Supporting Information

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SI Materials and Methods

Subjects. We present data from five subjects (all male, age range 25–39 y). One was left-handed. All were well-educated, with good mathematical abilities. All had normal or corrected-to-normal visual acuity. All were trained on tasks requiring numerosity judgments before scanning. All experimental procedures were cleared by the ethics committee of University Medical Center Utrecht.

A total of seven subjects was recruited. However, two subjects were excluded from analysis and no complete dataset was recorded, because the first scanning session revealed that the position of the superior sagittal sinus prevented imaging of the numerosity map (9).

Object Size and Numerosity Stimuli. Visual stimuli were presented by back-projection onto a 15.0 × 7.9-cm screen inside the MRI bore. The subject viewed the display through prisms and mirrors, and the total distance from the subject’s eyes (in the scanner) to the display screen was 41 cm. Visible display resolution was 1,024 × 538 pixels.

The stimuli were generated in MATLAB using the Psychophysics Toolbox (22). A large diagonal cross, composed of thin red lines, crossed the entire display, a design that facilitates accurate fixation. Subjects were asked to fixate the intersection of the cross. Stimuli consisted of single circles or groups of circles presented in the central 0.75° (radius) of the visual field, with the exception of the largest circle presented when characterizing object size selectivity, which reached a maximum eccentricity of 2.6°. This small central stimulus area decreased the need to make eye movements to view the circles. It also minimized the cortical surface extent of the visually responsive part of the brain activated by presentation of the stimulus, avoiding confusion between spatially tuned responses and object size- or numerosity-tuned responses.

Circles were randomly positioned at each presentation so that each circle fell entirely within the central 0.75° (except for the largest circle in the object size selectivity experiment, whose center was randomly positioned in the same area). Each of the many presentations (384 presentations for each object size or numerosity in each condition) contained circles placed in a new, random position. Averaging these responses to different visual positions minimized links between particular visual field positions and particular numerosities or object sizes (9). To prevent perceptual grouping, individual items in the numerosity experiments were distributed roughly homogeneously across the stimulus area (except for the high-density condition described below).

To characterize object size tuning, we varied the size of a single circle. Again, circles were randomly placed in the first condition (variable step condition) (Fig. 1A). However, because circles were always constrained to fit within the central 0.75° of the display, larger circles would take a shorter average step between consecutive presentations. As such, a second stimulus configuration (constant step) kept this step size constant at 0.06° across different circle sizes, with the direction of steps varied randomly.

To characterize numerosity tuning, we used various stimulus configurations (9) to ensure that responses to low-level visual features of the stimulus did not follow the same time course in different conditions. The first stimulus configuration (“constant area” condition) kept the total surface area of all of the circles combined constant across numerosities, ensuring equal luminance across conditions. The second (“constant object size”) kept individual circle size constant. The third (“constant circumference”) kept the total circumference constant, ensuring equal edge density. The fourth condition (“high density”) contained the same circles as the constant area condition but at higher density, with all circles falling entirely within a 0.375°-radius area that was randomly placed inside the stimulus area.

All patterns were presented as black circles on a gray background. Patterns were presented briefly (300 ms) to ensure subjects did not have time to sequentially count the objects. This was repeated every 700 ms, each time with a new random pattern presented, with a 400-ms presentation of a uniform gray background between pattern presentations. For object size tuning experiments, this was repeated three times, over 2,100 ms [one repetition time (TR)], fMRI volume acquisition, before the size changed. For numerosity tuning experiments, this was repeated six times, over 4,200 ms (two TRs), before the numerosity changed. This allowed a slow progression through the numerosity range while only presenting whole numbers of objects. On 10% of pattern presentations, the circles were shown in white instead of black. Subjects were instructed to press a button when this happened to ensure they were paying attention to the patterns during fMRI acquisition. No object size or numerosity judgments were required. Subjects responded on 80–100% of white circle presentations within each scanning run.

In the object size tuning experiments, circles with diameters of 0.1°–0.7° were shown as the main stimulus (Fig. 1C, Top), first presented in linearly increasing order. This was followed by a longer period (16.8 s) where the circle was 3.7°-diameter, followed by the same object sizes in descending order, followed by another long period of 3.7° diameter.

In the numerosity experiments, the numerosities 1–7 were shown as the main stimulus (9), first presented in ascending order, followed by a longer period (16.8 s) where the stimulus contained 20 circles, followed by the numerosities in descending order, followed by another long period of 20 circles.

This sequence was repeated four times in each scanning run. The long period of 20 circles or a 3.7°-diameter circle had a similar function to the blank periods used in visual field mapping stimuli in population receptive field experiments, allowing us to distinguish between very small and very large tuning widths, that is, between populations that responded at all times and those that never responded (9, 11). During this period, little neural response was expected from neurons with small preferred object sizes or numerosities, because such a large object size or numerosity should be well outside of the range that elicits strong responses. This allows hemodynamic responses to return back to baseline between blocks of changing object size or numerosity. However, using numerous or large objects (rather than no objects) provides a stronger visual stimulus than the other stimulus. As such, neural populations responding to the contrast energy of the stimulus should respond most strongly during presentation of large or numerous circles, avoiding confusion with populations preferring a specific large object size or numerosity.

Stimuli were presented many times between changes (three times for object size tuning and six times for numerosity tuning measurements), ensuring strong fMRI responses and facilitating measurements of response preferences. As in many fMRI experiments, these stimuli likely cause some adaptation to the presented object sizes and numerosities (4, 23). We aim to minimize effects of adaptation on tuning estimates by modeling responses to stimuli with both ascending and descending changes. We thus counterbalance adaptation effects by presenting stimuli that give both higher and lower responses before presentation of any object size or numerosity. Because the tuning model must fit both of these response sequences with one set of tuning parameters, the resulting tuning parameters reflect the preferred stimulus without strong dependence on preceding stimuli.
MRI Acquisition. Anatomical MRI data for subjects 2, 3, and 4 were acquired on a Philips Achieva 3T scanner with a Quasar dual gradient set. T1-weighted anatomical MRI data were acquired at a resolution of $0.75 \times 0.75 \times 0.8$ mm. Repetition time was 10.029 ms, echo time (TE) was 4.6 ms, and flip angle was 8°. Anatomical MRI data for subjects 1 and 5 were acquired on a Philips 7T scanner using a 32-channel head coil. T1-weighted anatomical MRI data were acquired at a resolution of $0.5 \times 0.5 \times 0.8$ mm. TR was 7 ms, TE was 2.64 ms, and flip angle was 8°.

Functional T2*-weighted multislice echo planar images were acquired on a Philips 7T scanner using a 32-channel head coil at a resolution of $1.77 \times 1.77 \times 1.75$ mm, with a field of view of $227 \times 227 \times 71.75$ mm. TR was 2,100 ms, TE was 25 ms, and flip angle was 70°. We used a single-shot gradient echo sequence with SENSE acceleration factor 3.0 in the anterior–posterior (AP) encoding direction and 41 interleaved slices. Maximum gradient strength was 26 mT/m, and maximum slew rate was 140 T·m⁻¹·s⁻¹. We used a third-order image-based B0 shim of the field of view of the functional scans (in-house IDL software, version 6.3; RSI). Functional runs were each 182 time frames (382.2 s) in duration, of which the first six time frames (12.6 s) were discarded to ensure the signal was at steady state. Eight repeated runs were acquired within the same session for each stimulus condition. All stimulus conditions were acquired on different days.

We used 7T data acquisition because it produces better signal strength at high scanning resolutions than 3T, reducing required scan times. Because of extensive comparisons between responses to different stimulus sets, experiments required a total of 10.5 h of scanning per subject. 3T scanning would have required approximately twice as much scanning to produce similar data quality.

Preprocessing of Anatomical and Functional Images. Functional MRI analysis was performed in the mrVista software package, which is freely available at white.stanford.edu/software. T1-weighted anatomical scans were automatically segmented using FreeSurfer (freesurfer.net) and then hand-edited to minimize segmentation errors (24) using ITK-SNAP (www.itksnap.org). This provided a highly accurate description of the cortical surface and white matter, an anatomical segmentation space used for analysis of cortical organization. The cortical surface was reconstructed at the gray–white matter border and rendered as a smoothed 3D surface (25). Head movement and motion artifacts between and within functional scans were measured and corrected for (26). Functional data were aligned to the anatomical scans (26) and interpolated to the anatomical segmentation space. Data from several sessions, resulting from all stimulus conditions, were imported into the same anatomical segmentation space. fMRI time-series data from all stimulus conditions (for numerosity and object size separately) were averaged together to produce datasets with very high signal-to-noise ratios. Reconstruction of gray matter depth was stopped 4 mm from the gray–white matter border, or where recording points were outside the gray matter. Across cortical thickness, data from all vertices in the gray matter thickness were collapsed and averaged onto the nearest point on the gray–white matter surface (27). This increased signal strength and formed a (folded) 2D representation of the gray matter. All data were also analyzed using the same methods without collapsing onto a 2D surface, with very similar results. Note that the acquired data were averaged, rather than the model parameters. Data from each individual condition were also analyzed separately.

Exclusion of Vein Artifacts. A large draining venous system, consisting of the superior sagittal sinus and its branches, runs over medial parietal parietal lobe. Draining veins spatially and temporally distort the fMRI signal around this vein (21). Measurements from high-field MRI scanners (we used 7T here) are less susceptible to signals originating in large veins (28). Nevertheless, we identified these locations by the mean signal intensity of the BOLD signal averaged over all sessions (28, 29) and excluded these from further analysis (Fig. S3). Because we used the mean BOLD signal across all sessions to identify these vein artifacts, anatomically equivalent recording points were excluded from all conditions. Similar results are found if these vein regions are included in the analysis. However, this procedure excludes regions where the topographic representation and tuning width measurements are distorted.

fMRI Data Analysis. Object size and numerosity tuning models were estimated from the fMRI data and stimulus time course as previously described for numerosity tuning (9). This approach is based on methods we developed to estimate visuospatial population receptive field properties in human visual cortex (11).

Population receptive field models describe the aggregate tuning of the neural population within each fMRI recording site. A forward model predicts neural responses at each time point depending on which stimulus was shown (Fig. 1B). The models describe tuning to object size or numerosity using Gaussian functions characterized by (i) a preferred object size or numerosity (mean of the Gaussian distribution); (ii) a tuning width (SD of the Gaussian); (iii) and an inhibitory surround width (SD of a negative Gaussian with the same mean). By examining the overlap of the stimulus at each time point with this tuning model, a prediction of the neuronal response time course is generated. By convolving this with a hemodynamic response function (HRF), a predicted fMRI time course is generated. The predicted fMRI time courses were generated for all combinations of a large range of candidate preferred object size (or numerosity), tuning width, and inhibitory surround width parameters. For each recording point, the parameters were chosen from the prediction that fit the data most closely by minimizing the sum of squared errors ($R^2$, variance explained) between the predicted and observed fMRI time series. To convert these $R^2$s to probabilities of observing these model fits by chance, we generated a null distribution by fitting tuning models to recordings from 191,000 white matter recording points in the same scans. We then determine the proportion of fits exceeding any particular $R^2$. We correct these probabilities for multiple comparisons using false discovery rate correction (30), taking all gray matter voxels in the scanning volume into account.

The candidate preferred object sizes and numerosities extend beyond the range shown, allowing model fit parameters beyond this range. This allows us to be confident that returned parameters within the stimulus range are reported accurately, rather than the best fit of a limited set. However, recording points with preferences modeled outside the stimulus range must be treated with caution. In such recording points, response amplitude monotonically increases or decreases across the stimulus range. As such, we have little confidence that the preferred tuning estimate is correct here, so these recording points were not labeled on cortical surface renderings and were excluded from further analyses.

We estimate the HRF parameters across the whole acquired fMRI volume from the data using a near-identical procedure we use in visual cortex (29). Briefly, by having the stimulus pass through the stimulus range in both ascending and descending directions, we can derive the HRF properties. We estimated the HRF parameters by comparing predicted and measured time series and chose the HRF parameters that minimized the difference between prediction and measurements over the entire volume for each stimulus condition, including all object size and numerosity tuning conditions. Next, we averaged the HRF parameters determined from each condition’s data and used those HRF parameters to reestimate the tuning models. This procedure improved the goodness of fit and ensured that the same HRF is used in modeling responses to all conditions and at every point in the brain. Very similar results, although with not as good model fits, were obtained by fitting the data using a canonical HRF (31). We have reported analogous effects of fitting subject-specific HRFS in visual cortex (29).

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Comparisons Between Tuning Models. For both object size and numerosity tuning, we compared different tuning functions describing the distribution of response selectivity, namely different relationships between the range of displayed stimuli and the measured response amplitudes. Here we split our repeated scanning runs into two halves of odd or even scans and, for each half, fit tuning as a logarithmic Gaussian function, linear Gaussian function, and logarithmic and linear difference of Gaussian functions. To compare object size tuning models, we also split our object size response data into two halves acquired in different sessions, finding very similar results. Because numerosity tuning parameters differ slightly between the stimulus conditions used in different scan sessions (9), we split numerosity response data into two halves from the first and second halves of each scan session. Again, this produces very similar results to an odd–even scan split. To evaluate the fits of these models, we quantified the variance each model explained in the fMRI signal from the complementary half of scans (Fig. 1E and F). This split-scan cross-validation approach allows us to compare the goodness of fit of different models without biases that would arise from additional free parameters in the DoG models: DoG models will only achieve better fits when the fit inhibitory surround captures repeatable signals.

Region of Interest Definitions. Because we aim to examine relationships between object size tuning and numerosity tuning, we focus on the area around the previously defined numerosity map in posterior parietal cortex (9). As previously described, numerosity tuning models fit the recordings from this area well in all stimulus conditions and participants.

Starting with a tuning model from the average of all numerosity stimulus conditions, we first rendered the preferred numerosities of each recording site on the cortical surface (Fig. 3A and Fig. S7). From this, we define our numerosity map region of interest (ROI). Medial and lateral borders of the ROI (the “ends”) each followed lines of equal preferred numerosity at the low and high ends, respectively, of the preferred numerosity range seen in each hemisphere. Anterior and posterior borders (the “sides”) describe the edges of the topographic organization, which coincided with decreases in the goodness of model fits.

Using a similar approach, we rendered onto the same area of the same cortical surface model the preferred object sizes from tuning models fit to the average of both object size stimulus conditions. Medial and lateral borders of object size map ROIs (the “ends”) each followed lines of equal preferred object size, again at the low and high ends, respectively, of the preferred object size range seen in each hemisphere. Again, anterior and posterior borders (the “sides”) describe the edges of the topographic organization, which coincided with decreases in the goodness of model fits.

Analysis of Changes Across the ROI. Having defined lines following the lowest and highest preferred object sizes or numerosities seen in each map ROI, we then calculated the distance along the cortical surface from each point in each ROI to the nearest point on each of these lines. The ratio between the distances to each end line gives a normalized distance along the ROI in the primary direction of change of object size or numerosity preferences. We multiplied this normalized distance by the mean length of the ROI in this direction. For every 2-mm increase in distance along the ROI, we formed a bin of recording points and then calculated the mean and SE of the preferred object sizes or numerosities of the sites within the bin. We fit lines to bootstrapped samples of the bin means that were the best-fitting straight lines (for object size maps) or logarithmic functions (for numerosity maps); for the progression of numerosity preferences, but not object size preferences, logarithmic functions fit better than straight lines. In both cases, the fits were described by a slope and an intercept term. From the set of bootstrapped fits, we took the median of each fit parameter as the best fit. We determined 95% confidence intervals by plotting all lines generated during bootstrapping iterations and finding the 2.5% and 97.5% percentiles on values for these fits. To determine the statistical significance of these topographic progressions, we tested whether the 95% confidence intervals of the slopes were above zero.

We also performed a permutation analysis to determine the significance of these slopes. We repeatedly (10,000 times) randomize which preferred object size or numerosity was associated with each distance bin and fit the slope of each of these permutations. We then determined the percentage of these permutations with equal or greater slopes than the observed data, giving a probability of observing this slope by chance.

Tuning Widths. To determine how tuning width changed with preferred object size, we followed the procedure previously used to examine relationships between preferred numerosity and tuning width (9). For each recording site within the map ROI, we first reconstructed the DoG function describing the relationship between presented object size and response amplitude. We measured the width of this function at half its maximum amplitude, the FWHM, and used this measure of tuning width. We then binned recording sites by their preferred object sizes, with preferred object size increments of 0.05° diameter between bins, up to a maximum of 0.9° diameter. Few recording sites with preferred object size above 0.9° diameter were seen, and near the edge of the stimulus range unstable fits are common, as there is little information to distinguish between different tuning widths (11, 29). Where the ROI did not contain recording sites with preferred object sizes over this whole range, fits were limited to the range of preferred object sizes seen. Lines and confidence intervals were fit as described above for the progression of preferences across the ROI. Again, we tested for significant relationships between preferred object size and tuning width by testing whether bootstrapped confidence intervals of these fits included zero slopes. Again, we also performed a permutation analysis.

Fig. 4 shows a set of example tuning functions for a range of object size preferences. To produce these tuning functions, we took tuning model parameters of all recording points in all hemispheres, specifically the widths and amplitudes of the best-fitting positive and negative (suppressive) Gaussian tuning functions. For each of these parameters, we took the best-fitting straight line describing how that parameter changes with preferred object size. We then evaluated these fit lines at values from zero to 1°, using the resulting parameters to plot the example tuning functions shown.

Visual Field Mapping Stimuli. Because posterior parietal cortex contains several visual field maps (32), we also acquired visual field mapping responses to ensure that we did not confuse visual field position-specific responses with object size- or numerosity-specific responses and to examine the relationship between these maps. The mapping paradigm was almost identical to that described in previous studies (11, 12, 29). The stimulus consisted of drifting bar apertures at various orientations, which exposed a moving checkerboard pattern. The stimulus had a radius of 6.35°, larger than the object size or numerosity mapping stimuli (0.75° radius). Two diagonal red lines, which intersected at the center of the display, were also presented throughout the entire scanning run to provide a target for accurate fixation even when the subject was not performing the task.

fMRI Analysis for Visual Field Mapping. Visual field mapping data were analyzed following a standard population receptive field analysis, as described elsewhere (11, 29). We identified visual field map borders based on reversals in polar angle of visual field position preference and identified particular visual field maps in parietal lobe with reference to previous studies (32) (Fig. S9).
Relationships Between Object Size, Numerosity, and Visual Field Position Preferences. Object size-, numerosity-, and visual field position-tuned responses were found in partially overlapping maps. To examine the relationship between any two of these response preferences in each subject, we first selected recording points that lay in both map ROIs. This yielded an ROI intersecting both maps. Across the recording points in this intersection ROI, we determined the Pearson’s correlation between object size and numerosity preferences, and between both of these and visual field position tuned pRF eccentricity and pRF size. Because these data were resampled to higher resolution when interpolating to the common anatomical space, we used the number of acquired recording sites within the intersection ROI to give the degrees of freedom in this statistical test.

To quantify the relationship between the directions of change of numerosity and object size preferences across the cortex, we first computationally flattened the area of cortex surrounding the center of the intersection ROI. Such computational flattening introduces slight spatial distortions into the cortical surface model, and so was not used in other analyses. However, using a 2D representation of the cortex makes calculation and comparison of directions far simpler. We then interpolated the numerosity map, object size map, and intersection ROIs onto this flattened surface.

For every recording site within the intersection ROI, we determined the largest circle that stayed entirely within the ROI. We determined the angle between the vector joining maximum and minimum object size preferences and the vector joining maximum and minimum numerosity preferences. This gave a set of differences between directions of greatest numerosity and size preference changes.

To demonstrate that this difference between map directions was greater than differences between repeated measures, we then computed a set of direction differences between numerosity maps measured in different sessions, computed in the same way. For the set of recording sites remaining in both sets of direction differences, we compared the absolute magnitude of the direction differences using paired t-tests in each hemisphere.

To determine whether tuning for visual field positions presented in our stimuli contributed to the responses to our object size stimuli, we first determined the cumulative positions of the object bodies and their edges shown for each presented object size (Fig. S11A). We then used these as inputs to conventional visual field mapping pRF models. We allowed the models to find the best-fitting possible pRF and also constrained the models taking the pRF properties already determined from visual field mapping experiments. For each of the resulting pRF models, we compared the variance explained by each model with the variance explained by object size tuning (Fig. S11B). We then used the best-fitting predictions of each of these models as regressors in a single general linear model to ask whether visual field stimulation parameters explained additional response variance that was not captured by the object size tuning model. We quantified the response variance predicted by components tuned to object size and visual field position (Fig. S11C).
Fig. S1. Stimuli varying in object size and numerosity over time yield different responses captured by different tuning models. (A) Two example fMRI time courses from sites in right posterior parietal cortex, about 2 cm apart, elicited by the presented object size sequence (Top). Points represent mean response amplitudes; error bars represent the SE over repeated runs. In the Upper panel, the largest response amplitude occurs after the presentation of small objects, whereas in the Lower panel the largest response occurs with larger objects, considering the hemodynamic response delay. The tuning model prediction captures much of the variance ($R^2$) in the time courses, indicated by the colored lines. However, different tuning models capture different amounts of this variance. (B) Representation of the tuning models that best fit each time course. The best-fitting models describe linear Gaussian tuning functions with inhibitory surrounds. Tuning models describing other tuning functions perform less well, failing to capture features of the fMRI time courses in A. (C) fMRI time courses from the same two sites in A, elicited by the presented numerosity sequence (Top). Although these time courses are very different, the largest response amplitude in the Upper panel again occurs after the presentation of small numerosities, whereas in the Lower panel the largest response occurs with larger numerosities, considering the hemodynamic response delay. Again, tuning models capture much of the variance in the time courses, and different models capture different amounts of variance. (D) Representation of the tuning models that best fit each time course. The best-fitting models describe logarithmic Gaussian tuning functions. Tuning models describing linear tuning functions perform less well, failing to capture features of the fMRI time courses in C. Dashed lines show the continuation of tuning functions outside the presented object size range.
Fig. S2. Responses to luminance-varying stimuli from the example recording sites shown in Fig. 1C and Fig. S1 (Upper and Lower panels here correspond to Upper and Lower panels of Fig. 1C and Fig. S1 A and C). To distinguish object size tuning from tuning to mean display luminance, we recorded responses to a stimulus where the mean luminance of the object size stimulus was distributed evenly across the largest object in the stimulus set, 1.3° diameter. During the long period that contained a 3.7°-diameter circle in the object size stimuli, the sequence also contained a 3.7°-diameter circle. Responses differed considerably from responses to stimuli of varying object size: They did not show tuned responses to a specific, low luminance, and response amplitudes increased when a larger circle was shown, which covered visual field positions that were not stimulated by the rest of the stimulus sequence.

Fig. S3. BOLD signal strength at each recording point in the average data across all object size and numerosity stimulus conditions, rendered on inflated cortical surfaces showing the same views as used in all other figures and supporting figures. Large draining veins on the pial surface and the superior sagittal sinus and its branches can be seen as areas of low signal strength. These are outlined with dashed lines, which correspond to the red dashed lines seen in other renderings of the cortical surface. Data from these areas are distorted, and the blood flow and oxygenation here result from neural activity elsewhere. Based on a subject-specific threshold of minimum signal strength in the average data, such recording points are excluded from analysis of preferred number and tuning width. The lines highlighting these areas are for illustration only. AU, arbitrary units.
Fig. S4. Preferred object size varies across the cortical surface of right and left posterior parietal lobes in both stimulus conditions. Colors represent different object size preferences rendered on an inflated back view of the cortical surface. An area of clear topographic organization in all stimulus conditions is defined in black and white. The borders of this area representing minimum and maximum equal preferred object sizes are shown as white lines at the medial and lateral ends of the map. The posterior and anterior borders of this topographic representation are shown as black lines. Data are thresholded based on goodness of fit: In the average data, only recording points where $R^2$ is above 0.3 ($P < 0.018$ after false discovery rate correction) are shown; for all individual conditions the $R^2$ threshold is 0.25 ($P < 0.031$). Recording points where the model fits a preferred object size outside of the stimulus range are not shown. Dashed red lines outline distortions in the data caused by the presence of large veins on the pial surface (Fig. S3). This shows the areas around the previously described numerosity maps, whose borders are shown as black and white dashed lines.
Fig. 55. Progression of preferred object size with distance along the map (shown in Fig. S4) for both stimulus conditions and the average data for each subject. Points represent the mean preferred object size in each distance bin, with error bars representing the SE. Solid lines are the best linear fit to the bin means. Dashed lines represent 95% confidence intervals determined by bootstrapping fits to the bin means. Object size preferences increase significantly across the map, at $P = 0.01$ or less in each hemisphere (permutation analysis).
Fig. S6. Tuning width changes across the cortical surface with preferred object size. (A) Change in tuning width across the cortical surface for average data, showing the same views seen in Fig. S4, with the same threshold criteria. Tuning width decreases from the medial to the lateral ends of the map. (B) Tuning width shown as a function of preferred object size: Tuning width decreases as preferred object size increases. Recording points are binned based on preferred object size. Points represent the mean tuning width in each bin; error bars represent the SE. Solid lines are the best linear fit to the bins. Dashed lines represent 95% confidence intervals determined by bootstrapping fits to the bin means. Tuning widths decrease significantly with preferred object size, all at $P = 0.007$ or less in each hemisphere (permutation analysis).
Fig. S7. Maps of preferred numerosity. (A) Preferred numerosity varies across the cortical surface, in data averaged over all numerosity stimulus conditions. Topographic organization is clearer in the right hemisphere than in the left. Colors represent different preferred numerosities rendered on an inflated back view of the cortical surface, in the same area of cortex shown in Fig. S4. An area of clear topographic representation is defined in black and white. The borders of this area representing minimum and maximum equal preferred numerosities are shown as white lines at the medial and lateral ends of the map. The posterior and anterior borders of this topographic representation are shown as black lines. Data are thresholded based on goodness of fit: In the average data, only recording points where $R^2$ is above 0.3 ($P < 0.007$) are shown; for all individual conditions the $R^2$ threshold is 0.25 ($P < 0.015$). Recording points where the model fits a preferred numerosity outside of the stimulus range are not shown. Dashed red lines outline distortions in the data caused by the presence of large veins on the pial surface (Fig. S3). The object size maps described in Fig. S4 are shown as black and white dashed lines. (B) Progression of preferred numerosity with distance along the maps shown in A in the average data for each subject. Different stimulus conditions are represented as colored lines joining the condition-specific bin means. In the left hemisphere, the rate of change of preferred numerosity across the cortical surface is less than in the right hemisphere, as is the interquartile range of preferred numerosities present in the map. Map organization in the right hemisphere is also more consistent between conditions. Points represent the mean preferred numerosity in each distance bin, with error bars representing the SE. Solid lines are the fit to the bin means. These fit lines are straight in logarithmic space. Dashed lines represent 95% confidence intervals determined by bootstrapping fits to the binned points. For the average of all stimulus conditions, numerosity preferences increase significantly across the map, at $P < 0.0001$ in each hemisphere (permutation analysis).
Fig. S8. Among recording sites that lie in both numerosity and object size maps, numerosity and object size preferences are correlated in both hemispheres. Although smaller numerosities are consistently found with smaller object sizes, the slope of this relationship differs between hemispheres. Significant correlation was absent in one hemisphere where the overlap of object size and numerosity maps covers little of the range of object size or numerosity preferences. $r$ values are Pearson’s correlation coefficients. When calculating corresponding $P$ values, the number of recording sites is adjusted to compensate for upsampling of data during transformation to cortical surface models. Lines represent the best-fitting linear relationship between object size and numerosity preferences.
**Right Hemisphere**

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**Fig. S9.** Visual field map representations around the object size and numerosity maps, showing the same views seen in Figs. S4, S7, and S8. Borders between visual field maps are marked by purple lines. Dashed red lines show locations of veins, solid black and white lines show the borders of numerosity maps, and dashed black and white lines show the borders of object size maps, as in previous figures. Although visual field maps overlap with the object size numerosity maps, their borders do not correspond and there is no clear relationship between them. *(Middle)* Relationship between displayed color and preferred visual field position in visual field eccentricity and polar angle.
Fig. 510. Among recording sites that lie in both object size maps and visual field maps, object size preferences and pRF properties of recording sites are not consistently correlated. (A) Preferred object size is not significantly correlated with pRF eccentricity. (B) Preferred object size is not significantly correlated with pRF size. (C) Preferred numerosity is not significantly correlated with pRF eccentricity. (D) Preferred numerosity is not significantly correlated with pRF size. r values are Pearson’s correlation coefficients, although Spearman’s rank correlation gives similar results. When calculating corresponding P values, the number of recording sites is adjusted to compensate for upampling of data during transformation to cortical surface models. Lines represent the best-fitting linear relationships between object size preferences and pRF properties. Although some P values do reach significance at P = 0.05 in individual hemispheres, the directions of these correlations are not consistent between hemispheres, and only 1 of 49 remains significant after Bonferroni correction for multiple comparisons.
Fig. S11. Distribution of visual field stimulation for different object sizes, and the potential predictive accuracy of retinotopic stimulation in explaining recorded responses. (A) Stimuli are designed to place object bodies randomly in the same stimulus area for all object sizes, minimizing links between particular visual field positions and particular object sizes. Furthermore, the largest object shown (3.7°) completely covers the area where other object sizes could be presented. This stimulates all these visual field positions but reduces response amplitudes. However, the positions of object edges are unavoidably linked to object size: Larger object sizes tend to have edges at higher eccentricities. Furthermore, the largest object has no edges in the central visual field, consistent with a decrease in response amplitude. Light intensities show positions where object bodies or edges are most likely to appear for a particular object size. (B) Response variance explained by separate models tuned to object size or visual field positions responding to object bodies or edges. Object size tuning predicts responses most closely, but tuned responses to object edge position can predict response well if allowed to choose any position tuning parameters. Here, pRF preferred positions are consistently at the visual field center, with position tuning widths (i.e., pRF sizes) increasing with preferred object size. Responses to conventional visual field mapping (VFM) stimuli, on the other hand, demonstrate that these recording sites prefer visual field positions outside the visual field center. If visual field position tuning properties are taken from VFM models, they predict responses poorly. (C) Response variance explained by the same response predictions when used as components of a single general linear model. Object size tuning continues to predict responses well, but any visual field position tuning captures little additional response variance. Error bars show 95% confidence intervals.