**Description of uploaded data**

We used multivariate pattern analysis (MVPA) to discriminate BOLD responses related to near vs. far disparity stimuli across cortical layers in visual cortex. For each ROI and participant, we calculated per voxel a t-score statistic by comparing activity for stimuli vs. fixation. We used this statistic to rank the voxels within cortical depths (deeper, middle, superficial layers) per ROI and selected 175 voxels per layer with the higher t-score to include in the MVPA, as MVPA accuracy saturated across all participants for these voxel pattern sizes in the corresponding regions. This voxel selection procedure ensured that comparisons of MVPA accuracy could not be confounded by varying number of voxels across participants. We then extracted mean normalized fMRI responses between 3rd to 7th TR (i.e., 4–14 s) after block onset for this pattern of voxels per ROI and participant. We trained a linear classifier using LIBSVM with default C value (C = 1) (https://www.csie.ntu.edu.tw/~cjlin/libsvm/) implemented in MATLAB to discriminate the near from the far disparity stimulus. We computed MVPA accuracy using a leave-one-run-out cross-validation. That is, we divided the data set into training (60–180 patterns depending on the number of scanning runs per participant) and test (20 patterns) data. We averaged the MVPA accuracy across folds. We used repeated-measures ANOVAs to assess differences in MVPA accuracy across conditions (correlated, anti-correlated RDS), cortical depths (deeper, middle, superficial layers), and ROIs (V1, V3A, V7).

We conducted a cross-validated linear discriminant contrast (LDC) analysis. The linear discriminant contrast is centred on zero under the null hypothesis of no reliable differences between the near vs. far conditions. We used the same data and voxels as in the MVPA analysis. We divided the data set into training and test data and performed a leave-one-run-out cross-validation. For each cross validation, we contrasted signals from the near against the far stimulus blocks to generate the representation distance metric for both the training and test datasets. The distance matrix from the training datasets was normalized using the sparse covariance matrix of the noise residuals to produce the weights vector. The LDC is the dot product of the representation distance metric for the test dataset and the weight matrix estimated from the training dataset. Finally, we averaged the LDC values across cross validations per participant.

We used informational connectivity (IC) to identify layers that share synchronized discriminability of activity related to stimulus-specific multi-voxel pattern information. We examined intercortical informational connectivity based on shared changes (fluctuations) in pattern discriminability over time, as this approach has been shown to be more sensitive than univariate functional connectivity. To track the flow of multivariate information across time (i.e., across blocks), we measured the fluctuations (covariance) in MVPA discriminability by calculating distance information from the classification hyperplane. In particular, we selected 175 voxels with the higher t-score and used the same multivoxel near vs. far disparity patterns as in the MVPA analysis. For each ROI and layer, we extracted distance information for the test data per block from the trained classifiers. We calculated layer-specific connectivity by Spearman correlation between the fold-wise distance of different layers. We transformed the correlation coefficients using Fisher’s z-transform and conducted repeated-measures ANOVAs to compare across conditions (correlated, anti-correlated RDS) and ROI pairs (V1-V3A, V3A-V7, V1-V7) per pathway (feedforward, feedback).

fMRI Data were acquired using a 2D Gradient Echo-Echo Planar Imaging (GE-EPI) sequence (Moeller et al., 2010; TR = 2 s, TE = 25 ms, voxel size = 0.8 mm isotropic, FOV = 148 × 148 mm2, number of slices = 56, partial Fourier = 6/8, GRAPPA factor = 3, Multi-Band factor = 2, bandwidth = 1168 Hz/Pixel, echo spacing = 1 ms, flip angle = 70º). The field of view covered occipito-temporal and posterior parietal areas; manual shimming was performed prior to the acquisition of the functional scans. Anatomical images were acquired using MP2RAGE T1-weighted sequence (TR = 5 s, TE = 2.51 ms, voxel size = 0.65 mm isotropic, FOV = 208 × 208 mm2, 240 sagittal slices).

fMRI pre-processing included the following steps: 1. Distortion correction. 2. Slice scan timing correction, head motion correction, high pass temporal filtering and removal of linear trends. 3. Align the functional data across session (if needed).

Raw and pre-processed data are available upon request from zk240@cam.ac.uk.