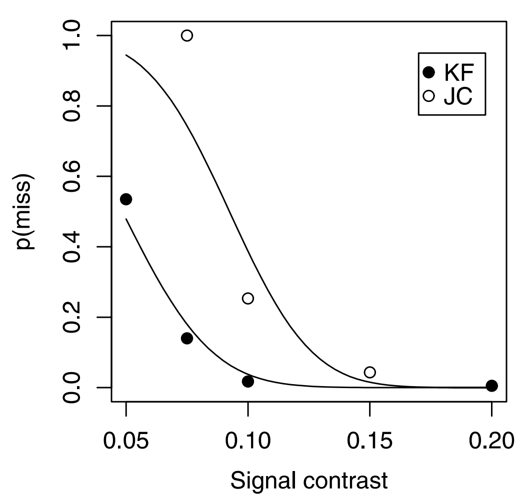

Fig. 6. The proportion of misses as a function of the signal contrast for observers KF and JC. If the criterion is fixed, each observer's data should be described by a normal ogive. The curves are maximum likelihood fits of normal ogives.

5. Discussion

We measured visuomotor sampling efficiency and internal noise in the detection of suprathreshold Gabor patches by comparing the variance of human RT to that of an ideal observer. We found that the sampling efficiency increased and the internal noise remained constant as the signal contrast increased.

The ideal observer in the RT experiment cross-correlates the noisy received waveform with an internal representation of the expected signal. One source of low sampling efficiency is the use of an internal representation that is poorly matched to the signal. We have found that sampling efficiency increases as the signal contrast increases. This may mean that the observer is able to create a better template of the signal when it is more visible. The signal can be detected more efficiently if the observer uses an internal representation that is closely matched to the signal.

A very simple assumption of how internal noise arises in the detection of Gabor patches would be that it is caused by the variable response of V1 cells. The variance of V1 cells' output increases as the signal contrast increases (Tolhurst, Movshon, & Thompson, 1981; Tolhurst, Movshon, & Dean, 1983). Thus one might have expected the estimated internal noise variance to increase with signal contrast. The important psychophysical detection study of Burgess and Colborne (1988) also points towards the existence of an induced internal noise whose size grows as the signal contrast increases. How can we resolve the conflict between these prior results and our own? We have argued previously that a large part of RT variability is likely due to the motor system. If the internal noise that we are measuring has a large motor component, and if this motor noise is independent of signal level, then the measured internal noise would remain fixed as signal level rises. In any case, the observed contrast-invariant internal noise is in accordance with the inefficient cross-correlator or "linear amplifier" model (Burgess, Wagner, Jennings, & Barlow, 1981; Pelli, 1990; Pelli & Farrell, 1999) that we and others have used.

One way to find the contribution of the motor system to RT variability would be to run a go-no go detection experiment. If a signal embedded in noise is presented, the observer hits the button and otherwise makes no response. If a range of signal-to-noise ratios (SNRs) are presented there will be a region where both d' and RT can be measured. Thus sampling efficiencies and internal noise variances estimated with d' and RT data can be compared and motor effects isolated. We are beginning to run such experiments.

Recent studies of saccadic choice RT support the idea that a motor response is preceded by an accumulation of neural activity (Hanes & Schall, 1996; Schall & Thompson, 1999). Once the accumulated activity reaches a fixed threshold, the action is executed. RTs are variable because the rate of accumulation varies from trial to trial. Carpenter has put forward the idea that the accumulation proceeds linearly with a rate that varies according to a normal distribution (Carpenter, 1988; Carpenter & Williams, 1995). Our theoretical results show that an ideal observer will produce a normally distributed estimate of the signal's time of arrival. It is possible that output of the early signal detection and estimation stage determines the rate of accumulation of neural activity which precedes a motor response. The variability of the rate of accumulation may be due to the statistical nature of detecting a signal in noise with unknown time of arrival. We suggest that neurons in V1 perform the cross-correlation operation and that the variability of this output has a large role to play in the variability of the ultimate motor response.

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References

Burgess, A. E. (1990). High level visual decision efficiencies. In C. Blakemore (Ed.), *Vision: Coding and efficiency* (pp. 431–440). New York: Cambridge University Press.

Burgess, A. E., & Colborne, B. (1988). Visual signal detection. IV. Observer inconsistency. *Journal of the Optical Society of America A., 5*, 617–627.

Burgess, A. E., Wagner, R. F., Jennings, R. J., & Barlow, H. B. (1981). Efficiency of human visual signal discrimination. *Science, 214*, 93–94.

Carpenter, R. H. S. (1988). *Movements of the eyes*. London: Pion.

Carpenter, R. H. S., & Williams, M. L. L. (1995). Neural computation of log likelihood in control of saccadic eye movements. *Nature, 377*, 59–62.

Eckstein, M. P., Whiting, J. S., & Thomas, J. P. (1996). Detection and contrast discrimination of moving signals in uncorrelated Gaussian noise. *Society of Photo-optical Instrumentation Engineers Proceedings, 2712*, 9–25.

Faraway, J., 2000. Practical regression and anova using R. http://www.stat.lsa.umich.edu/~faraway/book/.

Hanes, D. P., & Schall, J. D. (1996). Neural control of voluntary movement initiation. *Science, 274*, 427–430.

Harwerth, R. S., & Levi, D. M. (1978). Reaction time as a measure of suprathreshold grating detection. *Vision Research, 18*, 1579–1586.

Kersten, D. (1987). Statistical efficiency for the detection of visual noise. *Vision Research, 27*, 1029–1040.

Legge, G., Kersten, D., & Burgess, A. E. (1987). Contrast discrimination in noise. *Journal of the Optical Society of America A, 4*, 391–406.

Luce, R. D. (1986). *Response times*. New York: Oxford University Press.

Nagaraja, N. S. (1964). Effect of luminance noise on contrast thresholds. *Journal of the Optical Society of America, 54*, 950–955.

Pelli, D. G. (1990). The quantum efficiency of vision. In C. Blakemore (Ed.), *Vision: Coding and efficiency* (pp. 3–24). New York: Cambridge University Press.

Pelli, D. G., & Farrell, B. (1999). Why use noise? *Journal of the Optical Society of America A, 16*, 647–653.

Pelli, D. G., & Zhang, L. (1991). Accurate control of contrast on microcomputer displays. *Vision Research, 31*, 1337–1350.

Schall, J. D., & Thompson, K. G. (1999). Neural selection and control of visually guided eye movements. *Annual Review of Neuroscience, 22*, 241–259.

Tolhurst, D. J., Movshon, J. A., & Thompson, I. D. (1981). The dependence of response amplitude and variance of cat visual cortex neurones on stimulus contrast. *Experimental Brain Research, 41*, 414–419.

Tolhurst, D. J., Movshon, J. A., & Dean, A. F. (1983). The statistical reliability of signals in single neurons in cat and monkey visual cortex. *Vision Research, 23*, 775–785.

Whalen, A. D. (1971). *Detection of signals in noise*. New York: Academic Press.

Woodward, P. M. (1953). *Probability and information theory, with applications to radar*. New York: Pergamon.