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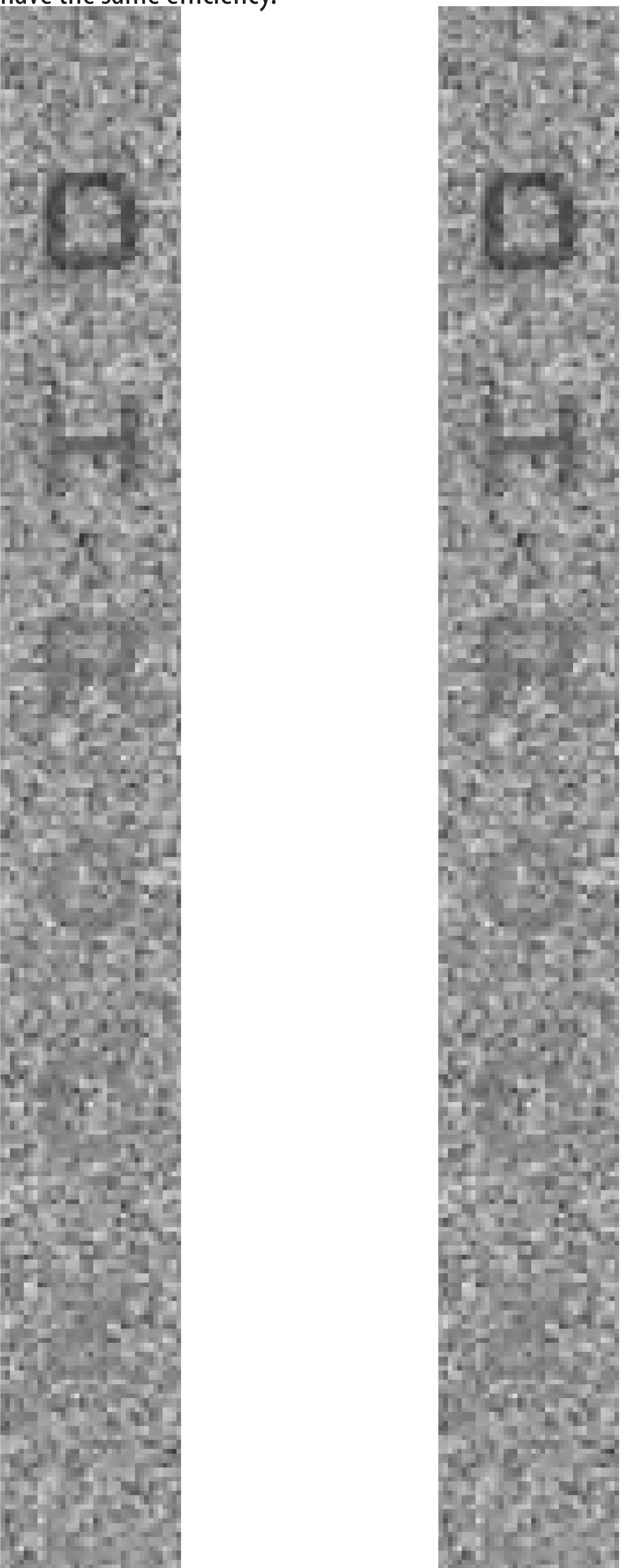
Fig. 1. Efficiency demo. Below are two identical eye charts to measure efficiency. The lower you can read, the higher your efficiency is. Note that when you reach your threshold in one chart you can, without moving your eyes, also just barely read the corresponding letter in the other chart,(your central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

Fig. 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 $\varphi = 0°, 8°, 16°, 32°$, 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 line, 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. Thresholds in noise (higher) 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

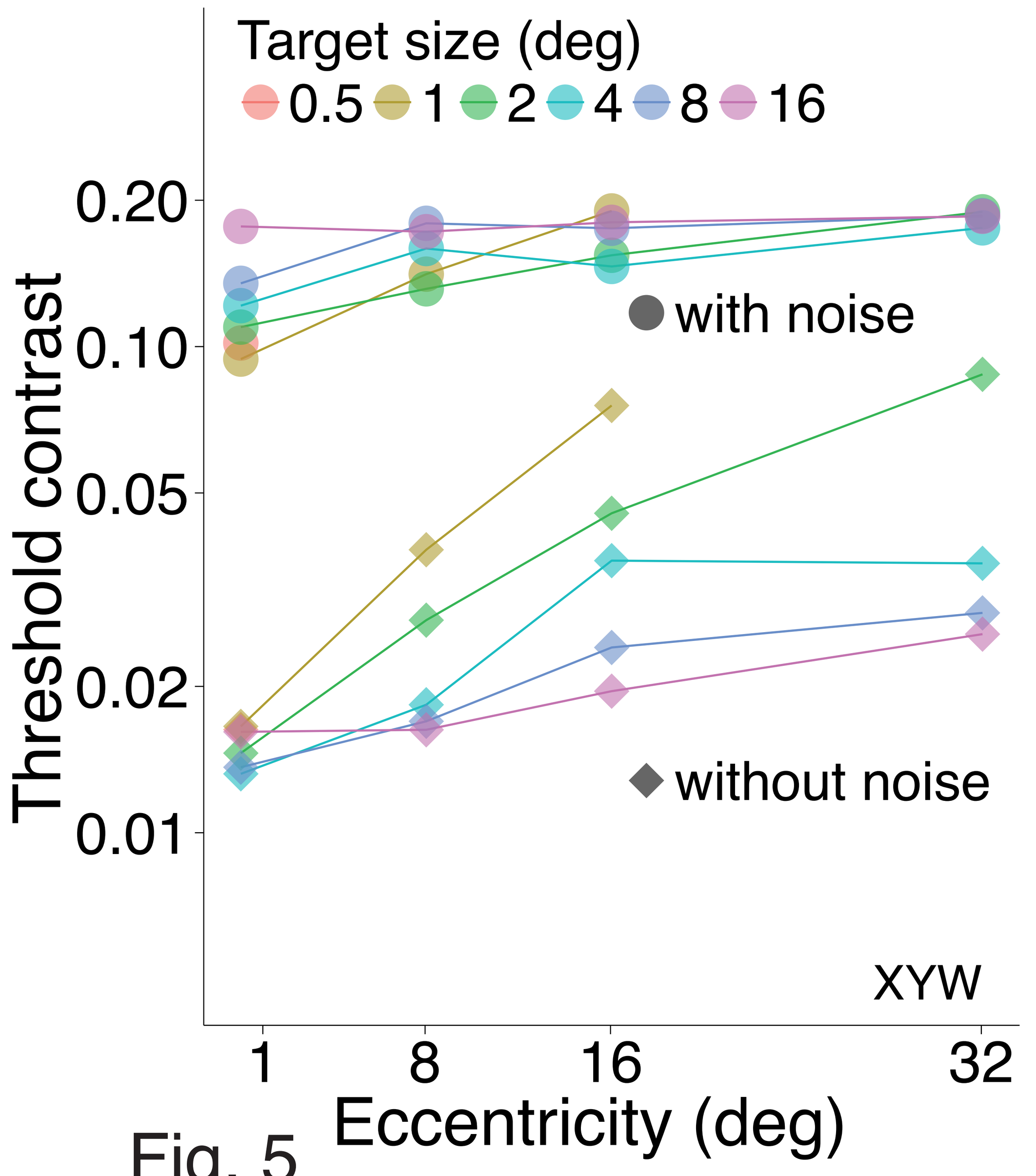


Fig.3

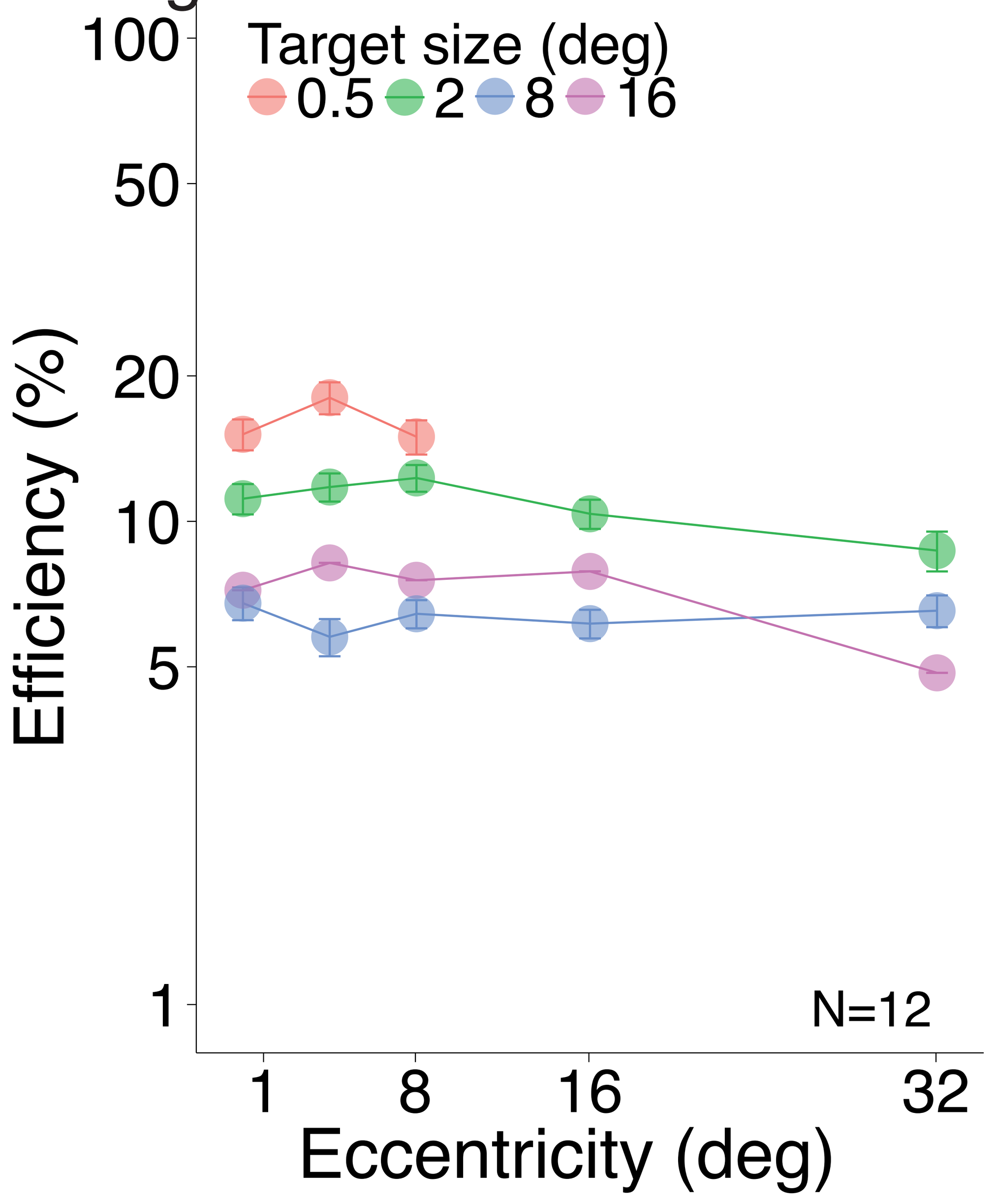


Fig.4

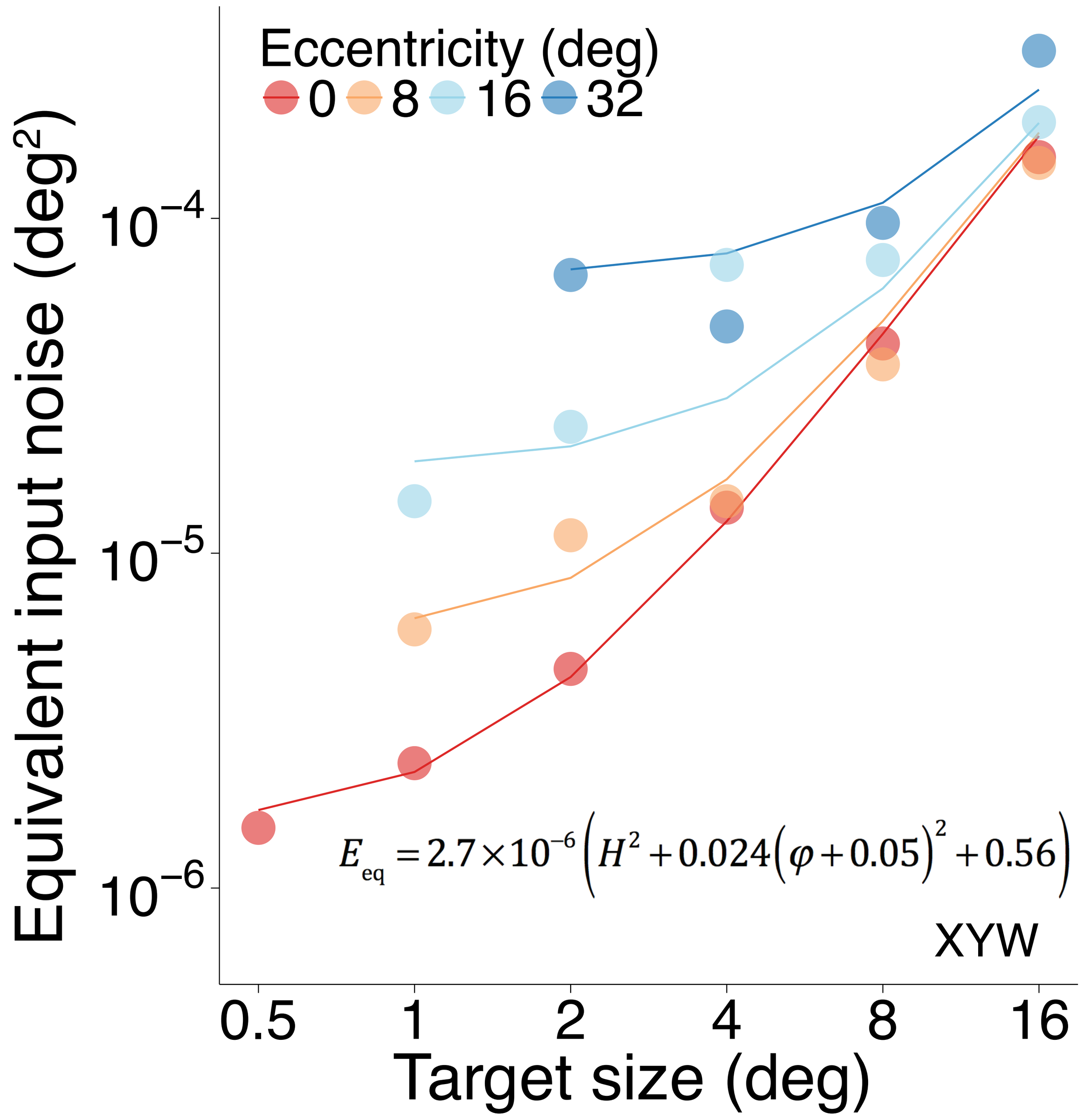
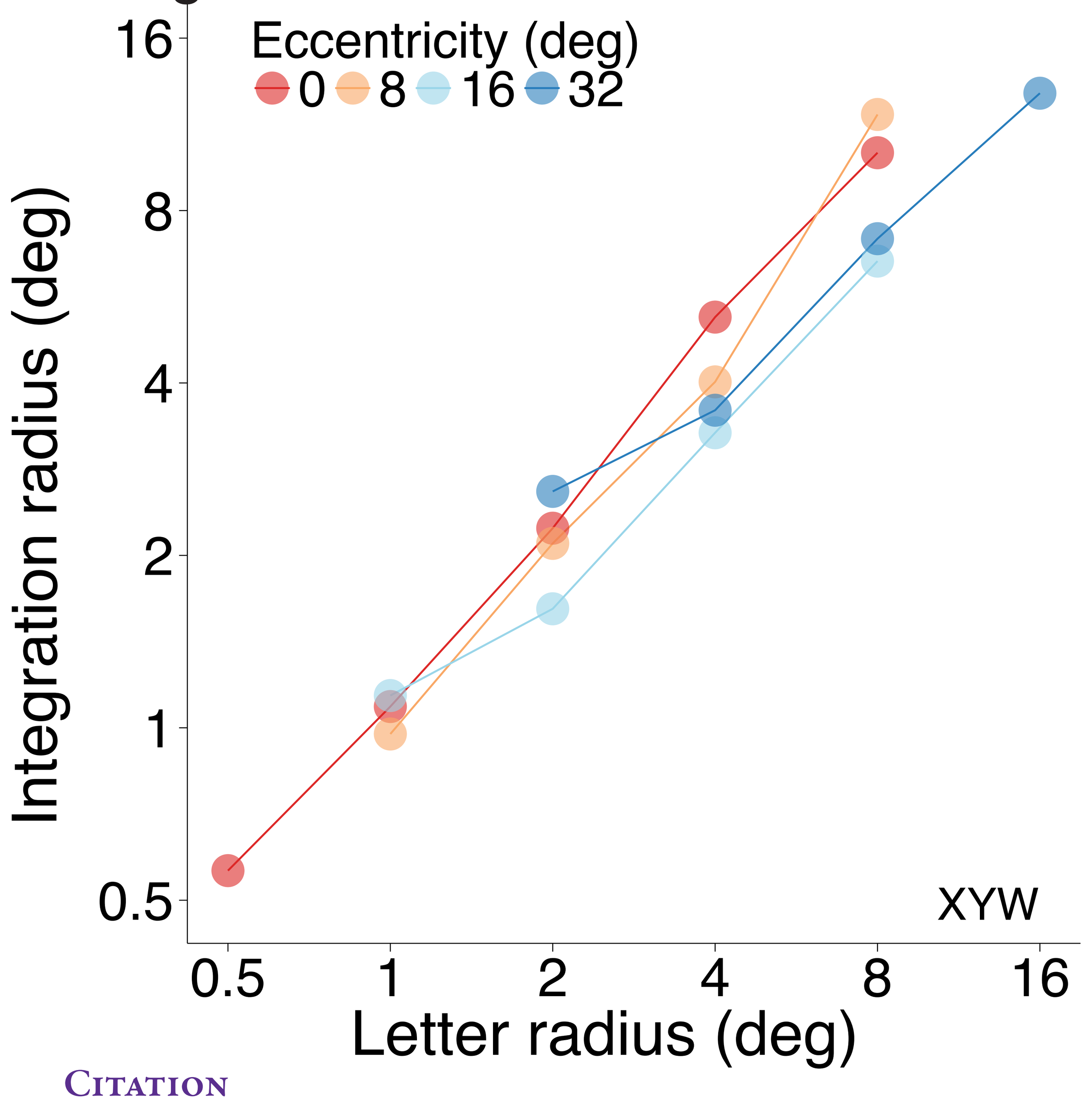


Fig. 5



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 tested identification performance by systematically controlling the noise radius in addition to eccentricity and target size. We softened the noise edge using a Gaussian envelope. We find that the radius of the integration tracks letter radius, indepednet of eccentricity

Conclusions

The computation of letter identification is efficient, independent of eccentricity and only weakly depdent 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: a "photon" noise independent of size and eccentricity, a "cortical" noise proportional to letter area, and a retinal gnanglion cell noise proportional to eccentricity squared.

Citation

Yiltiz, H., Wu, X. Y., & Pelli, D. G. (2016) Crowding area sets a lower bound on the neural noise that limits letter identification. 16th Annual Meeting of the Vision Sciences Society, May 13-18, 2016 in St. Pete Beach, Florida. https://psych.nyu.edu/pelli/posters.html http://hyiltiz.com/en/publication/

References

Pelli, D. G. & Farell, B. (1999) Why use noise? Journal of the Optical Society of America A, 16, 647-653.
Pelli, D. G., and Raghavan, M. (2016) Photon and cortical noises limit what we see. Computational and Systems Neuroscience (Cosyne) 2016, February 25 - 28, 2016 in Salt Lake City.

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