Description of uploaded data

Behavioral data: Performance was measured by the 3-down-1-up staircase with 15 reversals. The mean angle difference of the last 8 reversals was taken as the threshold of each staircase run. The measured orientation discrimination thresholds were used as the dependent factor. Using a within-subject factorial design, we manipulated three independent factors, the reference orientation (trained and untrained orientation), stimulus location (trained and untrained location) and test session (pre-test, post-test), to evaluate the learning effect and learning specificity. Further, we calculated the mean percent improvement index (MPI, (pre-test threshold – post-test threshold) / pretest threshold * 100%)) for each condition.

fMRI data: We used multivariate pattern analysis (MVPA) to decode: a) trained versus control orientation, b) untrained versus control orientation. For each ROI and participant, we calculated per voxel a t-score statistic by comparing activity for stimuli that were presented left versus right of the fixation (V1) or activity for task versus fixation (IPS). We used this statistic to rank the voxels within each ROI and selected voxels (500 for visual areas; 200 voxels for IPS) with the higher t-score to include in the MVPA, as classification accuracy saturated across all participants for these voxel pattern sizes in the corresponding regions. We used the same number of voxels (i.e., 200 voxels) when comparing data between V1 and IPS and for the informational connectivity analysis. 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 4th to 8th TR (i.e., 6.18 – 14.42 s) after block onset for this pattern of voxels per ROI, participant and test session. We trained a linear classifier using LIBSVM implemented in MATLAB to discriminate: a) the trained from the control orientation, b) the untrained from the control orientation. As both the trained and untrained orientation differed equally from the control orientation (55), we hypothesized that differences in the accuracy between these two classification tasks would be due to training rather than stimulus differences. We computed classification accuracy using a leave-one-run-out cross-validation. That is, we divided the dataset into training and test data with maximum 72 training patterns (for n = 7 participants with 8 runs) and 8 patterns for the test run. We averaged the classification accuracy across folds, separately for each test session. We used repeated-measures ANOVAs to assess differences in classification accuracy across conditions (orientation * session). Similar to the MPI for behavioral data, we defined the MPI for decoding accuracy as (post-test accuracy – pre-test accuracy) / pre-test accuracy * 100%).

fMRI Data were acquired using a 2D Gradient Echo, Echo Planar Imaging (GE-EPI) sequence (TR = 2060 ms, TE = 26.4 ms, FOV = 148 * 148 mm^2, flip angle: 70, resolution 0.8 * 0.8 * 0.8 mm^3, number of slices: 56, partial Fourier = 6/8, GRAPPA factor = 3, Multi-Band factor = 2, bandwidth = 1034 Hz/Pixel, echo spacing = 1.09 ms). The field of view covered occipito-temporal and posterior parietal areas; manual shimming was performed prior to the acquisition of the functional scans.

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.

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