

Retinal ganglion cells – spatial organization of the receptive field reduces temporal redundancy

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Abstract

According to the 'redundancy reduction' hypothesis, a visual neuron removes correlations from an image to reduce redundancy in the spike train, thus increasing the efficiency of information coding. However, all elaborations of this general hypothesis have treated spatial and temporal correlations separately. To investigate how a retinal ganglion cell responds to combined spatial and temporal correlations, we selected those cells with center-surround receptive field and presented a stimulus with strong spatiotemporal correlations: we presented a random sequence of intensities (of white noise) to the receptive field center and then activated the surround with the same sequence. We found that, for most cells, activating the surround reduced temporal redundancy in the spike train. Although the surround often reduced the information rate of the spike train it always increased the amount of information per spike. However, when the surround was modulated by a different white-noise sequence than the center, eliminating spatial-temporal correlations, the surround no longer reduced redundancy or increased information per spike. The proposed mechanism for redundancy reduction is based on the temporal properties of the center and surround: the surround signal is delayed behind the center signal and subtracted from it; this implements a differentiator which removes low frequencies from the stimulus, thus reducing redundancy in the spike train. These results extend the redundancy reduction hypothesis by indicating that the spatial organization of the receptive field into center and surround can reduce temporal redundancy within the spike train of a ganglion cell.

Introduction

Natural images are inherently redundant due to the presence of objects that introduce spatiotemporal correlations. Information about these images is processed by the retina, coded as spikes by retinal ganglion cells and transmitted along the optic nerve. To faithfully reproduce correlations at the retina's output would be a waste of the coding capacity of the optic nerve because many spikes would provide the same information. Thus it has been proposed that the visual system reduces redundancy in order to compress information into fewer spikes (Barlow, 1961). Redundancy reduction is a technique by which statistical dependencies between symbols are reduced: for example, to compress files onto a computer hard drive, a long string of 0's is recoded as a shorter sequence of binary digits, thus gaining more information per digit. Analogously, it has been proposed that neural filters deemphasize low temporal frequencies (whitening), which eliminates stretches of the spike train in which the spike rate changes little (Srinivasan *et al.*, 1982; van Hateren, 1992; Dan *et al.*, 1996).

To date, theoretical elaborations of this basic redundancy reduction hypothesis have treated space and time separately, mostly as a means of simplifying the necessary mathematical derivations. It is proposed that the spatial organization of a visual neuron's receptive field into center and surround is to reduce spatial redundancy, meaning redundancy between the spike trains of multiple visual neurons (Atick, 1992). It is also proposed that the temporal properties of a visual neuron's response reduces temporal redundancy between spikes

in the spike train of a single visual neuron (Srinivasan *et al.*, 1982; van Hateren, 1992; Dan *et al.*, 1996). However, in practice the spatial and temporal aspects of a visual neuron's response cannot be separated so cleanly: in the case of the retinal ganglion cell, the receptive field surround is delayed behind the center, suggesting that spatial organization of the receptive field would contribute to temporal filtering (Frishman *et al.*, 1987). Here we demonstrate a consequence of this space-time inseparability: we find that the spatial organization of the ganglion cell's receptive field into center and surround reduces temporal redundancy in the spike train.

We wondered whether redundancy-reducing strategies are consistent across visual neurons and so we investigated the mammalian retina, in which different ganglion cell classes have different information-coding strategies. One ganglion cell class is termed 'brisk' because it fires at short latencies and high rates; another class is termed 'sluggish' because it fires at long latencies and at low rates (Cleland & Levick, 1974a, b). Brisk cells are known to transmit information at higher rates but with lower efficiency than sluggish cells (Koch *et al.*, 2004, 2006). Brisk cells comprise at least four types, brisk-sustained and brisk-transient of On and Off varieties, and invariably have concentric receptive field centers and surround. Sluggish cells comprise multiple types, some with complex receptive fields that respond to specific stimulus features, others with simpler center-surround receptive fields (Cleland & Levick, 1974b; Stone & Fukuda, 1974; Rowe & Cox, 1993).

To quantify redundancy and coding efficiency we used a standard information theoretical method that distills the number of distinct spike patterns and their frequency of occurrence into a single convenient unit of measurement: bits/s (de Ruyter van Steveninck

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et al., 1997). To obtain spike trains, we viewed the intact guinea pig retina *in vitro* with infrared-differential interference contrast optics and visually targeted individual ganglion cells for loose-patch extracellular recording. By using spots of light modulated by white noise to activate the center and then adding an annulus modulated by white noise to activate the surround, we tested the effect of the surround on information transmission. We found that activating the surround of brisk-transient and sluggish cells, but not brisk-sustained cells, reduced temporal redundancy. Thus we found that the spatial organization of the receptive field into center and surround, heretofore implicated in the reduction in spatial redundancy between the spike trains of different ganglion cells, is capable of increasing information per spike and reducing the temporal redundancy of a single spike train.

Materials and methods

Recording

Forty-three adult Hartley guinea pigs (400–600 g, >8 weeks) were used in this study. Each was anesthetized with ketamine (133 mg/kg), xylazine (13 mg/kg) and pentobarbital (100 mg/kg), and an eye was removed. The animal was then killed by anesthetic overdose. All procedures were performed in accordance with University of Pennsylvania and National Institutes of Health guidelines. Pieces of retina, attached to pigment epithelium, choroid and sclera, were mounted, ganglion cells up, in a chamber on an upright microscope. The tissue was superfused with Ames' medium (Sigma; <http://www.sigma.com>) that was saturated with 5% CO₂ and 95% O₂, adjusted with glucose to ~300 mOsm, and which contained (in mM): NaCl, 120; KCl, 3.1; KH₂PO₄, 0.5; Na₂HCO₃, 23; MgSO₄, 1.2; CaCl₂, 1.15; plus amino acids and vitamins (pH 7.4, 34°C).

Under visual control (infrared differential contrast optics, 60× lens, 0.9 NA), a glass pipette (12 MΩ) filled with interference Ames'

solution was used to peel off the inner limiting membrane from several ganglion somas. The tip of another identical pipette was applied to a ganglion cell soma; when suction was introduced the tip formed a loose (<1 GΩ) seal with the ganglion cell body. Then a patch amplifier in current-clamp mode was used for extracellular recording of spike trains. The receptive field center was identified by flashing a spot of light onto the retina, and noting the diameter and position that evoked the greatest change in spike rate. The surround diameter was found by enlarging the spot, observing a decline in response amplitude due to center-surround antagonism, and noting the diameter where response no longer declined (Fig. 1).

Visual stimulus

A visual stimulus was displayed on a 1-inch-wide computer monitor with a green phosphor (Lucivid MR1-103; Microbrightfield, Colchester, VT, USA; Demb *et al.*, 1999). The monitor face was set in the microscope's camera port and was projected onto the photoreceptor layer through a 4 × 0.1 NA lens to a final size of 3 × 4 mm (600 × 800 pixels, 72 Hz refresh rate). Stimuli were programmed in Matlab (Mathworks, Natic, MA, USA) using procedures provided by the Psychophysics Toolbox (Brainard, 1997). The monitor had a measured gamma value of 1.7; using this gamma value produced a highly linear relationship between gun voltage and intensity ($R^2 = 0.995$). All stimuli had 256 different intensity levels with the mean level (128) equivalent to 27 nW/mm² on the retina, which provided 7×10^4 photons/μm²/s at 540 nm. Due to overlap of stimulus and photoreceptor spectra, this stimulus caused 2×10^4 isomerizations per second in an M cone, which is photopic illumination (for calculation method see Yin *et al.*, 2006). Stimuli had a line spread function over the retina that was described by a Gaussian with a SD of 19 μm (Demb *et al.*, 1999).

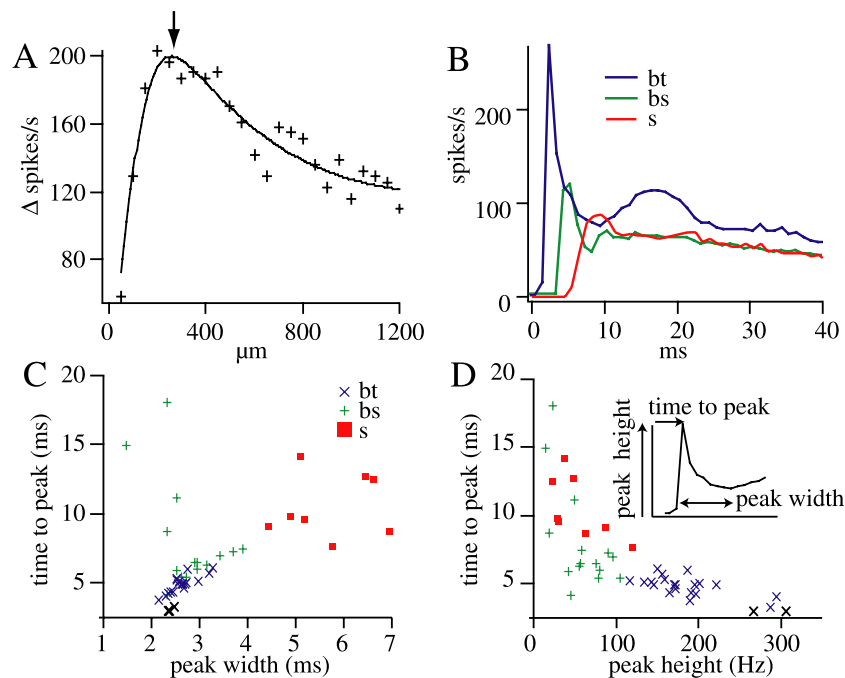


FIG. 1. Methods: determining center size and cell type of retinal ganglion cells. (A) Responses to flashing spots of increasing diameter (50% contrast, 50% duty cycle). Solid line is the equation for the convolution between a spot, representing the stimulus, and the difference between two Gaussians representing the center and surround: $z = k_c \exp(-r^2/r_c^2) - k_s \exp(-r^2/r_s^2)$, where r is the distance from the middle of the receptive field. The center region was 300 μm in diameter (arrow). (B) Autocorrelograms of spike times from three cells from different classes: brisk-transient (bt), brisk-sustained (bs) and sluggish (s). (C and D) K-means cluster analysis of 45 cells based on three measures of the autocorrelogram indicated three cell types (see inset in panel D).

Estimating information rate

The information rate of a spike train was estimated by the direct method (de Ruyter van Steveninck *et al.*, 1997). We presented a white-noise stimulus and then repeated this same temporal sequence of intensities. The resulting spike train was divided into 5-ms time bins, and the number of spikes in each bin was counted. Words were constructed from counts in multiple bins, the frequency of occurrence for each word ($P(W)$) was found, and word entropy was estimated as

$$H = - \sum_w P(W) \log_2 P(W) \text{ bits} \quad (1)$$

Entropy rates were calculated as word entropy multiplied by the word rate. Bin entropy (H_{bin}) was calculated from words of 1 bin in a stimulus repeat. Total entropy rate (H_{total}) was estimated from words of multiple bins in a stimulus repeat, averaged across repeats. Noise entropy rate (H_{noise}) was estimated from words of multiple bins at the same time across stimulus repeats.

H_{total} and H_{noise} were extrapolated to infinite word size and data size according to the method of Strong *et al.* (1998). The spike train was divided into segments: the segments were either intervals of time for H_{total} or a group of stimulus repeats for H_{noise} . We varied the number of segments (s) and plotted the resulting entropy rate against the inverse of the number of segments. This graph was then fitted with a second-order polynomial ($H_0 + H_1/s + H_2/s^2$), and H_0 was taken as the extrapolated entropy. Extrapolated entropy rate was plotted against inverse word length (1–6 bins) and extrapolated to zero inverse word length, i.e. infinite word length.

Information rate was calculated as the difference between total entropy and noise entropy:

$$H_{\text{info}} = H_{\text{total}} - H_{\text{noise}} \quad (2)$$

A 5-ms time bin was chosen because it was close to the average temporal precision of the spike train for both brisk and transient cells (jitter = 5 ms), and between the minimum and maximum precision (4–6 ms; Koch *et al.*, 2004). When we tried smaller bins (1–5 ms), increasing the number of bins to retain word length, the proportion of coding capacity filled by information rate, redundancy, and noise entropy rate did not change (CV = SD/mean < 0.07; $N = 16$ cells). Thus bin size had no effect on the conclusions reached in this study.

Refractory model of spike train

For a nonhomogeneous Poisson process, the probability of an interspike interval i after a spike at time t_0 is

$$\exp\left(-\int_{t_0}^{t_0+i} \bar{r}(t) dt\right) \quad (3)$$

where $\bar{r}(t)$ denotes the instantaneous rate averaged over stimulus repetitions. Consequently, the interval is a random deviate with an exponential distribution. Thus to obtain an exponential deviate we applied the inverse function, which is the natural logarithm, to a random deviate x uniformly distributed between 0 and 1 (Press *et al.*, 1989; Berry *et al.*, 1997):

$$-\ln(x) = \int_{t_0}^{t_0+i} \bar{r}(t) dt \quad (4)$$

Introducing a refractory period to this equation required that the instantaneous rate be adjusted upwards so that the overall rate matched

the observed rate despite the period of time when firing was impossible. To accomplish this, we defined $W_j(t)$ as the firing probability in a single trial, which is zero for a refractory period after each spike, and otherwise one. We then estimated the probability that firing is possible as

$$W(t) = \langle W_j(t) \rangle_j \quad (5)$$

where $\langle \dots \rangle_j$ denotes averaging across stimulus repetitions j . We then adjusted the observed firing rate upwards using this equation:

$$q(t) = \frac{\bar{r}(t)}{W(t)} \quad (6)$$

Then, to generate spikes, we use a modification of Eqn 3 to choose each new interval:

$$-\ln(x) = \int_{t_0}^{t_0+i} q(t)w(t-t_1)dt \quad (7)$$

where $w(t)$ represents the recovery of firing probability after each spike and is equal to zero from time zero to the duration of the refractory period, but otherwise equal to one. Thus in practice, after each spike, a new x was chosen at random, the left side of Eqn 5 was integrated numerically in 5-ms time steps until it equaled $-\ln(x)$, and at this time a new spike was produced.

Classification of cells

Cells were classified by constructing spike train autocorrelograms (spot stimulation, temporal white noise) (Devries & Baylor, 1997; Freed *et al.*, 2003) (Fig. 1B). From each autocorrelogram we measured three features: to quantify the relative refractory period we measured the time to peak, to quantify the burst duration we measured the peak width and to quantify spike frequency during the burst we measured the peak height. We submitted these measures to k-means cluster analysis and found three clusters (Fig. 1C and D). We then matched these clusters with descriptions of spike train autocorrelograms of cells of known morphology and/or receptive field structure (Devries & Baylor, 1997; Freed *et al.*, 2003; Koch *et al.*, 2004, 2006). Thus we classified cells with peak width of < 4 ms as brisk; the remaining cells we classified as sluggish. To divide the brisk cells, we classified cells with peak frequency >100 spikes/s as brisk–transient and the rest of the brisk cells as brisk–sustained.

Results

Stimulating the center and surround using temporal white noise

We recorded spikes from ganglion cells in an intact *in vivo* preparation of the mammalian (guinea pig) retina and selected those with a concentric and antagonistic receptive field center and surround (see Materials and methods; Fig. 1A). To classify cells, we applied established criteria to the statistics of the spike train and so divided them into brisk–transient, brisk–sustained and sluggish classes. We stimulated the receptive field center with a spot matched to its size and activated the surround with an annulus whose inner diameter matched the spot diameter and whose outer dimension was beyond the receptive field. The intensities of spot and annulus were modulated by the same white-noise sequence: a new intensity was selected randomly every 56 ms from a Gaussian distribution whose SD was equal to one-third of the mean. We

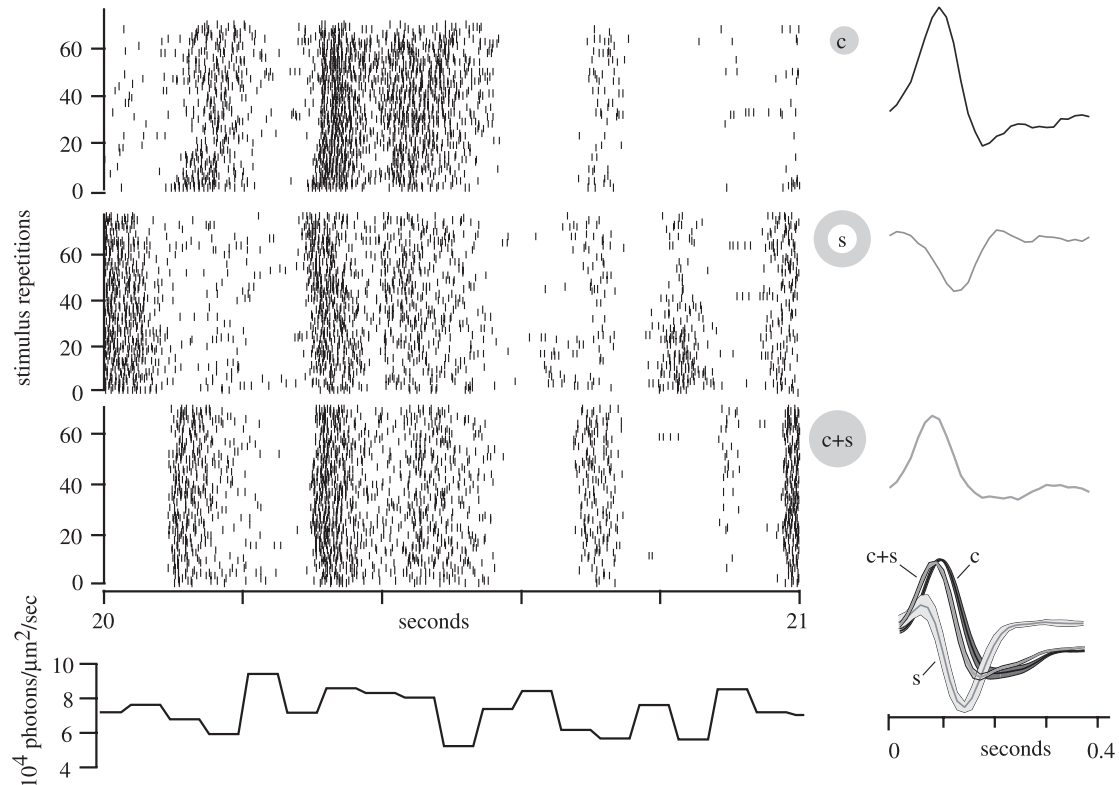


FIG. 2. Responses to temporal white-noise stimulation of center and surround. Spike trains from an On brisk-transient cell evoked by three stimuli: a spot matched to the receptive field center (c), a concentric annulus matched to the surround (s) and a spot and annulus presented together (c + s). Spot and annulus intensities were modulated by the same temporal white-noise sequence (bottom trace). Sequence was 25 s long: only 1 s is shown. To the right are the impulse responses and to the bottom right are the impulse responses averaged from multiple cells and normalized to their peak amplitude (11 brisk-transient cells both On and Off; gray bands show average \pm SEM; the impulse responses of Off cells are inverted). Note that the surround response attains a minimum after the center response attains a maximum, and thus the surround is delayed behind the center.

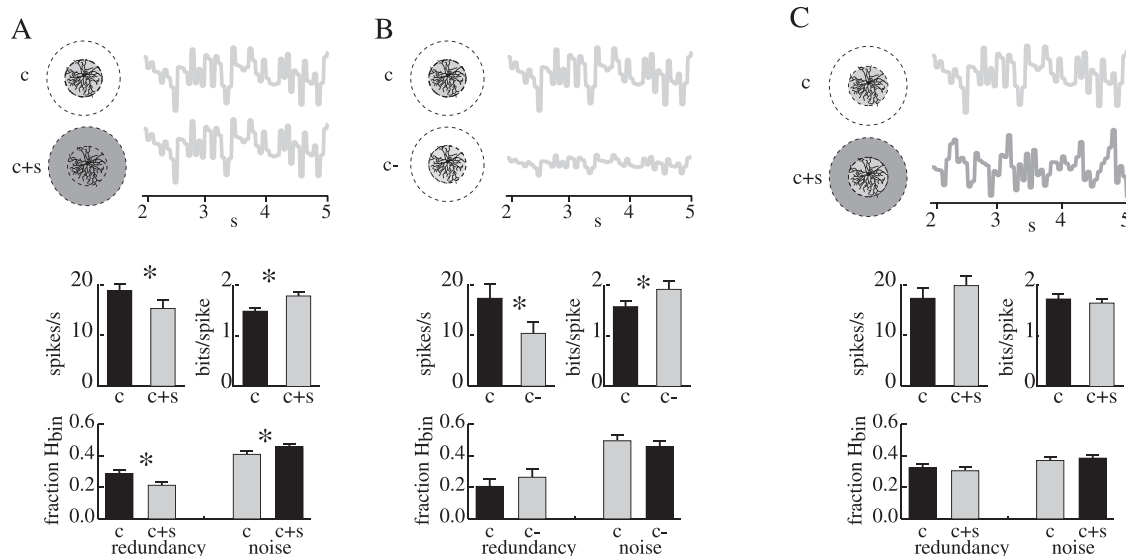


FIG. 3. Comparison of three stimulus configurations. Summarized for brisk-transient and sluggish cell classes combined (see Table 1 for data divided by cell class). (A) Activating the surround with the same white-noise sequence as the center reduced redundancy and increased noise (the measures R and N ; see text). Error bars show SEM. Asterisks (*) show significant differences (Student's t for paired data, $\alpha = 0.02$) (B and C) Reducing center contrast (B) or activating the surround with a different white-noise sequence (C) had no significant effect on redundancy or noise.

chose this update rate and contrast because it evoked robust responses from all cell classes and was the highest contrast we could provide without truncating the Gaussian distribution. The

stimulus lasted 10–25 s and was repeated 100 times, and it evoked bursts of spikes interposed with quiescent periods devoid of spikes (Fig. 2; also, Berry & Meister, 1998).

It might be assumed that, when the center and surround are stimulated by the same sequence of intensities, the surround signal would cancel the center signal, resulting in a weak response. However, it has been shown that a ganglion cell responds robustly because the surround signal is delayed behind the center signal and thus cancellation is incomplete (Frishman *et al.*, 1987). To see whether this were true of our recorded cells, we constructed impulse responses by dividing the spike train into 5-ms time bins, constructing a rate histogram, then calculating the cross-correlation function between stimulus and rate histogram. We were able to obtain clear center and surround impulse responses of opposite polarity from brisk-transient and brisk-sustained cells but not from sluggish cells. The average time to peak of the impulse response was 77 ± 2 ms for the center and 125 ± 5 ms for the surround. Thus the surround was delayed ~ 50 ms behind the center (Fig. 2).

Surround reduced temporal redundancy

Our general method for analyzing information coding by the spike train was to consider that the capacity of the spike train to code information is set by the spike rate, and that some of this capacity is lost on noise and redundancy, leaving what remains to code information (MacKay and McCulloch 1952; Reinagel *et al.* 1999; Rieke *et al.* 1997). Then we determined whether the surround

ameliorated losses of capacity due to redundancy or noise. Expressed more formally, information rate H_{info} would be maximal and equal to the coding capacity of the neuron if there were no noise and if time bins were statistically independent (i.e. there were no redundancy). However, the coding capacity of a neuron is invariably reduced by the noise entropy and redundancy to yield the information rate:

$$H_{\text{info}} = C - H_{\text{noise}} - (C - H_{\text{total}})(\text{bits/s}) \quad (8)$$

Thus in order for the surround to increase information per spike, it must reduce the proportion of capacity lost to either noise entropy or redundancy.

To quantify coding capacity we used bin entropy ($C = H_{\text{bin}}$), which is the entropy of the spike train assuming that all bins are statistically independent. Because the coding capacity of the spike train depends on spike rate, which is different for each cell, we normalized redundancy to coding capacity:

$$R = (H_{\text{bin}} - H_{\text{total}})/H_{\text{bin}} \quad (9)$$

We found that the surround reduced the redundancy of brisk-transient and sluggish cells by 24 and 60%, respectively, but actually increased the redundancy of brisk-sustained cells by 15% (Fig. 3A; Table 1).

TABLE 1. Effect of stimulating center and surround regions of the receptive field (c, s) on information coding by three classes of ganglion cell: brisk-transient, brisk-sustained and sluggish

	Spike rate (Hz)	Information rate (bit/s)	Information (bits/spike)	Redundancy (R)	Noise (N)	Cells (n)
Same sequence						
Brisk-transient						
c	19.6 ± 1.4	27.5 ± 2.0	1.4 ± 0.1	0.33 ± 0.02	0.38 ± 0.02	23
c + s	17.2 ± 1.8	27.5 ± 2.6	1.6 ± 0.1	0.25 ± 0.02	0.43 ± 0.02	
Difference (%)	-12	0	17	-24	13	
Brisk-sustained						
c	14.6 ± 3.4	25.8 ± 4.9	1.8 ± 0.0	0.15 ± 0.03	0.50 ± 0.03	5
c-	10.8 ± 2.7	20.2 ± 4.7	2.4 ± 0.2	0.17 ± 0.04	0.48 ± 0.03	
Difference (%)	-26	-22	30	15	-4	
Sluggish						
c	14.9 ± 1.8	27.2 ± 2.5	1.8 ± 0.0	0.11 ± 0.01	0.53 ± 0.02	5
c + s	6.6 ± 0.6	15.7 ± 1.6	2.4 ± 0.2	0.05 ± 0.01	0.58 ± 0.04	
Difference (%)	-56	-42	30	-60	9	
Reduced contrast						
Brisk-transient						
c	22.8 ± 2.8	30.9 ± 3.3	1.4 ± 0.1	0.24 ± 0.08	0.24 ± 0.08	5
c-	15.3 ± 1.6	24.3 ± 2.6	1.6 ± 0.1	0.22 ± 0.07	0.22 ± 0.07	
Difference (%)	-33	-21	15	-9	-9	
Sluggish						
c	10.5 ± 2.6	17.9 ± 3.2	1.8 ± 0.2	0.16 ± 0.06	0.55 ± 0.05	5
c-	4.4 ± 1.1	9.7 ± 1.8	2.3 ± 0.2	0.32 ± 0.10	0.44 ± 0.07	
Difference (%)	-58	-46	28	96	-19	
Different sequence						
Brisk-transient						
c	21.5 ± 2.6	30.5 ± 2.8	1.5 ± 0.1	0.36 ± 0.03	0.33 ± 0.03	10
c + s	23.3 ± 2.2	32.1 ± 2.6	1.4 ± 0.1	0.33 ± 0.04	0.36 ± 0.03	
Difference (%)	8	5	-3	-7	8	
Sluggish						
c	11.4 ± 1.4	23.2 ± 2.0	2.1 ± 0.1	0.28 ± 0.02	0.42 ± 0.03	7
c + s	14.8 ± 2.4	28.0 ± 3.5	2.0 ± 0.1	0.27 ± 0.02	0.42 ± 0.02	
Difference (%)	30	21	-7	-4	-1	

The stimulus configurations were: same sequence, stimulating center (c) and surround (s) with the same temporal white-noise sequence; reduced contrast, reducing the center contrast (c-); and different sequence, stimulating center and surround with different sequences. Mean values are \pm SEM. Measures of spike train redundancy and noisiness (R and N , respectively) are explained in the text.

Surround increased information per spike

The proposed purpose of redundancy reduction is to increase the efficiency of information coding and transmission down the optic nerve (see Introduction). Thus we quantified transmission efficiency by dividing information rate by spike rate to give information per spike. The surround increased this measure in all cell types, but this increase was greater for brisk-sustained and sluggish cells than for brisk-transient cells (30% vs. 17%; Fig. 3A, Table 1). This increase in efficiency occurred despite a reduction in information rate for brisk-sustained and sluggish cells, but not brisk-transient cells (Table 1). Thus for many cells there was a net reduction in information but an increase in the efficiency with which the remaining information was transmitted.

Coding capacity lost to noise

As implied by Eqn 8, if the surround could reduce the proportion of coding capacity lost to noise entropy this might leave more capacity for coding information. To see whether this occurred, we quantified the proportion of coding capacity lost to noise by normalizing noise entropy to coding capacity:

$$N = H_{\text{noise}}/H_{\text{bin}} \quad (10)$$

Unexpectedly, by this measure, noise actually increased for brisk-transient and sluggish cells but decreased slightly for brisk-sustained cells (Fig. 3B, Table 1). To confirm this result we used another measure of spike-train noise, the Fano factor:

$$F = \frac{\sigma^2(t)}{\bar{r}(t)} \quad (11)$$

where $\sigma^2(t)$ is the variance of the instantaneous rate and $\bar{r}(t)$ is the average over stimulus repetitions. Activating the surround with the same white-noise sequence as the center increased the Fano factor for brisk-transient and sluggish cells, confirming that the surround added noise to the spike train of these cell classes (Fig. 5C).

Fig. 4B shows changes in noise (N) against changes in redundancy (R), and demonstrates a significant correlation between these two measures (coefficient of determination, 0.58). Apparently the surround could not reduce redundancy without a proportional increase in noise. We will discuss the source of the noise increase below but this figure shows that, for brisk-transient cells, activating the surround had variable effects on redundancy and noise (Fig. 4A and B). The amount by which activating the surround changed redundancy or noise did not correlate with the response polarity, which was On or Off as judged by the polarity of the impulse response. Neither did these changes correlate with refractory period or our measures of autocorrelogram (as shown in Fig. 1). However, the brisk-transient class, in addition to being divided by response polarity (On/Off) may have additional features that divide it (as has been suggested by Wu *et al.*, 2004). Thus it is possible that this variability in the surround effect might result from the brisk-transient class containing a variety of cell types.

Reducing spike rate increased information per spike

Reducing spike rate reduces coding capacity and thus usually information rate, but also increases information per spike (Koch *et al.*, 2004, 2006). Analogously, a '1' or a '0' on a hard drive both code equal amounts of information, but using fewer 1's might decrease

the absolute amount of information coded but increase the amount of information coded per 1 written. Thus part of the surround's ability to increase information per spike might result from a reduction in spike rate. To test this idea, we returned to the experiment in which the surround was activated with the same white-noise sequence as the center: when we plotted change in information per spike against change in spike rate, we found a significant correlation ($R^2 = 0.58$; Fig. 4A), indicating that the surround increases information per spike at least in part by simply reducing spike rate.

We wondered to what extent a reduction in spike rate alone, without accompanying changes in redundancy, could increase information per spike. Thus we reduced spike rate by stimulating the receptive field center with a spot of the standard contrast (one-third of mean) and then reducing contrast to either one-sixth or one-ninth of the mean. Reducing contrast had no effect on the amount of coding capacity filled by redundancy or noise (R or N), but increased information per spike (Fig. 3B). This indicated that a spike rate decrease alone can increase information per spike but cannot ameliorate the loss of coding capacity to redundancy.

Spatiotemporal correlations were required for redundancy reduction

So far, by modulating the center and surround with the same white-noise sequence, we had introduced a perfect spatiotemporal correlation between center and surround. It has been proposed that visual neurons

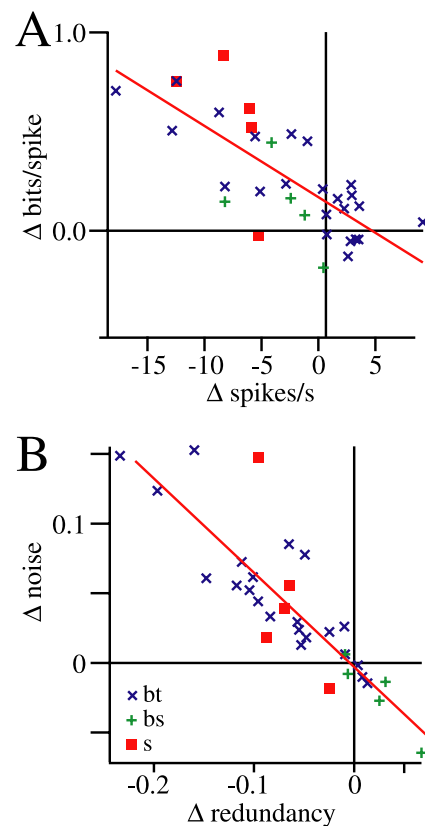


FIG. 4. Effects of activating the surround with the same white-noise sequence as the center. (A) Activating the surround reduced spike rate and increased information per spike in all cell classes ($R^2 = 0.58$). (B) The surround reduced redundancy (R) and increased noise (N) for brisk-transient and sluggish cells but had opposite effects for brisk-sustained cells ($R^2 = 0.75$).

reduce correlations in natural images in order to reduce redundancy into the spike train (Srinivasan *et al.*, 1982; Atick, 1992). If the center-surround organization of the receptive field removes spatiotemporal correlations in order to remove redundancy, then decorrelating center and surround should prevent the surround from reducing redundancy. To test this prediction, we recorded from brisk-transient and sluggish cells, which had previously shown redundancy reduction, and presented a spot and then an annulus modulated by different white-noise sequences. To ensure that the two sequences had the same distribution of intensities, we cut the 10-s white-noise sequence for the spot in half and then transposed the two halves to produce the sequence for the annulus. Activating the surround did not reduce redundancy, nor did it change information per spike or the loss of coding capacity to noise (Fig. 3B). Thus spatiotemporal correlations were necessary for the surround to improve the efficiency of information coding.

Source of the noise increase

The surround increased the proportion of coding capacity lost to noise. To investigate this noise increase, we constructed a stochastic model of the spike train (Berry & Meister, 1998). This model required no free parameters to fit iteratively, took as its sole input the instantaneous spike rate averaged across trials $\bar{r}(t)$, and used a Poisson-noise generator modified with a refractory period to set spike times (see Materials and methods). Returning to the experiment in which the center and surround had the same white-noise sequence and thus were spatiotemporally correlated, we selected

spike trains from brisk-transient and sluggish cells and used their absolute refractory period and $\bar{r}(t)$ as input to the model. The refractory period was measured for each spike train by constructing a interspike interval histogram and noting at what interval this histogram reached zero spikes; $\bar{r}(t)$ was constructed by counting the spike rate in 5-ms bins averaged across stimulus repeats. We analyzed the model's output exactly as we had analyzed the recorded spike train. The result was that the model was able to duplicate the observed increase in information per spike and the observed decreases in redundancy and noise (R and N , respectively; Fig. 5). The model was also able to duplicate the observed increase in Fano factor. That the model was able to duplicate the noise increase was remarkable because it required no other source of noise beside the stochastic properties of spike generation. Therefore, the noise increase was due to an interaction between the firing rate $\bar{r}(t)$ and these stochastic properties, and required no additional source of noise such as would be required to model neural noise in the retinal circuit due to channel openings or synaptic vesicle release.

We noted a significant correlation between decreasing spike rate and increasing noise (Fano factor; Fig. 5C). A reasonable explanation for this correlation is that spike generation has a refractory interval and thus departs from Poisson statistics (Berry & Meister, 1998). The refractory interval regularizes spike rate and reduces noise when the spike rate is high enough that the characteristic interspike interval approaches the refractory interval. If, however, the spike rate declines and the interspike interval lengthens, then the refractory period no longer has effect, and the noisiness of the spike

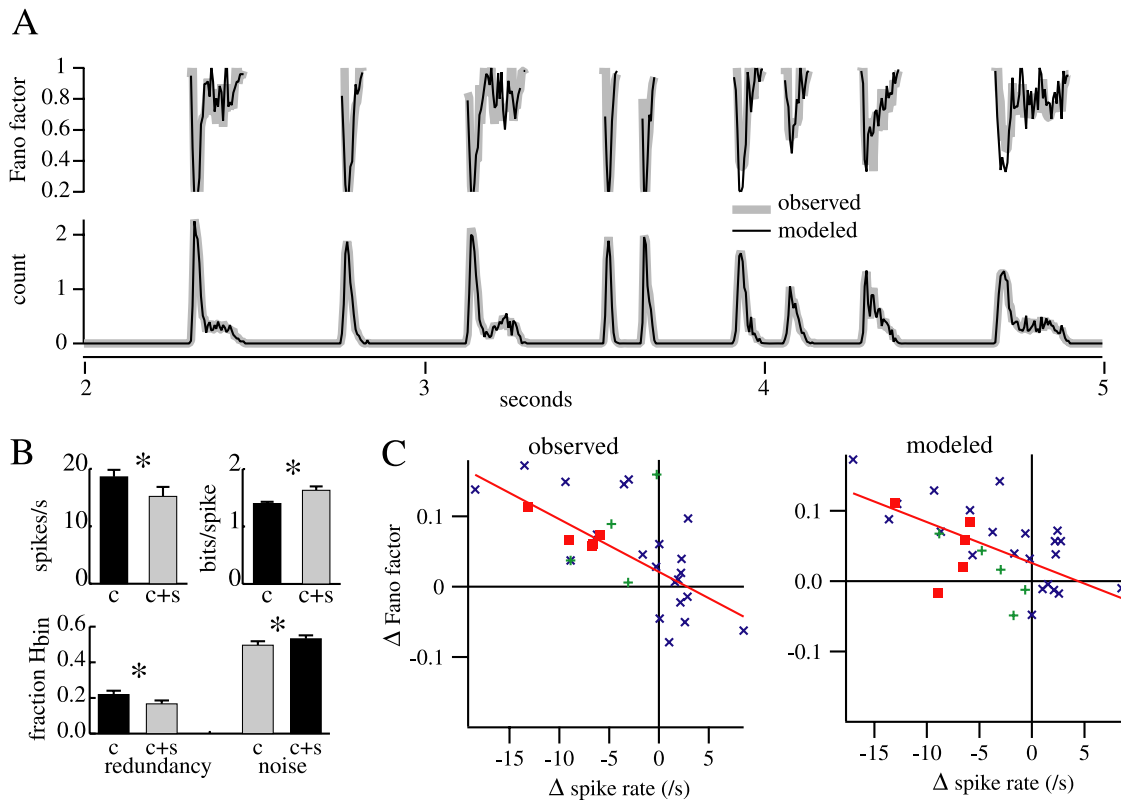


Fig. 5. A refractory model duplicated the main effects of adding a surround with the same white-noise sequence as the center. (A) A refractory model replicated both spike count and Fano factor in 5-ms bins (brisk-transient cell, spot stimulus). (B) The model duplicated the main effects: a decrease in redundancy (R) and an increase in noise (N) in brisk-transient and sluggish cells (compare to Fig. 3A). (C) Changes in Fano factor and spike rate were correlated for both observed and modeled spike trains ($R^2 = 0.48$ and 0.39 for observed and modeled, respectively). * $P < 0.05$, comparing c and cts; bar show means \pm SEM.

train increases to that of a Poisson process. To test this idea, we kept $\bar{r}(t)$ constant but decreased refractory period so that it no longer approached the interspike interval, and found that, as expected, noise (N) increased, indicating that the relative duration of refractory period and interspike interval determines the proportion of coding capacity lost to noise (Supplementary material, Fig. S1).

Activating the surround reduced low frequencies

Visual cells are thought to reduce redundancy by deemphasizing low spatial or temporal frequencies in their responses (Srinivasan *et al.*, 1982; Atick, 1992; van Hateren, 1992; Dong & Atick, 1995). Intuitively this idea makes sense because low frequencies convey information about unchanging and hence redundant aspects of a visual stimulus. To test this idea, we constructed power spectra of the spike train by dividing it into 5-ms time bins, constructing a rate histogram, Fourier transforming this rate histogram and calculating its magnitude squared. Because the stimulus had the same temporal frequency distribution throughout the experiment, any changes in the frequency content of the spike train must be due to changes in filtering properties. We found that activating the surround with the same white-noise sequence as the center caused a marked reduction in power at low frequencies but activating with a different white-noise sequence did not, supporting the idea that redundancy reduction is implemented by filtering out low frequencies (Fig. 6).

Discussion

Our results confirm and extend the basic proposal that the retina increases the efficiency of information transmission by reducing redundancy (Barlow, 1961). This general hypothesis has been elaborated into spatial and temporal versions. A spatial elaboration states that the surround deemphasizes low spatial frequencies, thus removing spatial correlations in natural images, reducing redundancy between the spike trains of different ganglion cells (Atick, 1992; Dong & Atick, 1995). A temporal elaboration states that the bandpass character of the response deemphasizes low temporal frequencies from the spike train of a single ganglion cell. Either elaboration of the basic hypothesis is supported by experimental evidence: starting with redundancy reduction as an optimizing principle, it is possible to derive spatial or temporal filters that match those measured for ganglion cells and other visual neurons (Srinivasan *et al.*, 1982; Atick, 1992; van Hateren, 1992; Dong & Atick, 1995). However, it was not clear whether a visual neuron, when confronted with combined spatial and temporal correlations, would in fact reduce redundancy. Here we show that, in the presence of such spatiotemporal correlations, the surround can reduce temporal redundancy in a single spike train. An exception to this general rule is the brisk-sustained cell, for which we were unable to demonstrate redundancy reduction.

The receptive center and surround act together to remove low frequencies that contribute to temporal redundancy (Fig. 6). This has been previously demonstrated for brisk-transient cells by

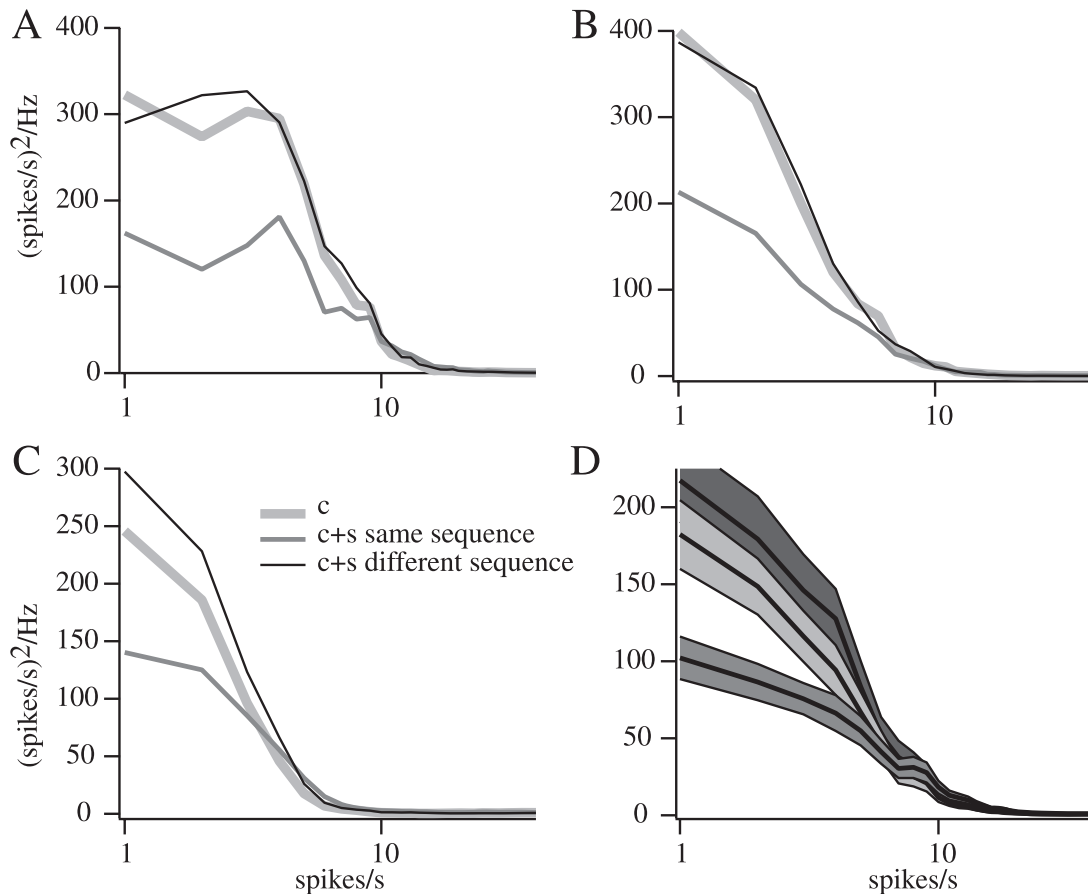


FIG. 6. Activating the surround with the same white-noise sequence as the center de-emphasized low frequencies in the spike train. (A and B) Brisk-transient cells; (C) a sluggish cell; (D) averaged spectra for 14 brisk-transient and sluggish cells (grey bands show average \pm SEM). The surround reduced power at low frequencies, but only if the surround was stimulated with the same temporal white-noise sequence as the center.

Frishman *et al.* (1987), who derived pure center and surround 'mechanisms' that have the same frequency response. The surround was, however, delayed behind the center. Due to this delay, and because the center and surround are antagonistic, the center and surround would act as a differentiator, performing a 'running subtraction' of the visual stimulus, and by this method filter out low frequencies. We confirm that surround's impulse response is delayed behind the center, although by means of spot and annulus we cannot obtain pure center and surround mechanisms, and thus cannot confirm that these mechanisms have similar frequency responses. Thus it is possible that the surround, if it responds to lower frequencies than the center, could remove these frequencies by subtraction and by this method implement a high-pass filter instead of a pure differentiator.

'Predictive coding' is a theory that explains the center-surround structure of the receptive field by positing that the surround estimates the most probable signal at the center, which is subtracted from the actual center signal, effectively reducing spatial redundancy between ganglion cells (Srinivasan *et al.*, 1982). Our results imply a predictive coding strategy to deal with spatiotemporal correlations. Thus, the surround collects over a wider area than the center to make a prediction of what will happen next at the center; then this prediction is delayed and subtracted from the center. Such a mechanism would be useful for removing redundancy from objects that cross over the surround and into the center, as might occur during saccadic eye movements.

A spike train's coding capacity is set by the firing rate (MacKay and McCulloch 1952; Reinagel *et al.* 1999; Rieke *et al.* 1997). Only some of this capacity is actually used to transmit information; the remainder is lost to redundancy and noise entropy. Therefore reducing redundancy increases the amount of entropy available for information. Reducing the amount of entropy wasted on noise would also increase available entropy, but we found that brisk-transient and sluggish cells fail to take advantage of this strategy. Indeed the surround, when confronted with spatiotemporal correlations, increases noise in the spike train. Our results are consistent with the idea that the noise increase is due to an interaction between spike rate and the refractory nature of the spike train: surround antagonism reduces spike rate, so that the characteristic interval of the spike train exceeds the refractory period which, in turn, obviates the normal effect of refractory period, which is to reduce spike train noise (Berry & Meister, 1998).

Visual cells in the lateral geniculate nucleus reduce redundancy more effectively and code information more efficiently when stimulated with natural scenes than with temporal white noise, suggesting that if we had used natural images we would have found more information coded per spike (Dan *et al.*, 1996). However, a comparison of ganglion cell responses to these two stimuli shows no difference in coding efficiency (Koch *et al.*, 2004, 2006). Thus we choose artificial stimuli as a tractable way of controlling the contribution of the surround. So far, this is not possible for natural stimuli; pharmacologic means of blocking the surround (e.g., GABA and glycine antagonists) are nonspecific in their effects (Freed, 1992). If, however, such a means of modulating the surround could be found, our results predict that a retinal ganglion cell would remove the spatiotemporal correlations inherent in natural scenes more effectively with a functioning surround than without one.

Supplementary material

The following supplementary material may be found on <http://www.blackwell-synergy.com>

Fig. S1. Decreasing refractory period increases noise.

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Abbreviations

N, noisiness; *R*, redundancy.

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