Normalizing population receptive fields

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The visual system is spatially organized. Each neuron responds to stimulation at a specific region in the visual field—its "receptive field"—and is largely unresponsive to stimulation elsewhere. For decades, electrophysiologists have characterized the receptive fields of neurons with invasive recordings (1, 2), providing the foundation for visual neuroscience. More recently, a technique was introduced that allows for noninvasive measurement of receptive field properties in humans using functional MRI (fMRI). This technique, known as population receptive field (pRF) mapping (3, 4), uses a model-based approach to measure the receptive fields of voxels, the small volumes of tissue from which responses are measured with fMRI. This is where the method gets its name: Because a voxel aggregates the activity of many neurons, the resulting receptive field is called a "population receptive field."

In the first instantiation of the pRF method (3), the receptive field of each voxel was modeled as a simple two-dimensional Gaussian that could vary in its size and position in the visual field. The size and position of a voxel's receptive field are estimated by finding the values that best predict the voxel's response to a variety of stimulus sequences (e.g., a bar sweeping through the visual field in different directions). This simple but powerful tool has been widely adopted in human neuroscience. Early studies validated the method, finding that measured pRFs largely square with established electrophysiological findings in animals. For instance, pRF size increases systematically across the visual hierarchy (3). Researchers have begun to leverage the pRF approach to characterize how receptive field properties are modulated by cognitive states (5, 6), and how they are impacted in ophthalmologic (7, 8) and neurological (9, 10) disorders. The growing adoption of pRFs as a tool for understanding brain function necessitates more-mechanistic models of pRF. While current instantiations of the pRF method do an excellent job of characterizing the size and position of voxel receptive fields, there are well-known response properties in vision that current pRF models do not account for. In PNAS, Aqil et al. (11) introduce and validate a model that accounts for these response properties in a unifying computation—divisive normalization.

A Putative Canonical Neural Computation Put to the Test

Neural responses are believed to be governed by the balance between excitation and inhibition, a principle of neuroscience that is captured by a computation known as divisive normalization (12). Under divisive normalization, a neuron's response to a stimulus is determined by local stimulus drive, but is also suppressed by the pooled responses of neighboring neurons (12). This simple computation has been shown to explain a wide variety of perceptual phenomena in vision and other sensory modalities, leading researchers to propose that normalization may be a canonical computation that regulates neural responses throughout the brain (13). Aqil et al. (11) put this hypothesis to the test by examining whether normalization can provide a unifying account of responses across the human visual processing hierarchy. To this end, they have the insight to upgrade the pRF model, replacing the descriptive Gaussian model with a more-mechanistic divisive normalization model. In doing so, they discover they can parsimoniously account for two nonlinear response properties that were overlooked in the standard pRF model.

Two well-documented nonlinearities in the visual system are center-surround suppression, the finding that stimulation outside a cell's classical receptive field suppresses its response, and response saturation, the tendency for neuronal responses to plateau no matter how intense the input drive gets (for a review, see ref. 13). Similar nonlinearities also rear their head in fMRI data. Like neurons, the response of a voxel is often suppressed below baseline by stimulation just outside its receptive field (14). Furthermore, a voxel's response increases in a sublinear manner when a

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Author contributions: J.J.F. and S.L. wrote the paper.

The authors declare no competing interest.

See companion article, "Divisive normalization unifies disparate response signatures throughout the human visual hierarchy," 10.1073/pnas.2108713118.

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Published November 17, 2021.

larger portion of its receptive field is stimulated (15). Aqil et al. (11) term these empirical patterns in pRF data "suppression" and "compression," respectively. These two phenomena are not accounted for by the standard pRF model, and, although subsequent instantiations have successfully modeled suppression and compression separately (14, 15), those variants of the pRF model were descriptive: Modeling suppression alone did not account for compression, and vice versa. More importantly, these pRF variants fell short of providing a mechanistic account for visual responses measured with fMRI.

Aqil et al. (11) take a different approach. Motivated by classic work that has shown that divisive normalization can explain nonlinearities seen in the responses of individual neurons (12), Aqil et al. develop a normalization-based pRF model. Aqil et al. scaled normalization up to the neuronal population level, modeling the response of a voxel as the ratio between an excitatory field and a larger inhibitory field, with the latter reflecting the suppressive influence of neighboring neuronal populations—the essence of normalization (12). Taking advantage of ultra-high-field fMRI, Aqil et al. pit their model against existing models, and find that their normalization model outperformed all other models, explaining more variance in voxel responses to a range of stimulus sequences. Importantly, where past models have fallen short, Aqil et al.'s normalization model captures both suppression and compression. Furthermore, they identify model parameters that are specifically linked with suppression and compression, and find that these parameters vary predictably across the visual hierarchy, consistent with previous work that has shown that suppression is greater in early visual areas (14) and compression is greater in later visual areas (15). Taken together, these findings demonstrate the power of Aqil et al.'s pRF model, which provides a mechanistic account of suppression and compression in voxel responses measured with fMRI, and add to growing evidence that divisive normalization is a canonical computation in the brain.

Moving toward Mechanistic Models in Functional Neuroimaging

In recent years, there has been a shift in human neuroscience toward developing formal computational models to shed light on the mechanisms that support perception and cognition (e.g., refs. 16 and 17). These model-based approaches hold enormous potential, moving from descriptive accounts of human brain activity to testable mechanistic accounts. With a rich enough dataset, one can pit numerous mechanistic models against each other. Indeed, Aqil et al.'s (11) study provides a promising road map for exactly how we can move toward such mechanistic models of brain function. It should be noted that Aqil et al.'s pRF model may not be the right choice for all applications. A common use of the pRF method is to map the retinotopic organization of visual cortex, delineating the various visual areas. In this case, the position of voxel receptive fields is all that is needed, and simpler, descriptive models may still be the best choice, because they can be reliably fit with less data (4).

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However, for those that seek a mechanistic understanding of brain function, this normalization-based pRF model may prove invaluable. For example, divisive normalization is thought to play a central role in attention (18, 19), but there is sparse functional neuroimaging evidence in support of this hypothesis (20). This model may provide an opportunity to test that class of theories, allowing researchers to examine how normalization-related parameters relate to attentional modulation within and across visual areas. This model could also shed light on the mechanisms underlying anomalies in visual function that occur in ophthalmologic and neurologic disorders. For instance, disorders such as schizophrenia have been theorized to be associated with poor neural suppression (10), and future work employing the normalization-based pRF modeling approach may play a pivotal role in unraveling this puzzle.

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1 H. K. Hartline, The receptive fields of optic nerve fibers. *Am. J. Physiol. Legacy Content* **130**, 690–699 (1940).
2 D. H. Hubel, T. N. Wiesel, Receptive fields of single neurones in the cat's striate cortex. *J. Physiol.* **148**, 574–591 (1959).
3 S. O. Dumoulin, B. A. Wandell, Population receptive field estimates in human visual cortex. *Neuroimage* **39**, 647–660 (2008).
4 B. A. Wandell, J. Winawer, Computational neuroimaging and population receptive fields. *Trends Cogn. Sci.* **19**, 349–357 (2015).
5 B. P. Klein, B. M. Harvey, S. O. Dumoulin, Attraction of position preference by spatial attention throughout human visual cortex. *Neuron* **84**, 227–237 (2014).
6 V. A. Vo, T. C. Sprague, J. T. Serences, Spatial tuning shifts increase the discriminability and fidelity of population codes in visual cortex. *J. Neurosci.* **37**, 3386–3401 (2017).
7 H. A. Baseler *et al.*, Large-scale remapping of visual cortex is absent in adult humans with macular degeneration. *Nat. Neurosci.* **14**, 649–655 (2011).
8 A. Papanikolaou *et al.*, Population receptive field analysis of the primary visual cortex complements perimetry in patients with homonymous visual field defects. *Proc. Natl. Acad. Sci. U.S.A.* **111**, E1656–E1665 (2014).
9 D. S. Schwarzkopf, E. J. Anderson, B. de Haas, S. J. White, G. Rees, Larger extrastriate population receptive fields in autism spectrum disorders. *J. Neurosci.* **34**, 2713–2724 (2014).
10 E. J. Anderson *et al.*, Visual population receptive fields in people with schizophrenia have reduced inhibitory surrounds. *J. Neurosci.* **37**, 1546–1556 (2017).
11 M. Aqil, T. Knapen, S. O. Dumoulin, Divisive normalization unifies disparate response signatures throughout the human visual hierarchy. *Proc. Natl. Acad. Sci. U.S.A.* **118**, e2108713118 (2021).
12 D. J. Heeger, Normalization of cell responses in cat striate cortex. *Vis. Neurosci.* **9**, 181–197 (1992).
13 M. Carandini, D. Heeger, Normalization as a canonical neural computation. *Nat. Rev. Neurosci.* **13**, 51–62 (2012).
14 W. Zuiderbaan, B. M. Harvey, S. O. Dumoulin, Modeling center-surround configurations in population receptive fields using fMRI. *J. Vis.* **12**, 10 (2012).
15 K. N. Kay, J. Winawer, A. Mezer, B. A. Wandell, Compressive spatial summation in human visual cortex. *J. Neurophysiol.* **110**, 481–494 (2013).
16 K. N. Kay, J. L. Gallant, I can see what you see. *Nat. Neurosci.* **12**, 245 (2009).
17 M. D. Lescroart, J. L. Gallant, Human scene-selective areas represent 3D configurations of surfaces. *Neuron* **101**, 178–192.e7 (2019).
18 J. H. Reynolds, D. J. Heeger, The normalization model of attention. *Neuron* **61**, 168–185 (2009).
19 J. Lee, J. H. R. Maunsell, A normalization model of attentional modulation of single unit responses. *PLoS One* **4**, e4651 (2009).
20 I. M. Bloem, S. Ling, Normalization governs attentional modulation within human visual cortex. *Nat. Commun.* **10**, 5660 (2019).