Why efficiency, unlike sensitivity, is highly conserved across eccentricity and size
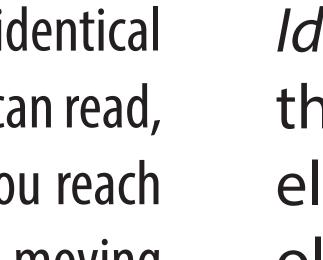
Originally: Crowding area sets a lower bound on the neural noise that limits letter identification

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Fig. 1. Efficiency demo. Below are two identical eye charts to measure efficiency. The lower you can read, the higher your efficiency is. Note that when you reach your threshold in one chart you can, without moving your eyes, also just barely read the corresponding letter in the other chart. This shows that your central and peripheral vision have the same efficiency.

Introduction

Identifying letters in noise. Visual sensitivity is the reciprocal of threshold contrast. Contrast threshold for letters (and everything else) depends strongly on size and eccentricity. However, threshold on a white noise background depends only weakly on letter size and eccentricity. Here we decompose sensitivity into efficiency and equivalent input noise (Pelli and Farell, 1999).

Efficiency η is the fraction of the contrast energy used by the human observer that would be required by the optimal algorithm (ideal observer),

$$\eta = \frac{E_{ideal}}{E - E_0} \qquad (1)$$

where E and E_{ideal} are the human and ideal thresholds in noise N, and E_0 is human threshold in zero noise.

Equivalent input noise N_{eq} is the amount of display noise that would be required to account for the measured threshold *without noise*, assuming the efficiency measured at high noise.

$$N_{eq} = \frac{E_0}{E - E_0} N \qquad (2)$$

Methods

Figs. 1-4. We measured threshold contrast for identifying a (square) Sloan letter **DHKN ORSVZ** with size (i.e. height) H = 0.5°, 1°, 2°, 4°, 8°, 16°, 32° at eccentricity φ = 0°, 8°, 16°, 32°, with and without visual noise. The noise was full-field Gaussian white noise with RMS contrast 0.16, consisting of i.i.d. square checks each 1/20 of letter height. We used a 10-bit-per-channel display to measure thresholds without noise.

Fig. 5. To measure integration area, we vignetted the noise with a Gaussian envelope (with variable radius) centered on the letter, and measured the letter threshold as a function of the noise radius. For small radii, threshold rose in proportion to radius, and then reached an asymptote. We fit straight lines, by eye, in log-log coordinates, to the rise and plateau, and took the intersection to be the radius of integration (Fig. 5).
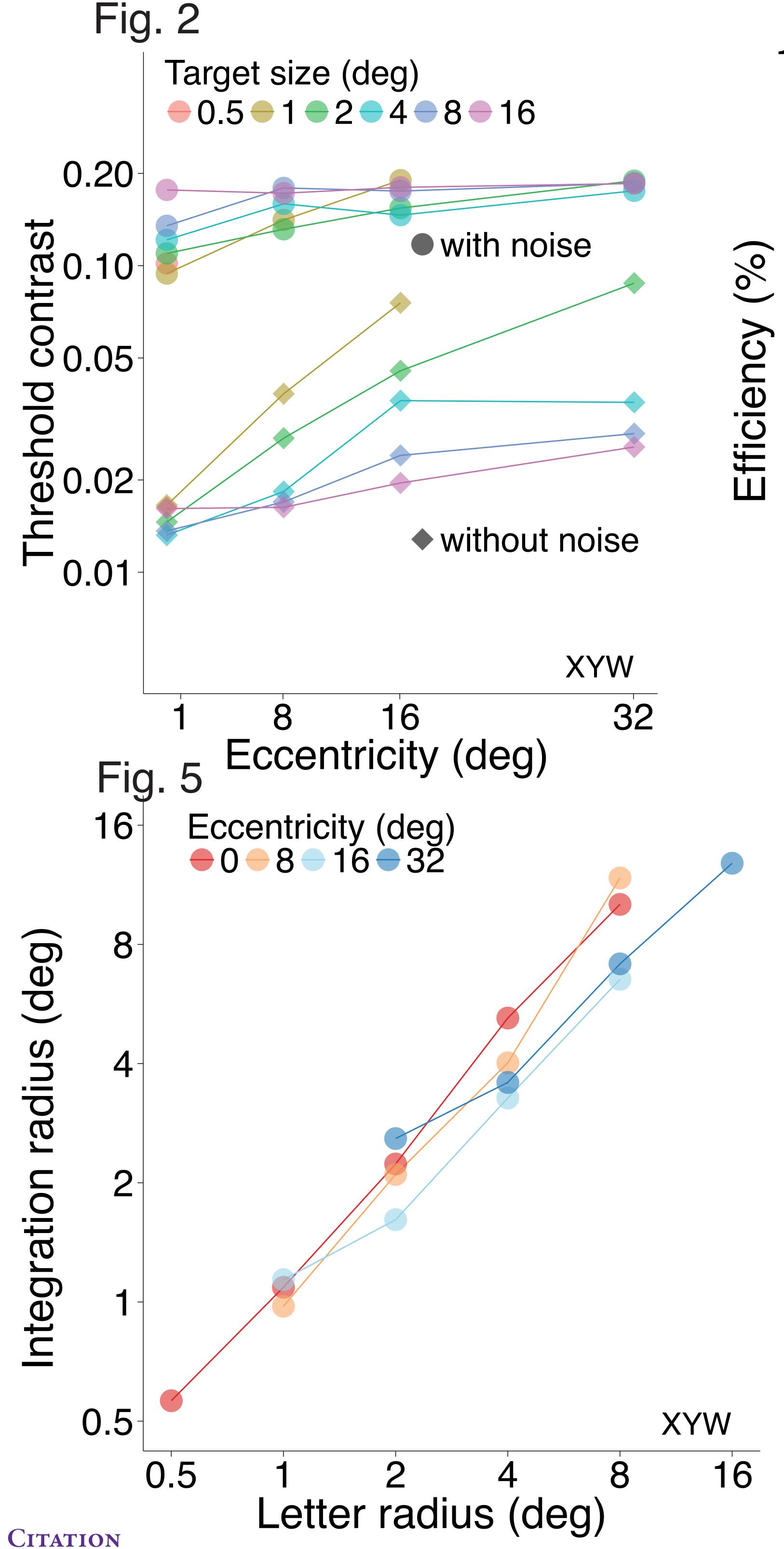
Results

Fig. 2. As previously noted by Rovamo et al. (1992), thresholds in noise (upper) vary much less than those without noise (lower).

Fig. 3. Efficiency is highly conserved: only weakly dependent on letter size and, surprisingly, eccentricity. This predicts, and we confirm, that, contrary to what one might expect from crowding, the integration area for a letter in noise is matched to the letter size, independent of eccentricity.

Fig. 4. Equivalent input noise is the sum of two components, one dependent on letter size (and consistent with scale-invariant processing in the cortex) and another dependent on eccentricity (possibly reflecting ganglion cell noise).
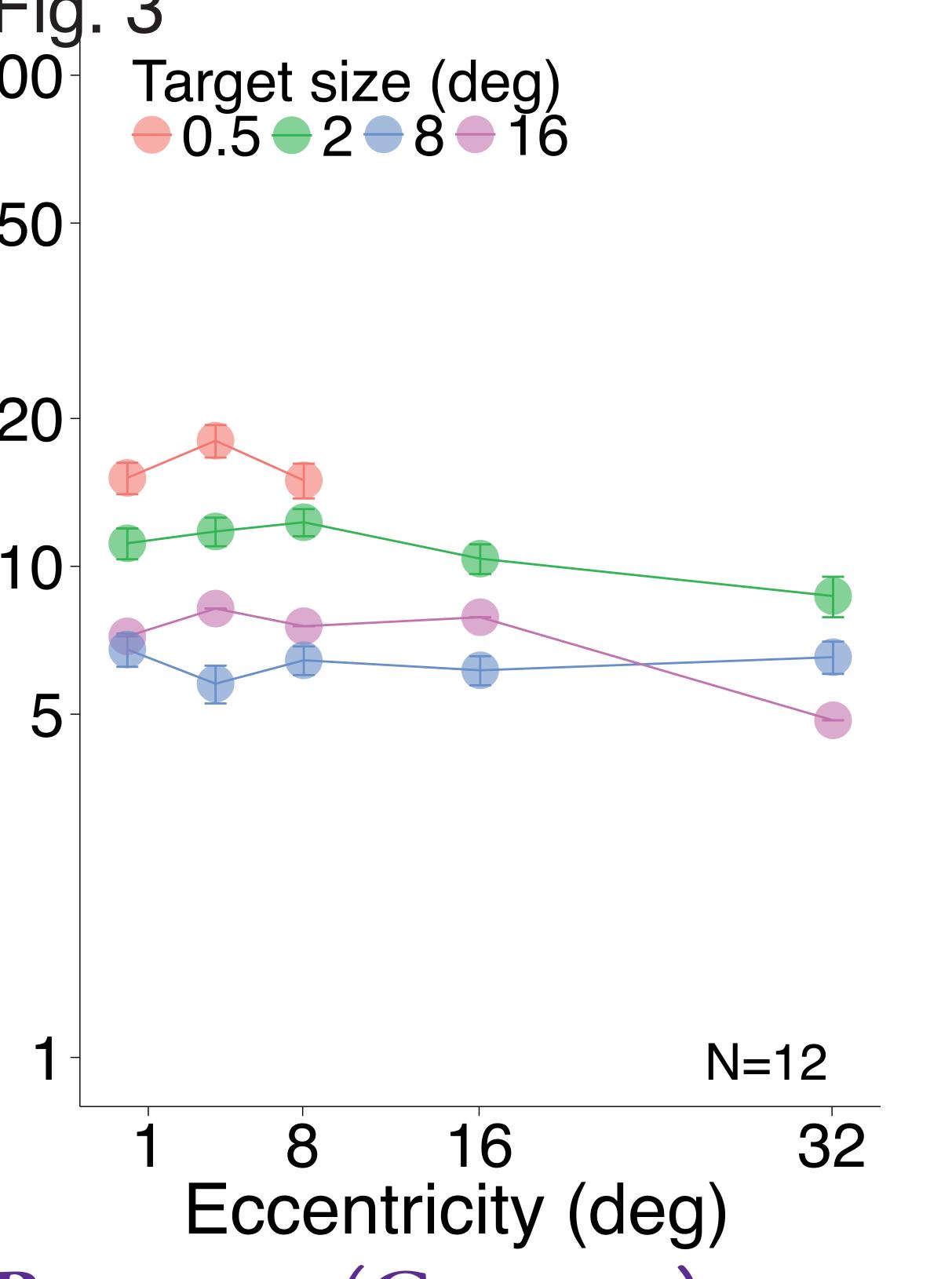
Equivalent noise proportional to signal area: $N_{eq} \propto H^2$. That efficiency depends only weakly on size suggests nearly scale-invariant computation. Pelli and Raghavan (2016) showed that supposing that the cortical computation, including noise, is
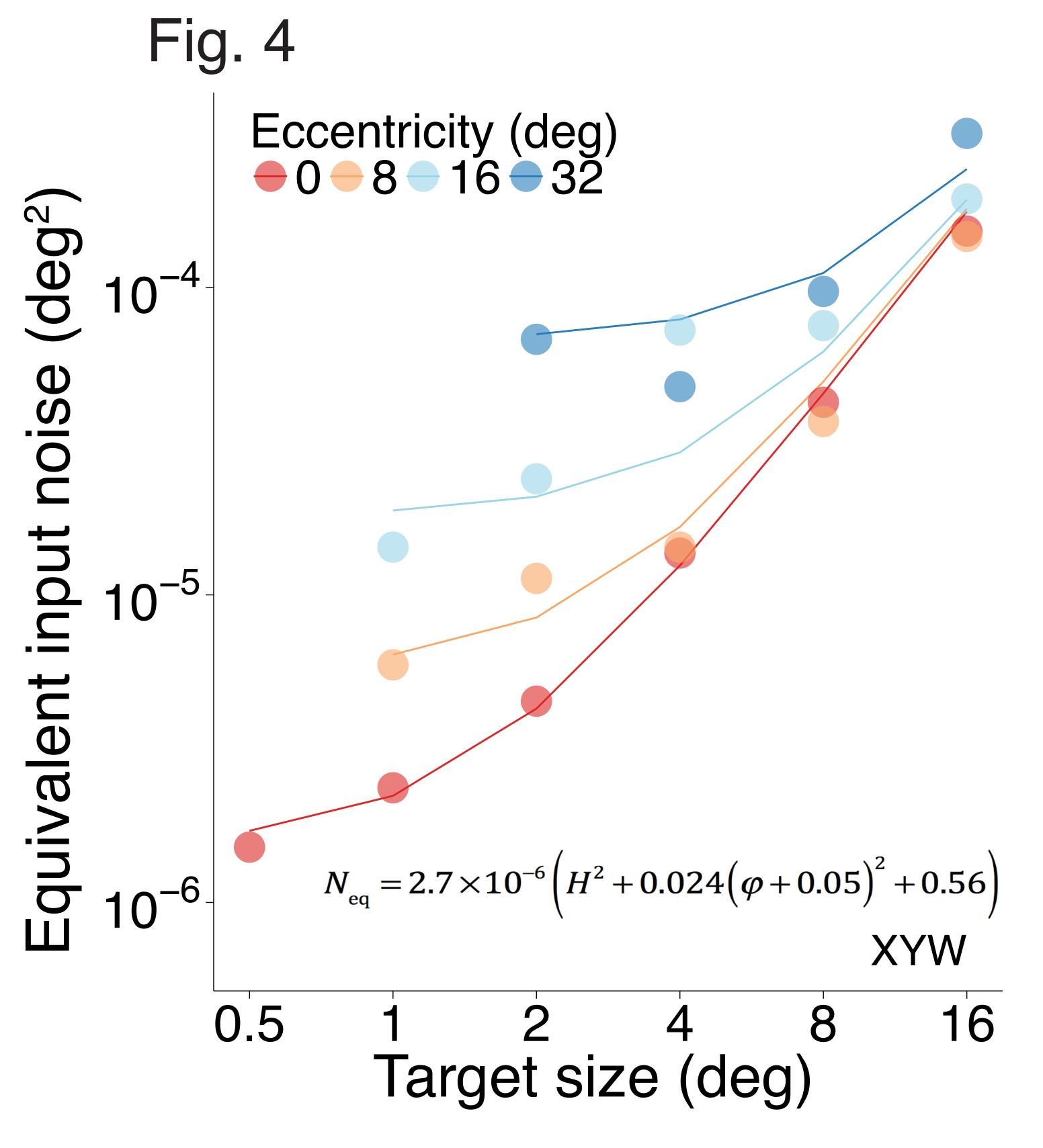
Fig. 2

Fig. 3

Fig. 4

$$N_{eq} = 2.7 \times 10^{-6}\left(H^2 + 0.024(\varphi + 0.05)^2 + 0.56\right)$$

Fig. 5

Results (Contd.)

scale invariant implies that the equivalent input noise scales as well. Scaling an image with white noise by a magnification factor of M horizontally and vertically will increase its power spectral density by a factor of M^2. This predicts that the equivalent input noise of any scale-invariant cortical computation will scale with letter area H^2. Pelli & Raghavan reported that component in foveal measurements of equivalent input noise. We confirm that, and extend results to many eccentricities.

Equivalent noise proportional to eccentricity squared: $N_{eq} \propto \varphi^2$. We find a new component of equivalent input noise that is proportional to squared eccentricity (Eq. 3). This might be ganglion cell noise, since the area occupied by a fixed number of ganglion cells increases as the square of eccentricity.

Fig. 5. The integration radius approximates the letter radius at all eccentricities. We vignetted noise by a Gaussian envelope centered on the letter. We measured the observer's *integration radius* by measuring threshold for a given letter size as a function of the noise radius, for several eccentricities and target sizes. We find that the integration radius is roughly equal to the letter radius (half height), independent of eccentricity. This is utterly unlike what one might expect from crowding, for which the area of "feature integration" has a radius of about one third the eccentricity.

Conclusions

The computation of letter identification is efficient, independent of eccentricity and only weakly dependent on letter size. The variations in sensitivity with size and eccentricity are mostly due to variations in equivalent noise. The noise has three additive components, corresponding to different intrinsic sources of visual noise, similar to those proposed by Pelli and Raghavan (2016): a photon noise independent of size and eccentricity, a retinal ganglion cell noise proportional to eccentricity squared, and a cortical noise proportional to letter area.

References
Pelli, D. G. & Farell, B. (1999) Why use noise? *Journal of the Optical Society of America A*, 16, 647-653.
Pelli, D. G., & Raghavan, M. (2016) Photon and cortical noises limit what we see. CoSyNe 2016.
Rovamo, J., Franssila, R., & Näsänen, R. (1992). Contrast sensitivity as a function of spatial frequency, viewing distance and eccentricity with and without spatial noise. *Vision research*, 32(4), 631-637.