

Volitional modulation of higher-order visual cortex alters human perception

Article

Accepted Version

Ekanayake, J., Ridgway, G. R., Winston, J. S., Feredoes, E., Razi, A., Koush, Y., Scharnowski, F., Weiskopf, N. and Rees, G. (2019) Volitional modulation of higher-order visual cortex alters human perception. NeuroImage, 188. pp. 291-301. ISSN 1053-8119 doi: https://doi.org/10.1016/j.neuroimage.2018.11.054 Available at

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To link to this article DOI: http://dx.doi.org/10.1016/j.neuroimage.2018.11.054

Publisher: Elsevier

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- 37 Conflict of Interest: Nil
- 38

39 Abstract

40

41 Can we change our perception by controlling our brain activation? Awareness 42 during binocular rivalry is shaped by the alternating perception of different 43 stimuli presented separately to each monocular view. We tested the possibility 44 of causally influencing the likelihood of a stimulus entering awareness. To do 45 this, participants were trained with neurofeedback, using realtime functional 46 magnetic resonance imaging (rt-fMRI), to differentially modulate activation in 47 stimulus-selective visual cortex representing each of the monocular images. 48 Neurofeedback training led to altered bistable perception associated with 49 activity changes in the trained regions. The degree to which training 50 influenced perception predicted changes in grey and white matter volumes of 51 these regions. Short-term intensive neurofeedback training therefore sculpted 52 the dynamics of visual awareness, with associated plasticity in the human 53 brain.

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55 Word count 123 (150 max)

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59 Highlights	5
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- 60
- Our of the second second
- 63 Participants unknowingly modulated two brain regions to control
 64 feedback signal
- 65 Short-term neurofeedback training over 3 days induced functional
 66 plasticity
- Neurofeedback may strengthen neural representations and alter prior
 expectations
- 69 Potential avenue for behavioural shaping and therapeutic reduction of70 aberrant perception
- 71

73 Introduction

74

75 The ability to causally modify how we perceive the world has potential 76 implications in health and disease. Altering perceptual biases, which may be 77 conscious or unconscious, could modify pathological perception such as 78 hallucinations, or provide а means of selective cognitive 79 enhancement(Miranda et al., 2015). Such attempts to deliberately manipulate 80 higher-order sensory perception have, until now, proven to be unsuccessful. 81 For example, attempting to alter perception using mental imagery, a cognitive 82 process which utilises similar neural substrates to perception(O'Craven and 83 Kanwisher, 2000), does not increase the vividness of the imagery. Most 84 importantly, mental imagery training has no effect on perception linked to the 85 imagery strategy used during training, as demonstrated with binocular rivalry (BR) between images specifically associated with the mental imagery 86 87 training(Rademaker and Pearson, 2012). BR is a unique perceptual 88 phenomenon that has been used to provide a window into the unconscious 89 and conscious processes underlying visual perception. It is produced by 90 simultaneously presenting conflicting monocular stimuli to each eye. 91 Paradoxically, the brain cannot form a stable image. Instead, each image 92 randomly competes for exclusive perceptual dominance. Until now, producing 93 unconscious shifts in higher-order perception by directly modifying brain 94 function has proven to be unsuccessful.

95

96 Neurofeedback training using realtime functional magnetic resonance imaging
97 (rt-fMRI) is an emerging technique which allows participants to control target

98 brain regions by voluntarily modulating online feedback of activity in those 99 regions(Sitaram et al., 2016). Feedback is typically provided via a visual interface during concurrent MR scanning. Online modulation of the Blood 100 101 Oxygen Level-Dependent (BOLD) signal using neurofeedback involves 102 abstract cognitive strategies, as well as mental imagery that maybe explicitly 103 linked to the brain region-of-interest (ROI). This approach can produce 104 changes in behaviour through the functional modulation of trained brain 105 regions, including low-order visual perception (e.g. grating orientation, colour) 106 by modulating primary retinotopic cortex(Amano et al., 2016; Shibata et al., 107 2011), pain and craving by modulating anterior cingulate cortex(deCharms et 108 al., 2004; Li et al., 2013), and motor function by modulating supplementary 109 motor area and primary motor cortex(Blefari et al., 2015; Subramanian et al., 110 2011). We hypothesised that rt-fMRI neurofeedback might prove more 111 powerful than previous approaches, such as mental imagery alone, in 112 enabling participants to modify brain activity associated with higher-order 113 visual perception, and consequently directly influence how they perceive the 114 world.

115

To test this hypothesis, we trained human participants using mental imagery *combined* with neurofeedback to voluntarily control the difference in activation between two higher-order visual cortical regions (Fusiform Face Area, FFA and Parahippocampal Place area, PPA). The human FFA responds strongly to faces(Kanwisher et al., 1997; McCarthy et al., 1997), but not to other types of non-face stimuli, while the PPA responds to houses and places, but not faces(Epstein and Kanwisher, 1998). Further, both of these regions activate

during mental imagery of faces or places respectively, even in the absence of visual stimuli(O'Craven and Kanwisher, 2000). The differential response properties of these two regions enabled participants in the study to have a visually presented neurofeedback training signal that represented the difference in activation between the two regions i.e. a *differential signal*.

128

129 The use of a differential signal provided an internal control for global brain 130 activation, and helped focus the training effect on the two selected brain 131 regions in a manner that might not occur with mental imagery training only. 132 We tested participants with a BR task, where they were exposed to rivalrous 133 monocular face and house images, before and after neurofeedback training. 134 During BR, participants are consciously aware of only one of the perceptual 135 stimuli at a time, while the other stimulus is temporarily suppressed. The 136 perceptual fluctuation is spontaneous and stochastic, with both top-down (i.e. 137 cognitive modulation) and bottom-up (i.e. salience-based) processes being 138 implicated(Dayan, 1998; Parker and Alais, 2007; Tong et al., 2006). In this 139 study, the ensuing BR, where perception alternated spontaneously between 140 each monocular view, provided a test of whether neurofeedback training had altered the likelihood of either stimuli entering awareness. We investigated 141 142 whether any perceptual changes were associated with differences in brain 143 activity and structure (see also Supplementary Materials).

144

To anticipate our findings, following neurofeedback training, there was a sustained influence on the perceptual dynamics of BR, suggesting functional plasticity. This effect was additionally observed when participants performed

148 concurrent modulation of brain activity during BR. Further, a multivariate
149 analysis of changes in brain structure produced by neurofeedback training
150 predicted changes in BR dynamics.

152 <u>Methods</u>
153
154
155 <u>Main experiment:</u>
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157 Participants

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Ten neurologically normal adult volunteers (24–35 years of age; mean age 28
years; 8 females) with normal or corrected-to-normal visual acuity participated
in the experiment. Each participant gave written informed consent. The study
was approved by the local ethics committee (UCL Ethics Committee code:
09/H0716/14).

164

165 Stimuli and Materials

166

167 All visual stimuli were generated and displayed via scripts in MATLAB created 168 with the Cogent 2000 toolbox (http://www.vislab.ucl.ac.uk/cogent 2000.php), 169 on a viewing screen with a visual angle of 23 degrees by 17 degrees, (30 x 26 170 LCD projector (LT158; NEC). The mirror-mounted viewing screen was set on 171 the top of the scanner bore (optical distance 52 cm). During the 172 neurofeedback sessions, participants saw a fluctuating thermometer bar at 173 the centre of the screen. During the BR sessions only, participants wore a pair 174 of prism glasses. Additionally, a black cardboard divider was placed between 175 the forehead and the screen to ensure that each eye could see one side of 176 the screen only, and provide a stable base for fixation. Two identical box 177 stimuli were displayed side-by-side on the monitor, each with a central white fixation cross (0.68 visual angle) and tile frame surround (11.78 visual angle), 178

upon a uniform grey background (background luminance ¼ 65 Cd/m²).
Optimal perceptual fusion of the two box stimulus images was confirmed with
the participant prior to commencing each BR session. Face or house stimuli
were presented (20 exemplars each). Responses for durations were obtained
via a pair of custom-built, MR-compatible, response boxes.

184

185 FMRI Scanning

186

187 Scanning was performed on a 3T Allegra head-only scanner (standard 188 transmit-receive head coil). Functional data was acquired with a single-shot 189 gradient echo planar imaging sequence (matrix size, 64x64; field of view, 190 192x192mm; isotropic in-plane resolution, 3x3 mm; 32 slices with ascending 191 acquisition; slice thickness, 2 mm; slice gap, 1 mm; echo time (TE), 30 ms; 192 repetition time (TR), 1920 ms; flip angle, 90°; receiver bandwidth, 3551 193 Hz/pixel). Although the nominal slice thickness was 2mm, the effective slice 194 profile achieved in practice is typically larger such that the effective slice 195 thickness is closer to 3mm. Allowing a gap additionally minimised any risk of 196 saturation effects upon excitation of the subsequent slice (again due to 197 imperfect slice profiles). This is particularly important in the case of ascending 198 acquisition order, as used here. Ascending acquisition order was chosen to 199 minimise the impact of any participant motion, which again could lead to 200 saturation effects if the motion resulted in any part of the previously excited 201 slice being re-excited in a time shorter than the TR.

202

203 Within each scanning session, double-echo fast, low-angle shot sequence

(FLASH) field maps (TE1, 10 ms; TE2, 12.46 ms; resolution, 3 x 3 x 2 mm;
slice gap, 1 mm) were acquired and used to correct geometric distortions.

207 High Resolution Structural Scans

208

209 A whole brain high-resolution T1-weighted structural scan was performed 210 before and after training. This was in addition to structural scans performed on each neurofeedback training day. The scan was a 3D-modified, driven 211 212 equilibrium Fourier transform (MDEFT) scan (1mm isotropic resolution; matrix 213 size, 256x240 mm; field of view, 256x240 mm; 176 sagittal partitions; TE, 2.4 ms: TR. 7.92 ms; inversion time, 910 ms; flip angle, 15°; readout bandwidth, 214 215 195 Hz/pixel; spin tagging in the neck with flip angle 160° to avoid flow 216 artifacts for superposition of functional maps(Deichmann et al., 2004)).

217

218 Realtime fMRI Set-up for Neurofeedback

219

220 Turbo Brain Voyager(Goebel et al., 2006) was used, with custom realtime 221 image export tools programmed in ICE VA25 (Siemens Healthcare)(Weiskopf 222 et al., 2004), and custom MATLAB based scripts. Participants were shown 223 visual representations of BOLD signal changes in brain regions previously 224 identified with a functional localiser scan (i.e. target ROIs). Realtime data 225 encompassed 3D motion correction, smoothing, preprocessing and 226 incremental linear detrending of time series. The ROI time course(s) were 227 extracted from the prescribed ROI masks, averaged and exported. Signal drift, spikes and high frequency noise were further removed in realtime from 228

the exported time courses with custom MATLAB scripts(Koush et al., 2012).
The feedback signal (a 'fluctuating' thermometer bar) was displayed to the
participants with a delay of 2 s from the acquisition of the image.

232

233 Binocular Rivalry Set-up and Behavioural data acquisition

234

235 Inside the scanner, participants, wearing custom-made prism glasses, were 236 shown two stimuli equidistant from a central viewing screen divider. During 237 the viewing blocks, a face stimulus and a house stimulus were presented in 238 the left and right hemi-fields respectively. The stimuli were pseudorandomised 239 with regards to which eye received the face or house stimuli. Each viewing 240 block (40 s followed by rest 20 s) was performed with a new pair of stimuli 241 from the pool of 20 stimuli. Six blocks were performed per session, for three sessions. 242

243

During the BR sessions, participants pressed one of three buttons to record their percept of 'face', 'house' or 'mixed'. The participants were instructed to switch as accurately and rapidly as possible between the three possible button presses linked to the three percepts. This was the only instruction given during pre-training BR and post-training BR, which were identical save for being performed either side of neurofeedback training. Additional instructions were given for two further post-training BR conditions (see below,

251

252 **Day 5: Post-training BR**).

253

254 Cumulative dominance durations were calculated, which were equal to the 255 total amount of time each monocular stimulus was perceived, and averaged 256 across blocks. The three percepts were then pooled as follows: (1) strategy-257 *related percept* e.g. face percept for the neurofeedback group advised to use face mental imagery ('Face' group) or house percept for the neurofeedback 258 259 group advised to use house mental imagery ('House' group) (2) strategy-260 unrelated percept' e.g. house percept for the 'Face' group, face percept for the 'House' group); and (3) 'mixed percept'. 261

262

263 Experimental Outline

264

The experiment was divided into multiple days, with each participant attending five consecutive scanning days (Figure 1). The participants were split into two groups, with five participants in the 'face' group and five participants in the 'house' training group.

- 269
- 270 Day 1: Pre-training BR and Localiser

271 A Pre-training BR scan was performed as described above for all 272 participants. They then underwent a functional localiser scan to identify FFA 273 and PPA regions (12 minutes, 16 blocks of face stimuli, 16 blocks of house 274 stimuli, and 20 different exemplars per block). Each stimulus was presented 275 for 600 ms (400 ms interstimulus interval). A one-back task was performed (3 276 targets per block), requiring a button press upon detection of the same 277 stimulus. Two contrasts were used; Houses vs. Faces and Faces vs. Houses. 278 Using the Juelich histological atlas to provide an anatomical

landmarks(Eickhoff et al., 2006, 2005), voxel selection for the ROIs were
defined along the ventral and lateral surfaces of the temporal lobe in proximity
to the fusiform gyrus for FFA, and lateral to the collateral sulcus in the
parahippocampal region for PPA respectively.

283

284 Day 2-4: Neurofeedback Sessions

285 Each neurofeedback training day comprised three scanning sessions, each 286 six blocks of 60 s with an 'upregulate' period (40 s) followed by 'rest' (20 s). 287 During an upregulation period, participants viewed a fluctuating red bar and a 288 fixed horizontal black bar. The latter was placed towards the top of the screen, 289 and the participants were asked to push the red bar above it. Participants 290 were told that the fluctuating red bar was linked to their brain activity, and that 291 they should drive the red bar up to the level of the black bar using a mental 292 imagery strategy. They were advised to maintain the red bar at that level, for 293 as long as possible, during the 'upregulate' period. Participants were told that 294 there was a delay related to the training signal (produced by the 295 hemodynamic response function, HRF) of approximately 6-8 s. During rest, 296 participants were instructed to perform a mental arithmetic task (serial 297 subtraction of 7 from 100).

298

299 Controlling the Neurofeedback Training Signal

300

Participants were pseudorandomised into two groups – a 'Face' group and a
'House' group. Each group was instructed to use mental imagery strategies.
They were given examples of what might work (Figure 1), although the

304 participants could use their own interpretation. Specific examples for the 305 house group were 'think about your house, or a building you are familiar with such as a school or church', or 'think about walking down the road looking at 306 307 buildings'. Specific examples for the face group were 'think of faces of people 308 you know', 'think of celebrity faces', or 'think of memorable faces you have 309 seen recently'. Both groups were instructed to pay close attention to the 310 fluctuating red bar, and to find the best way of pushing the bar up for as much 311 and as long as possible. Both groups were instructed to use whatever 312 strategy worked best, including their own, and to vary the strategy to ensure 313 continuous control of the fluctuating red bar.

314

315 Each group was unaware of the precise nature of their feedback signal. 316 During neurofeedback training, the fluctuating red bar was driven by brain activity in which the signal from PPA was subtracted from FFA for the 'Face' 317 group, and the reverse subtraction (PPA - FFA) for the 'House' group. 318 319 Participants were trained to modulate a *differential* training signal. Therefore, 320 the 'Face group' learned to voluntarily increase the difference in BOLD 321 between FFA and PPA. In contrast, the 'House group' learned to voluntarily 322 increase the difference in BOLD between PPA and FFA.

323

For each group there was a *strategy-related ROI* (e.g. FFA for the Face group and a *strategy-unrelated ROI* (e.g. PPA for the Face group, and vice versa for the House group, Figure 2A).

327

328 Day 5: Transfer Session

After the final neurofeedback training session, there were two transfer sessions, each comprising six blocks. Each block lasted 60 s and consisted of an 'upregulate' period (40 s) followed by 'rest' (20 s). During upregulation, participants were required to drive their brain activity 'up', using the mental imagery strategies successfully used to drive the bar during neurofeedback training, but now in the absence of a feedback signal.

335

336 Day 5: Post-training BR

All participants then performed post-training BR, with the same set-up 337 338 described for pre-training BR. Three different BR conditions were performed 339 (2 sessions each) pseudorandomised and counterbalanced across all 340 participants: (1) Post-training BR. The instruction was identical to the pre-341 training BR; (2) Post-training BR with 'concurrent trained upregulation'. 342 Both groups were instructed to use their trained mental imagery strategies 343 that had worked best during the training sessions while simultaneously 344 performing BR; and (3) Post-training BR with 'concurrent non-trained 345 mental imagery'. Participants were instructed to use mental imagery related 346 to either houses if in the 'Face group', or faces if in the 'House group'. Mental 347 imagery was to be performed while concurrently performing BR.

348

349 Brain Imaging

350

Functional data was analysed using SPM12 (<u>http://www.fil.ion.ucl.ac.uk/spm</u>). To allow for T1 equilibration the first five images of each session were discarded. Preprocessing involved bias correction, realignment of each EPI to the mean EPI, unwarping, and co-registration of the functional data to the

355 structural image. Normalisation was not performed, as initial analyses were 356 performed in native space. Data was smoothed with a 6 mm FWHM Gaussian 357 kernel and high-pass filtered (128s cut-off) to remove low-frequency noise, 358 while at the same time preserving as many of the spontaneous fMRI 359 fluctuations as possible(Cordes et al., 2001). Session-specific grand mean 360 scaling was applied with no global normalisation.

361

362 Offline ROI Analysis: Fusiform Face Area and Parahippocampal Place

- 363 Area
- 364

365 Neurofeedback

BOLD signals across the 9 training sessions (acquired on Days 2-4) were 366 367 modeled using a GLM, with regressors for each of the 9 sessions. Boxcar functions were created for the six upregulation blocks, convolved with the 368 canonical HRF. Six regressors for movement and a global constant were 369 370 included. Beta values from the GLM were averaged across all the voxels in 371 the ROI masks (FFA and PPA ROIs based on the functional localiser). Mean 372 percentage signal change (PSC) was then calculated. For each participant, 373 the differential mean PSC between the two ROIs (i.e. strategy-related ROI 374 minus strategy-unrelated ROI) was calculated across sessions. From this, the 375 average mean PSC across participants over the training was calculated.

376

377 Transfer Sessions

378 Two transfer sessions were performed, with participants performing six blocks 379 of upregulation of brain activity as trained, but now in the absence of a

neurofeedback signal. In a similar manner to the neurofeedback sessions
(see above), the differential mean PSC between the two ROIs (i.e. strategyrelated ROI minus strategy-unrelated ROI) was calculated across sessions,
and from this, the average mean PSC across participants over transfer was
calculated.

385

386 Binocular Rivalry

Boxcar functions were created to model the onset of the BR block, convolved with the canonical HRF, for each BR condition. A GLM was performed at the single participant level. Beta values for each of the trained ROIs were averaged for each condition and adjusted for the global brain signal. Mean percentage signal change (PSC) was then calculated.

392

For inferential statistical analyses, SPSS 21 (IBM Corp. Armonk, USA) was
used to perform ANOVAs and follow-up planned paired sample t-tests, which
were two-tailed unless otherwise stated.

396

397 Control Experiment- Mental Imagery:

398 399

400 Experimental outline

401

Ten different participants (age range = 22-39 years, mean age 30. years, 8 females) were recruited for a control BR experiment. They viewed a Dell LCD monitor (width: 43.5 cm; resolution: 1600 900; refresh rate: 60 Hz) from a distance of 43 cm (fixed using a chin rest) through a mirror stereoscope. The stereoscope reflected the left and right sides of the screen into the 407 participants' left and right eyes, so that each eye was presented with only one 408 of the two images (house or face). In order to ensure robust fusion of 409 binocular images, prior to the start of BR task, fusion was achieved for each 410 participant by slowly moving two grey squares from the edge toward the 411 centre of the screen. At the beginning of this process the participants would 412 see two squares. By the end of this process the participants would report 413 when they were seeing one square. All testing took place in a darkened room. 414 During the viewing blocks, a face stimulus and a house stimulus were 415 presented in the left and right hemi-fields respectively. The stimuli were 416 pseudorandomised with regards to which eye received the face or house 417 stimuli. Each viewing block (40 s followed by rest 20 s) was performed with a 418 new pair of stimuli from the pool of twenty stimuli. Six blocks were performed 419 per session, for three sessions. Participants were instructed to indicate a 420 perceptual shift only if the whole exemplar was perceived; any combination or 421 'patchwork' percept regardless of the predominance of the exemplar category 422 was reported as a 'mixed' percept. The participants were instructed to switch 423 as accurately and rapidly as possible between three possible button presses 424 linked to the three perceptual states (face percept, house percept, mixed 425 percept). This resulted in measures of the cumulative duration of the percept 426 throughout the BR measurement period.

427

428 BR was performed in this manner prior to and after 3 days of consecutive 429 mental imagery training (see below).

430

431 Mental Imagery Training over 3 Days

433 Participants returned to perform mental imagery training. Participants were 434 pseudorandomised into two equal groups, and were explicitly advised to use 435 mental imagery strategies that involved faces ('Face group') or house/places 436 ('House group'). Mental imagery was undertaken while viewing a LCD monitor 437 screen with a fixed horizontal black bar. They were told to imagine pushing a 438 bar above the fixed black bar, while performing their mental imagery 439 strategies. Each mental imagery training session comprised three sessions, 440 each including six blocks of 60 s with a 'perform mental imagery' period (40 s) 441 followed by 'rest' (20 s).

442

443 Brain Structural Analysis

444

The structural analysis was performed using Tensor Based Morphometry (TBM), an emerging computational analysis technique(Ceccarelli et al., 2009; Farbota et al., 2012; Li et al., 2009; Wang et al., 2013; Welch et al., 2013), which is better suited to studies with smaller participant samples. TBM enables longitudinal quantitative assessment by identifying regional structural differences from the gradients of the deformation fields that nonlinearly warp each individual image to the template.

452

For each participant, high-resolution T1 structural images were reoriented placing the anterior commissure at the MNI origin. Longitudinal nonlinear registration(Ashburner and Ridgway, 2012) was performed to align the two time-points (before and after training) to their within-subject average,

457 characterising the relative volumetric expansion or contraction (as the 458 divergence of a velocity field) of each voxel in each time-point with respect to 459 the average. The within-subject average images were then segmented to 460 produce grey and white matter segmentations for each participant(Ashburner 461 and Friston, 2005). These segmentations were nonlinearly aligned to their 462 group-wise average using Dartel (Ashburner, 2007), and the final Dartel 463 average template was affinely registered to MNI space. The resultant 464 between-subject transformations were then used to spatially normalise the 465 divergence maps of the velocity fields, which were finally smoothed with a 466 6mm FWHM Gaussian kernel.

467

468 Divergence measures for each participant were then extracted within 469 spherical ROIs for FFA and PPA (6 mm). The spheres were centered on 470 coordinates that demonstrated the highest functional activity within the 471 localiser ROIs across training. A t-test was then performed to establish if a 472 specific brain region had changed significantly before versus after training.

473

474 **Canonical Variate Analysis**

475

We used a Canonical Variate Analysis (CVA) to demonstrate that measures of change in brain activation and brain structure following neurofeedback training predicted changes in behavioural measures. Also known as a multivariate analysis of variance, or ManCova (Friston et al., 2014, 1995), CVA enables statistical inferences to be made about associations between the imaging data, and behavioural data that are distributed over variables. It

482 was chosen for analysis of this dataset because it can accommodate 483 statistical dependencies between multivariate predictor variables (behavioural 484 changes) and multivariate outcome variables (functional or structural 485 measures). Neither the behavioural nor imaging data had to be examined in 486 isolation, which had the advantage that distributed changes could be 487 identified, while minimising the multiple comparisons problem. The 488 behavioural changes for each participant was the change in dominance 489 duration of each the three percepts (e.g. strategy-related percept, strategy-490 unrelated percept, mixed percept) between the pre-training BR condition and 491 post-training BR (Figure S3), and between the pre-training BR condition and 492 post-training BR with concurrent trained up-regulation (Figure S3). As the 493 behavioural and structural measures were taken prior to and immediately after 494 neurofeedback training, the functional measures for each participant were the 495 change in the different signal between the first and the last training run (e.g. 496 run 1 and run 9). The structural measures for each participant were the 497 divergence measures for each ROI, FFA and PPA (6 mm).

498

499 The objective of the CVA was to find the linear combination of outcome 500 variables that was best predicted by a linear mixture (contrast) of structural or 501 functional components. The weights of these linear combinations are called 502 canonical vectors. The canonical variates of the outcome and predictor 503 variables are the expression of each canonical vector in each subject. Other 504 quantities generated by the CVA include Bartlett's approximate chi-squared 505 statistic for Wilks' Lambda and its associated significance, or p-value, which test for the significance of a linear mapping or correlation between the 506

- 507 canonical variates (in other words, if one or more pairs of canonical variates
- 508 show a significant statistical dependency).

513 **Results**

514

515 We first examined the effect of neurofeedback training on behaviour using 516 three comparisons. We compared perceptual dynamics, specifically cumulative dominance durations, performed during BR before and after 517 518 training. We then examined the effects of learned upregulation on BR by comparing pre-training BR versus post-training BR with concurrent 'learned' 519 520 upregulation of brain activity. For the final comparison, we examined the non-521 trained mental imagery on BR, by comparing perceptual dynamics during pre-522 training BR versus post-training BR with concurrent non-trained mental imagery. The effects of trained mental imagery were additionally examined 523 524 separately - see Mental Imagery Control Experiment and Figure S1 525 (Supplementary Materials).

526

527 As the durations of the three percepts were dependent on each other, a 528 change in one percept occurred linked to changes in one or both of the other 529 percepts.

530

531 Within Condition Comparisons:

532 Comparison 1. Pre-training BR vs. Post-training BR

533 Comparing behavioural measures of pre-training BR and post-training BR 534 indicated an effect of training (Figure 3). Paired t-tests revealed a significant 535 reduction in the cumulative dominance durations (i.e. how long a percept type 536 was perceived) for the strategy-unrelated percept (t(9)=2.88,p=0.02), and a 537 significant increase in mixed percept durations (t(9)=2.74,p=0.02), with no

538 significant change in the dominance duration of the strategy-related percept539 (t(9)=0.46,p=0.66).

540

541 Comparison 2. Pre-training BR vs. Post-training BR with Concurrent 542 Trained Upregulation

Paired t-tests revealed a significant reduction in the duration of the strategyunrelated percept (t(9)=4.76,p=0.001), and a significant increase in the duration of the mixed percept (t(9)=2.68,p=0.03). There was no significant change in the dominance duration of the strategy-related percept (t(9)=0.53,p=0.61) (Figure 3). The changes in BR dynamics were similar to those observed with pre-training BR vs. post-training BR (Comparison 1).

549

550 Comparison 3. Pre-training BR vs. Post-training BR with concurrent

551 Non-trained Mental Imagery

Paired t-tests indicated a significant reduction in the duration of the strategyrelated percept (t(9)=2.41, p=0.04), and a significant increase in the duration of the mixed percept (t(9)=2.68, p=0.03). There was no significant change in

the dominance duration of the strategy-unrelated percept (t(9)=0.12, p=1.74).

556

557 We further examined differences between conditions.

558

559 Between Condition Comparisons:

560

561 **1.** Post-training BR vs. Post-training BR with Concurrent Trained 562 Upregulation (Comparison 1 vs. Comparison 2)

There was a significantly greater reduction in the dominance duration of the strategy-unrelated percept (t(9)=2.40, p=0.04) in Comparison 2 as compared with Comparison 1 (Figure 3B). There were no other significant differences between the two comparisons (strategy-related percept: t(9)=0.95, p=0.37; mixed percept: t(9)=0.90, p=0.39).

568

569 **2.** *Post-training BR vs. Post-training BR with Non-trained Mental Imagery* 570 (Comparison 1 vs. Comparison 3)

There was a significantly greater reduction in the dominance duration of the strategy-related percept (t(9)=3.12, p=0.01) (Figure 3B). There was also a significantly greater increase in the dominance duration of the mixed percept (t(9)=2.62, p=0.03). There were no significant changes in the strategyunrelated percept (t(9)=0.09, p=0.93)

576

577 **3.** Post-training BR with Concurrent Trained Upregulation vs. Post-578 training BR with Non-trained Mental Imagery (Comparison 2 vs. 579 Comparison 3)

There was a trend towards reduction in the dominance duration of the strategy-related percept (t(9)=2.23, p=0.05) in Comparison 3 as compared with Comparison 2 (Figure 3B). The other two comparisons were not significant (strategy-related percept: t(9)=0.95, p=0.37; mixed percept: t(9)=1.1, p=0.30).

585

586 Functional Changes during Neurofeedback Training

To test if neurofeedback training resulted in progressive learning, we 587 588 examined whether participants demonstrated increased control of the differential feedback signal over the three training days (Figure 2B). A 589 repeated-measures ANOVA with a factor of training day (3 levels; Days 1-3) 590 591 demonstrated a significant effect (F(2,16) = 3.74, p = 0.047). Post-hoc t-tests demonstrated a significant increase in the differential signal from Day 2 592 593 onwards, suggesting a learning effect (Day 1: t(9)=0.88, p= 0.40; Day 2: 594 t(9)=3.27 p=0.001; Day 3: t(8)=2.75, p=0.02).

595

596 Functional Changes during Transfer

597 Following neurofeedback training and prior to BR, voluntary control of brain 598 activation in the absence of neurofeedback was confirmed in a 'transfer 599 session'. Differential BOLD activation (strategy-related ROI minus strategy-600 unrelated ROI) pooled across the two transfer sessions, revealed a significant 601 effect (t(9)=2.38, p= 0.04).

602

603 Functional Changes during Binocular Rivalry

We examined task-related BOLD signals in the trained ROIs (FFA and PPA) comparing pre-training BR with post-training BR. We observed significant reductions in BOLD signals in both the strategy-related ROI (t(9)= 3.43, p= 0.007) and strategy-unrelated ROI (t(9)= 2.26, p=0.04), when comparing pretraining BR with post-training BR.

609

610 Comparing pre-training BR versus post-training BR with concurrent trained 611 upregulation, there was a significant reduction in the activation level of the

612 strategy-unrelated ROI (t(9)= 2.48, p= 0.03). No significant change was noted 613 for the strategy-related ROI (t(9)= 1.41, p=0.19). We performed one-tailed t-614 tests as we had an *a priori* hypothesis that following neurofeedback training, 615 participants should be able to increase the difference in BOLD activation 616 between the two trained ROIs (Figure 4).

617

618 There were no significant changes for pre-training BR versus post-training BR

619 with concurrent non-trained mental imagery (strategy related ROI: t(9) = 0.82,

620 p= 0.44; strategy unrelated ROI: t(9)= 0.83, p= 0.43).

621

622 Mental Imagery Control Experiment

623

There was no evidence of significant changes in the cumulative dominance durations of any of the three percepts (strategy-related percept t(9)=0.74, p= 0.48; strategy-unrelated percept, t(9)=1.00, p= 0.34; mixed percept, t(9)=2.00, p= 0.07).

628

629 Between Group Comparisons with 'Mental Imagery' Control Group

630 We performed an ANOVA with a within-subjects factor of percepts (strategy-

631 related percept, strategy-unrelated percept, mixed percept)) and a between-

- 632 subjects factor of group (Group 1: neurofeedback, Group 2: mental imagery).
- 633 There was a main effect of percept (F(2,36) = 4.64, p = 0.02). There was no
- 634 interaction (F(2,36) = 2.65, p = 0.08) between these two factors.

635

636 We performed a second ANOVA with a within-subjects factor of percepts 637 (strategy-related percept, strategy-unrelated percept, mixed percept)) and a between-subjects factor of group (Group 1: neurofeedback with concurrent-638 639 upregulation, Group 2: mental imagery). There was a main effect of percept 640 (F(2,36)=6.68, p=0.003), and an interaction between percept and group 641 (F(2,36) = 5.29, p = 0.01). Follow-up two-sample t-tests looking at changes in 642 durations of the similar percepts showed a significant difference for the 643 strategy-unrelated percept (t(9)= 2.35, p= 0.04), but not for strategy-related 644 percept (t(9)= 1.04, p= 0.32) or the mixed percept, (t(9)= 2.00, p= 0.08).

645

646 We performed a further ANOVA with a within-subjects factor of percepts 647 (strategy-related percept, strategy-unrelated percept, mixed percept)) and a 648 between-subjects factor of group (Group 1: neurofeedback with concurrent 649 non-trained mental imagery, Group 2: mental imagery). There was a main 650 effect of percept (F(2,36)= 6.70, p= 0.003), and an interaction between 651 percept and group (F(2,36)= 3.63, p= 0.04). Follow-up two-sample t-tests 652 looking at changes in durations of the similar percepts showed a significant 653 difference for the mixed percept (t(9) = 2.79, p = 0.02, but not for strategy-654 related percept (t(9)= 1.00, p= 0.86) or the strategy-unrelated percept, (t(9)= 655 0.29, p= 1.14).

656

657

659 Results - Structural

660

The results of the longitudinal non-rigid registration were used to determine volume changes in the ROIs by calculating the_divergence of the velocity fields. One-sampled t-tests of these values were used to calculate if any significant structural changes had taken place as a result of neurofeedback training. They were not significant for both ROIs i.e. FFA (t(9)= 0.36, p> 0.05), and PPA (t(9)= 0.46, p>0.05),

667

668 **Results – Canonical Variate analysis**

669

Plots for comparisons of combined measures in: (1) behaviour (dominance durations for the three perceptual reports) and functional (BOLD changes across training in FFA, PPA); and (2) behaviour and structural measures (measure of the volume changes in FFA and PPA following training) are presented in Figure S4, together with Bartlett's approximate chi-squared statistic for Wilks' Lambda and its p-value, for each comparison.

676

The participant neurofeedback training measures (i.e. differential BOLD brain activation) had a trend to being correlated with changes in BR behavioural dynamics as recorded during BR with concurrent trained upregulation of brain activation (compared with pre-training BR) (chi-squared value = 12.35, p = 0.05). Comparison of changes in the neurofeedback training measures with behavioural changes during 'simple BR' before and after training was nonsignificant (chi-square value = 11.43, p= 0.07). Significant correlations were

684 noted between structural changes in both ROIs and the change in BR 685 dynamics produced during concurrent trained upregulation of brain activation 686 (chi-squared value = 19.64, p= 0.03). Comparison of structural measures with 687 behavioural measures during 'simple BR' before and after training was non-688 significant (chi-square value = 13.77, p= 0.09).

689

690 Of note, the mapping weights obtained for the behavioural measures and the training-related BOLD measures were independent of the mapping weights 691 692 obtained for the behavioural measures and the structural measures. This is 693 because these multivariate mapping values were specific to the measures 694 used in the comparisons. Finally, the interpretation of the mapping weights in 695 relation to having a positive or negative value did not indicate a positive or 696 negative change in the values (e.g. an increase or decrease in structural measures). Rather they represent a positive (or negative) contribution to the 697 mapping between the multivariate predictor variable and the outcome 698 699 variables.

700

701 Discussion

702 703

704 Participants learned to differentially regulate the amplitude of BOLD activation 705 in two higher-order visual brain regions, FFA and PPA. This was achieved in 706 realtime, through volitional control using neurofeedback training with rt-fMRI. 707 The use of a 'differential' training signal was implemented by showing the 708 participants a 'thermometer bar' whose size represented the difference in the 709 mean BOLD signal between the two selected brain regions. By doing this, one 710 of the brain regions acted as an internal control for the other, accounting for 711 potential confounds produced by global changes in brain activation in 712 response to effects such as arousal. Furthermore, specific behavioural effects 713 linked with the direction of change of the differential training signal were 714 obtained, providing a comparison of behavioural metrics for the training effect(Thibault et al., 2018). The effect on visual perception was examined 715 716 with an independent BR task that employed stimuli specifically engaging 717 these stimulus-selective brain regions (face stimuli for FFA, house stimuli for 718 PPA). During BR, moment-to-moment stochastic alternations between two 719 competing visual percepts are observed, while concurrent brain activity can 720 be recorded and potentially manipulated(Blake et al., 2014; Blake and 721 Logothetis, 2002).

722

In this study, a change in BR perceptual dynamics was observed following neurofeedback training. Perception of the stimulus linked to neurofeedback training was rendered more stable e.g. strategy-related percept, with a reduction in the perception of the *other* stimulus e.g. strategy-unrelated

727 percept. This behavioural change occurred when comparing pre-training BR 728 with post-training BR, and additionally when participants performed post-729 training BR while concurrently performing learned 'upregulation' of brain 730 activity. We compared pre-training 'BR' with three post-training BR conditions: 731 'post-training BR', 'post-training BR with concurrent trained upregulation', and 732 'post-training BR with concurrent non-trained mental imagery'. The first 733 comparison, examining changes during BR before and after neurofeedback training, showed altered BR dynamics; specifically a reduction in the 734 735 cumulative dominance duration of the strategy-unrelated percept. These 736 findings are important, as they show that neurofeedback training produced a 737 behavioural effect that was: (1) counter-intuitive in that percept durations were 738 not increased in line with the verbally instructed neurofeedback training 739 strategy, which was initially expected. Rather, percept durations not linked to 740 the neurofeedback training strategy (e.g. strategy-unrelated percept) were 741 reduced; (2) aligned with a longstanding finding in the field, namely Levelt's 742 second proposition (discussed below); and (3) indicative of a lack of demand 743 characteristics (see also Mental Imagery Control Experiment).

744

There was a significant reduction in the levels of activation in both ROIs, comparing pre-training BR versus post-training BR. This linked neuroimaging finding was unexpected, as the prediction from existing literature(Tong et al., 1998) is that BOLD activation levels in extrastriate visual areas will reflect dominance durations. The expected finding might have been that activation levels would be lower in the strategy-unrelated ROI. Our findings instead showed that both regions were affected by neurofeedback training, as we

expected given that participants trained on a differential signal involving both ROIs. Both ROIs demonstrated a reduction in activation, which may reflect an increase in neural efficiency as a result of more precise tuning of neural representations(Gimenez et al., 2014; Haler et al., 1992; Heinzel et al., 2014; Vartanian et al., 2013). The exact mechanisms underlying this gain are unknown, particularly in the context of neurofeedback training and thus warrants further study(Poldrack, 2015).

759

760 The purpose of the second comparison ('pre-training BR' versus 'post-training 761 BR with concurrent upregulation') was to examine if there was an effect of 762 concurrent trained modulation of brain activation on BR dynamics that was 763 additive or different to the effect of neurofeedback training alone. We 764 observed a change in BR dynamics that was similar and greater to that 765 observed for pre-training BR vs. post-training BR, in that there was more of a 766 *reduction* in the mean dominance duration of the strategy-unrelated percept. 767 This confirmed that the effect of trained upregulation was directly aligned with 768 the effect of neurofeedback training on BR dynamics. There was a decrease 769 in the level of BOLD activation in the strategy-unrelated ROI only, with no 770 significant change in the strategy-related ROI. Interestingly, these BOLD 771 activation changes were the same as those observed during neurofeedback 772 training (a reduction in activation levels of the strategy-unrelated ROI, Figure 773 2B). This provides further evidence for a similar mechanism underlying the 774 changes in BR dynamics following training and for those observed with 775 concurrent trained upregulation. The counter-intuitive effect of training and up-776 regulation (during BR) on the brain activations in the two ROIs (i.e. opposite to

an *a priori* instruction and predicted direction of activation changes) is
intriguing and worthy of further investigation(Abel et al., 2015; Bueichekú et
al., 2016).

The third comparison ('pre-training BR' versus 'post-training BR with non-780 781 trained mental imagery') served to assess the impact of using a differential 782 training signal, which was hypothesised to have an effect on both ROIs in all 783 participants. It additionally helped reveal the role of non-trained mental 784 imagery in the context of prior neurofeedback training. No significant change in brain activation in either ROI was observed. However, BR dynamics 785 786 changed in a similar manner to the other two post-neurofeedback training BR 787 conditions, with a significant reduction in the duration of the percept not linked 788 to the training strategy used during training. This reduction was significant 789 when comparing changes in perceptual dynamics across conditions. These 790 behavioural findings would therefore suggest that neurofeedback training, 791 despite the lack of a statistically significant BOLD effect, produced a more 792 general effect on the neurobiology of the two trained ROIs. The exact nature 793 of this effect may be complex, given that behavioural changes observed for 794 this condition were opposite to the direction of neurofeedback training, but 795 nonetheless sufficient to produce an effect e.g. 'House' group participants 796 specifically underwent neurofeedback training with 'House-based' mental 797 imagery strategies, and yet they generated changes in BR dynamics simply 798 by using non-trained 'face' based mental imagery strategies during the 799 performance of BR. These behavioural findings are different from Rademaker 800 and Pearson's work, in which using mental imagery training *did not* produce training-related changes in BR dominance duration. Five successive days of 801

802 mental imagery training had no effect on BR, with no benefit being conferred 803 by expending increased effort during mental imagery generation(Rademaker 804 and Pearson, 2012). On the other hand, Rademaker and Pearson's findings 805 are in keeping with our own mental imagery control experiment, indicating the 806 relevance of neurofeedback training. We conducted a behavioural control 807 experiment in which a different group of participants performed BR before and 808 after three consecutive days of mental imagery training, which was analogous 809 to the neurofeedback training. The training was again explicitly linked to one 810 of the two stimuli used in BR (face mental imagery for a 'Face group', house 811 mental imagery for a 'House group'). However there was no targeted training 812 strategy for the brain, unlike with the neurofeedback-trained groups. No 813 significant changes in dominance durations of any of the three percepts were 814 observed.

815

816 Taken together, these results indicate that short-term intensive training over 3 817 days on a neurofeedback BOLD signal produced by two brain regions, 818 engages and alters the function and biology of both regions. This is 819 specifically supported by the shift in perceptual dynamics during BR following 820 neurofeedback training, and the activation changes observed in both ROIs 821 (see Results: Comparison 1). It is further supported more broadly by the 822 behavioural changes observed in all of the post-neurofeedback training BR 823 conditions, which were not observed in the mental imagery control 824 experiment. Habes et al. (Habes et al., 2016) have previously confirmed that 825 although differential regulation of category-specific visual areas can be 826 achieved after a single day of training, a linked change in BR dynamics was

not produced. We therefore suggest that in order for mental imagery to produce a change in perception, it must be linked with neurofeedback-led learning, conducted over a period of days. This may be attributable to the interposition of sleep with sequential daily training. Sleep has been directly linked with the offline processing necessary for the consolidation of neuroprosthetic learning(Gulati et al., 2014) and associated behavioural output(Gulati et al., 2017).

834

835 Mental imagery may be utilised for perceptual learning of low-level visual 836 features, and to activate stimulus-selective cortical representations(O'Craven 837 and Kanwisher, 2000; Tartaglia et al., 2009). Similarly, rt-fMRI neurofeedback 838 together with implicit operant reinforcement has been used to unconsciously 839 train patterns of activation in primary visual brain regions(Amano et al., 2016; 840 Shibata et al., 2011) to produce perceptual and associative learning of low-841 level visual features such as colour and orientation. However, to-date neither 842 approach has successfully yielded changes in higher-order visual perception. 843 In this study, we show that coupling explicitly instructed mental imagery with 844 rt-fMRI neurofeedback training of higher-order visual brain regions produces 845 an unconscious and targeted shift in the perceptual processing of visual 846 stimuli. This result is novel and significant in providing evidence for non-847 invasively manipulating higher-order brain function, potentially at the level of 848 directly strengthening neural representations to alter higher-order 849 perception(Fahle, 2002; Watanabe et al., 2002, 2001). From a mechanistic 850 perspective, an interesting next step might be to test if unconsciously inducing 851 specific patterns of brain activations related to category-specific stimuli will

produce linked shifts in perception in a similar manner to that observed in this
study(Watanabe et al., 2017). This would provide more direct evidence of
modulating neural representations.

855

856 The observed behavioural findings may constitute a neural analogue of 857 Levelt's second proposition(Levelt, 1966), as applied to stimulus perception. 858 The original proposition (see Supplementary Discussion) was based on the 859 physical properties of visual stimuli. It was recently modified to indicate that 860 'increasing the difference in stimulus strength between the two eyes will 861 primarily act to increase the average perceptual dominance duration of the 862 stronger stimulus' (Brascamp et al., 2015). Our work may provide evidence for 863 a neural reformulation of BR. Participants were trained on a differential signal, 864 rather than specifically training to increase the level of activation in the strategy-related ROI. During training, they appeared to reduce the level of 865 activation in the strategy-unrelated ROI across the three days, while 866 867 maintaining a fixed level of activation in the strategy-related ROI (Figure 2B). This difference in activation levels as a result of training was maintained when 868 869 the participants undertook the transfer sessions, an assessment of 870 upregulation in the absence of neurofeedback. The difference in ROI 871 activation levels may have therefore led to a relative difference in the 872 strengths of the neural representations linked to the visual stimulus 873 categories. In keeping with this view, we observed a reduction in the mean 874 dominance duration of the strategy-unrelated percept. This resulted in greater 875 mean dominance durations of the strategy-related percept, corresponding to the ROI with the strengthened neural representation. On the basis of this, we 876

877 propose a possible neural analogue of the Levelt's modified second 878 proposition as follows: 'increasing the difference in neural representation strengths between the two brain regions linked to the two monocular visual 879 880 stimuli will primarily act to increase the average perceptual dominance of the 881 percept linked to the stronger neural representation'. The effect of this would 882 be to produce unconscious perceptual biasing towards the strengthened 883 percept. This mechanism for perceptual 'shaping' (Lange et al., 2018) may 884 have real-world application in conditions requiring targeted enhancement of 885 perception such as in threat detection (Miranda et al., 2015), or the rapeutically 886 to reduce unwanted or aberrant percepts(Taschereau-Dumouchel et al., 887 2018).

888

889 Several mechanisms have been put forward to explain the neural 890 underpinnings of BR. Of note, known influences on visual perception such as 891 priming and cueing have not been shown to produce changes in BR 892 dominance durations (see also Supplementary Discussion). Neurofeedback 893 with rt-fMRI provides the most direct means of testing neuronal function 894 involved in processing visual stimuli. Using a hierarchical model of BR(Dayan, 895 1998), it may be proposed that neurofeedback training of higher order brain 896 regions strengthens neuronal representations linked to the processing of 897 specific visual stimuli, leading to unconscious perceptual biasing. Preferential 898 processing of strategy-related stimuli would result in decreased dominance 899 durations of the strategy-unrelated stimuli, as was observed here. The effect 900 of neurofeedback on BR may be further considered within a Bayesian 901 framework(Lange et al., 2018). During BR, the dominant percept at any given

902 time is maintained by the highest posterior probability, at the top of the cortical 903 hierarchy. Stimulus representations at lower levels generate error signals that 904 are compared with top-down predictions. The percept is rendered more or 905 less stable in relation to bottom-up inhibition i.e. the lower the error signal, the 906 more stable the percept(Alink et al., 2010; Hohwy et al., 2008; Summerfield 907 and Koechlin, 2008). In keeping with this, BR dynamics were shifted in the 908 direction of the information represented in the trained visual brain regions. 909 Therefore, perception of the stimulus linked to training was rendered more 910 stable, with a simultaneous reduction in the stability of the perception of the 911 other stimulus, leading to a reduction in its mean dominance duration.

912 The changes in high-level visual perception following neurofeedback training 913 in this study were associated with structural changes in the trained regions 914 (see Supplementary Materials). We used a multivariate analysis technique, 915 Canonical Variate Analysis, which can accommodate multiple measures of 916 behaviour, structure, and function to help determine the overarching effect of 917 neurofeedback training. The change in BR dynamics (i.e. cumulative 918 dominance durations) was linked with measures of structural changes in FFA, 919 and PPA (Figure S3, Supplementary Materials). These preliminary findings in 920 ten participants suggest that neurofeedback training, even over a relatively 921 short period of time (3 days) can alter perception as a result of plasticity in the 922 trained brain regions(Johansen-Berg et al., 2012; Sagi et al., 2012).

923

In this study, we provide a direct demonstration of the rapid changes in
perception and neural plasticity that can be produced by neurofeedback
training of higher-order visual areas using rt-fMRI. Imagery-related activation

927 in higher-order visual cortex, such as the ventral visual areas, are related to 928 semantic content, and are more flexible and abstract(Orban et al., 2014) as 929 compared to early visual cortex. Therefore, the use of higher-order visual 930 areas paired with rt-fMRI neurofeedback training may provide the most potent 931 and generalizable means of enacting a change on complex perception. Neural 932 representations that give rise to prior expectations can be directly shifted in 933 the direction of neurofeedback training, even in the presence of pre-existing 934 expectations. This could lead to targeted enhancement of specific responses 935 during discrete tasks as demonstrated here using BR, or in the reduction of 936 aberrant visual perception, such as hallucinations, for therapeutic 937 effect(Lange et al., 2018).

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1149 Acknowledgements

JE's contribution was supported by a Wellcome Trust Clinical Research Fellowship.

1152 G.R.R and A.R were supported by The Wellcome Trust Centre for 1153 Neuroimaging core funding from the Wellcome Trust 091593/Z/10/Z.

1154 EF was supported by core funding of the School of Psychology and Language1155 Sciences, University of Reading.

1156 FS and Y.K were supported by a grant from the Swiss National Science1157 Foundation (BSSG10_155915)

NW's contribution was supported by the BRAINTRAIN European research 1158 network (Collaborative Project) supported by the European Commission 1159 1160 under the Health Cooperation Work Programme of the 7th Framework 1161 Programme (Grant agreement n° 602186). The Wellcome Trust Centre for 1162 Neuroimaging is supported by core funding from the Wellcome Trust 1163 0915/Z/10/Z. The Wellcome Trust Centre for Neuroimaging has an 1164 institutional research agreement with and receives support from Siemens 1165 Healthcare.

1166 GR's contribution was supported by a Wellcome Trust Senior Research1167 Fellowship.

1168 Author contributions

J.E, F.S, and G.R designed the experiment. J.E, J.S.W, G.R.R, F.S and G.Rdiscussed and planned data analysis. J.E collected and analysed the data.

J.E, Y.K, G.R.R and F.S. developed the real-time acquisition and analysis
tools. J.E and E.F performed the mental imagery control experiment. A.R
performed the CVA analysis. J.E and G.R wrote the paper. All authors read
and commented on the manuscript.

- 1176 Figure legends
- 1177 Figure 1. Experiment procedure schematic.
- 1178 Stage 1 Pre-training BR

1179 Stage 2 *Neurofeedback training:* 10 participants were separated into two 1180 groups, a 'face' group and a 'house group', and were trained to increase a 1181 fluctuating thermometer bar (blue bar), up to a fixed mark (orange bar). After 1182 the neurofeedback training sessions, the participants performed a transfer 1183 session with brain modulation in the absence of neurofeedback signal.

1184 Stage 3 *Post-training BR*: Three types of sessions: a) BR; b) BR with 1185 'concurrent trained upregulation'; and c) BR with 'concurrent non-trained 1186 mental imagery'.

Figure 2A. Schematic showing group ROIs (FFA and PPA statistical masks) on inflated canonical brains. Activation was extracted from these regions for production of the differential signal for neurofeedback training. The direction of regulation of these ROIs was specific for each group i.e. House Group, PPA up/ FFA down, Face Group, FFA up/ PPA down.

1193

Figure 2B. Mean BOLD signal changes across groups, in the strategy-related ROI (red) and the strategy-unrelated ROI (blue), for each of the nine training sessions. The green line shows the difference in mean BOLD activation between the two brain regions and corresponds to the neurofeedback training signal that participants visualised in the scanner as a fluctuating bar. Error bars show ± 1 SEM.

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- 1201

Figure 3A. Cumulative dominance durations across participants for pretraining BR, and the three post-training BR sessions: Post-training, Posttraining BR with concurrent trained upregulation, and Post-training BR with concurrent non-trained mental imagery. Error bars show ±1SEM. The total duration of each BR block was 40s.

- 1208 Figure 3B. Changes in cumulative dominance durations for binocular rivalry
- 1209 (BR) sessions, showing comparisons before and after neurofeedback training
- 1210 collapsed across both groups. Error bars indicate ±1SEM

- 1212 A. Pre/post training BR comparison
- 1213 B. Pre/post-training BR with concurrent training upregulation
- 1214 C. Pre/post-training BR with concurrent non-trained mental imagery
- 1215
- 1216 *p<0.05. Double **p<0.01. Horizontal brackets indicate significant differences in
- 1217 the changes of cumulative dominance durations (p<0.05) ~ over a bracket
- 1218 indicates p=0.07.
- 1219
- 1220

1221Figure 4. BOLD activation changes in the trained ROIs, during binocular rivalry1222(BR) sessions, before and after neurofeedback training. There was a significant1223reduction in activation in both the strategy-related ROI and the strategy-1224unrelated ROI following training. When BR was performed with concurrent1225trained up-regulation, there was a significant further decrease in BOLD1226activation in the strategy-unrelated ROI only. Error bars indicate ± 1 SEM. (*1227p<0.05).</td>

1229 Figures

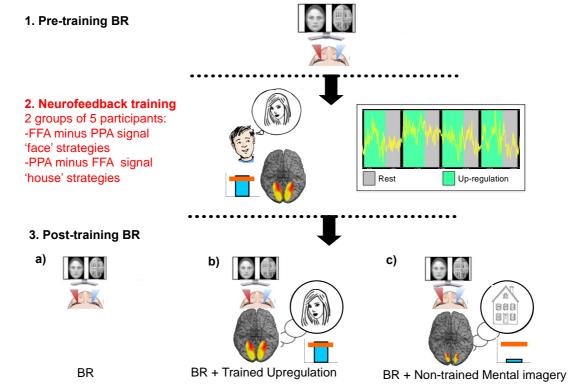
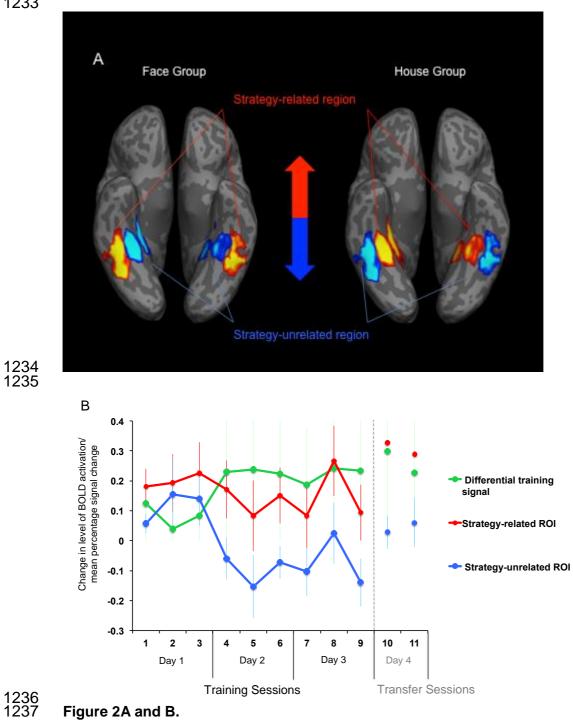
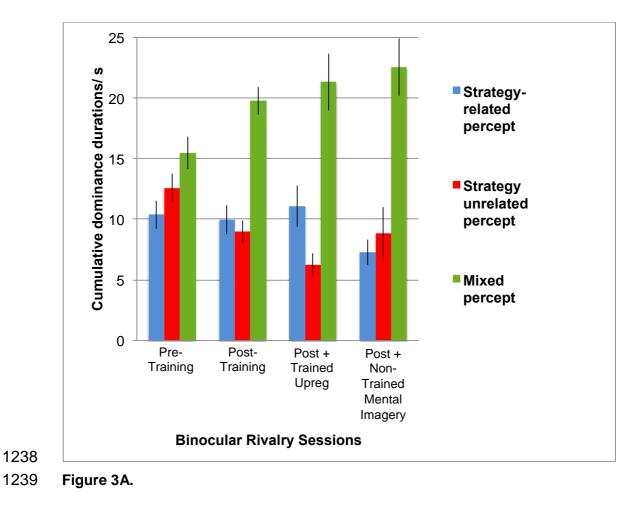
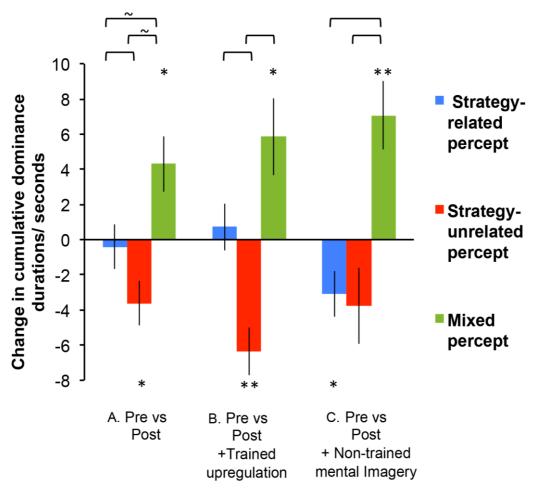


Figure 1

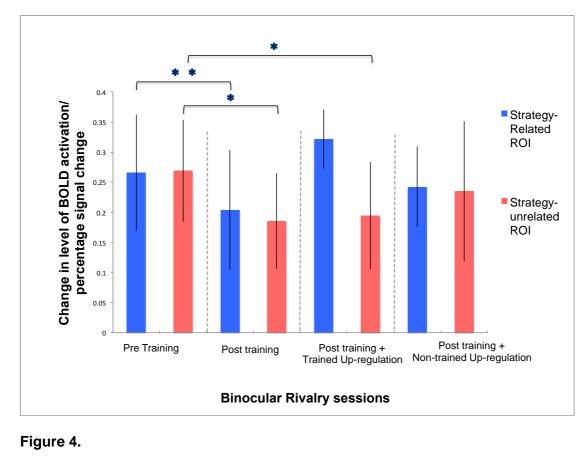






Binocular Rivalry Sessions Comparison

- **Figure**
- **Figure 3B.**



1249	Supplementary Materials List:
1250	Supplementary methods
1251	Supplementary results
1252	Supplementary discussion
1253	Supplementary references
1254	Supplementary figures S1-S4
1255	
1256	
1257	Supplementary Methods
1258	
1259	Learning Effect across Rt-fMRI Neurofeedback Training
1260	
1261	The learning effect measures the change in BOLD activation in trained brain
1262	region/s across the neurofeedback training sessions. The mean percentage
1263	signal change (PSC) for each training run and ROI was calculated and plotted
1264	(seeFigure2B in main paper, and compare with S1, S2).
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1269 Supplementary Results

1270 Results - Behaviour

1271

- 1272 **Binocular Rivalry Durations:**
- 1273 See main paper.
- 1274

1275 Results – Imaging

1276

1277 Strategy-related and Strategy-unrelated ROIs:

We first determined if the differential signal significantly changed over days across participants (see main paper, Result Section). We additionally examined the changes in the two ROIs used to produce the differential signal; the strategy-related ROI and the strategy-unrelated ROI (see Figure 2, main paper).

1283

1284 A one-way ANOVA (with 3 levels corresponding to the 3 training days) 1285 revealed a significant reduction in activation in the strategy-unrelated ROI 1286 over the 3 days of training (F(2,16)= 8.71, p= 0.003). On the other hand, a 1287 one-way ANOVA for the strategy-related ROI revealed no significant change 1288 (F(2,16)= 0.33, p= 0.72).

1289

1290 Sub-groups:

1291 To assess whether there was any difference between the face and house 1292 group during training, an ANOVA was performed on the differential training 1293 signal across the 3 training days, with a between-subjects factor with two

1294 levels (for the two sub-groups, 'Face' and 'House'). This did not reveal a 1295 significant interaction (F(2,14)=0.064, p=0.94) between the two factors.

1297 For neurofeedback training graphs for the two groups (mean percentage1298 signal change over 9 sessions), please see Figures S2 and S3.

1302 Supplementary Discussion

1303

1304 Levelt's Second Proposition, 1966

Levelt's second proposition(Levelt, 1966), as applied to stimulus perception was based on the physical properties of visual stimuli and states: *"Variation of the stimulus strength in one eye will only influence the mean dominance duration of the contralateral eye and not the mean dominance duration of the ipsilateral eye".*

1310

1311 Known Influences on Visual Perception

1312 The role of 'priming' and 'cueing' might also be invoked as possible causes for 1313 the perceptual changes observed following neurofeedback training in this 1314 study. Prior presentation of a specific orientation grating can cause an 1315 increase in the perception of the identical grating during BR. However, 1316 dominance durations were unchanged (Denison et al., 2011). Similarly, 1317 exogenous cueing prior to BR can increase the probability of the predominant percept being linked to the cue. For example prior to BR, hearing sentences 1318 1319 with the word 'face', results in FFA activation(Pelekanos et al., 2011). 1320 Nonetheless, no significant change in stimulus dominance between faces and 1321 houses on rivalry trials were observed when participants were cued with a 1322 word linked to one of the rivalrous stimuli. Dominance durations have also 1323 been demonstrated as being immune to the effects of volitional attention(Jung 1324 et al., 2016), and reflective of true differences in sensory processing(Dieter et 1325 al., 2016). It is therefore unlikely that the perceptual changes produced by neurofeedback training could be ascribed to participant expectation. Evidently, 1326

neither altering the level of activity in higher order brain regions involved in
perception, nor applying known influences on visual perception, provide a
comprehensive explanation for the lasting shifts in perceptual bistability
observed following neurofeedback training in this study.

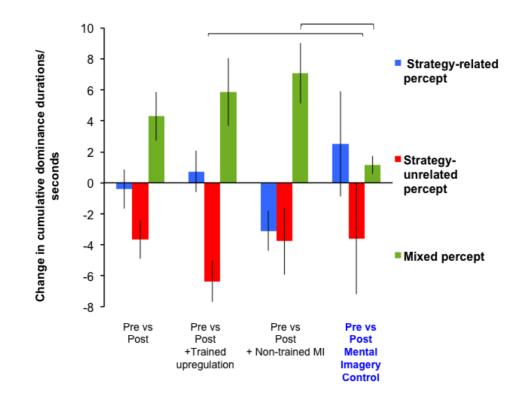
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1332 Controlling the Neurofeedback Signal

1333 With regards to the neurofeedback training signal itself (i.e. differential brain 1334 activation between two ROIs), there were five potential activation states which 1335 could increase the difference between the two brain regions (strategy-related 1336 ROI minus strategy-unrelated ROI), leading to upregulation of the training 1337 signal: These could be: (1) an increase in *strategy-related ROI*; (2) a decrease 1338 in strategy-unrelated ROI; (3) a combination of the two; (4) a relatively greater 1339 increase in strategy-related ROI as compared to strategy-unrelated ROI; and 1340 (5) a relatively greater decrease in the strategy-unrelated ROI. Based on our 1341 results (Figure 1B in main paper), the mechanism for the upregulation of the 1342 differential signal across groups during neurofeedback training appeared to be 1343 produced by maintenance of activation in the strategy-related ROI, and a 1344 reduction of activation in the strategy-unrelated ROI.

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1350 Supplementary figures



Binocular Rivalry Sessions and Groups Comparison

1351

Figure S1. Changes in cumulative dominance durations for binocular rivalry sessions, showing comparisons before and after neurofeedback training. This figure is the analogous to Figure 3B in the main paper, but additionally shows changes in dominance durations for the 'Mental Imagery' control group. Error bars indicate \pm 1SEM. Horizontal brackets show significant between group comparisons for percepts (p<0.05).

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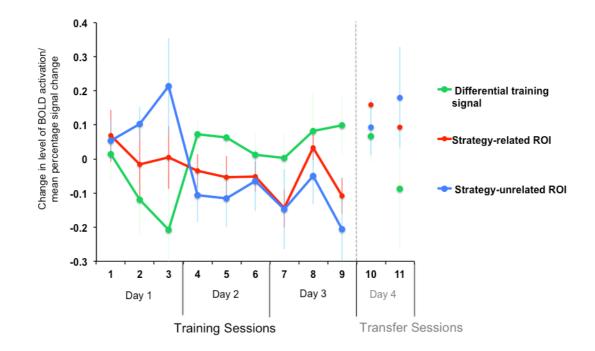
1359 A. Pre vs. Post-training BR comparison

1360 **B.** Pre vs. Post-training BR with concurrent training up-regulation

1361 C. Pre vs. Post-training BR with concurrent non-trained mental imagery

1362D. Pre vs. Post training BR comparison for Mental Imagery Control group

1363



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Figure S2. Mean BOLD signal changes across the House group, in the strategyrelated brain region (red) and the strategy-unrelated brain region (blue), for each of the nine training sessions. The green line shows the difference in mean BOLD activation between the two brain regions and corresponds to the neurofeedback training signal. Error bars show ±1SEM.

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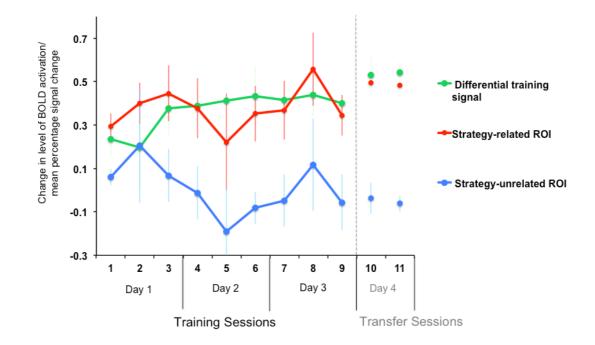
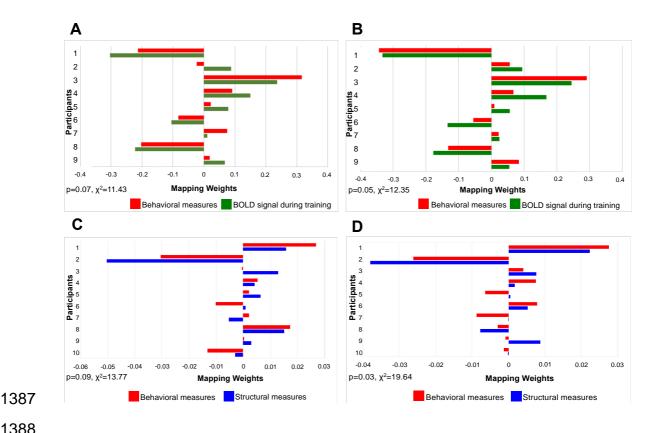


Figure S3. Mean BOLD signal changes across the Face group, in the strategyrelated brain region (red) and the strategy-unrelated brain region (blue), for each of the nine training sessions. The green line shows the difference in mean BOLD activation between the two brain regions and corresponds to the neurofeedback training signal. Error bars show ±1SEM.





1389 Figure S4. Canonical variate analysis illustrating the correlation between 1390 individual behaviour and physiological measures. For each participant 1391 mapping weights are shown for pairs of predictor and outcome variables. This 1392 approach aims to reveal relationships that may exist between multiple outcome 1393 variables following neurofeedback training.

1395 A,B: Comparison of BR behavioural measures (i.e. durations of mixed, 1396 strategy-related and strategy-unrelated percepts), and functional BOLD signal 1397 changes across training (i.e. differential signal). Nine of the ten participants 1398 were included, as one of the participants did not complete all nine training 1399 sessions. Participants 1-5 are Face Group, Participants 6-9 are House Group. A 1400 shows a non-significant relationship (p= 0.07) between individual participant BR measures (pre vs. post training) and functional BOLD signal changes 1401 1402 across training. B shows a non-significant relationship (p= 0.05) between

1403 individual participant BR measures (pre vs. post-training with concurrent

1404 trained upregulation) and functional BOLD signal changes across training.

1405

1406 C,D: Comparison of BR behaviour measures (i.e. durations of mixed, strategy-1407 related and strategy-unrelated percepts), and structural measures from FFA 1408 and PPA (pre vs. post training). Participants 1-5 are 'Face Group', Participants 1409 6-10 are 'House Group'. C shows a non-significant relationship (p= 0.09) 1410 between individual participant BR measures (pre vs. post training) and 1411 structural measures from FFA, and PPA (pre vs. post training). D shows a 1412 significant relationship (p= 0.03) between individual participant BR measures 1413 (pre vs. post-training with concurrent trained upregulation) and structural 1414 measures from FFAand PPA (pre vs. post training).

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