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Q1 Spatial attention enhances object coding in local and distributed representations of the lateral occipital complex

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The modulation of neural activity in visual cortex is thought to be a key mechanism of visual attention. The investigation of attentional modulation in high-level visual areas, however, is hampered by the lack of clear tuning or contrast response functions. In the present functional magnetic resonance imaging study we therefore systematically assessed how small voxel-wise biases in object preference across hundreds of voxels in the lateral occipital complex were affected when attention was directed to objects. We found that the strength of attentional modulation depended on a voxel's object preference in the absence of attention, a pattern indicative of an amplificatory mechanism. Our results show that such attentional modulation effectively increased the mutual information between voxel responses and object identity. Further, these local modulatory effects led to improved information-based object readout at the level of multi-voxel activation patterns and to an increased reproducibility of these patterns across repeated presentations. We conclude that attentional modulation enhances object coding in local and distributed object representations of the lateral occipital complex.

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38 1. Introduction

Attention is a cognitive process that enables us to focus on certain aspects of the environment for the benefit of improved performance (Bashinski and Bacharach, 1980; Cameron et al., 2002; Carrasco et al., 2000; Hawkins et al., 1990). One way in which attention has been found to impact neural processing is through an amplification of neural responses to attended spatial locations, objects, or features (for review, see Treue, 2003). In the visual domain, attentional amplification has been found throughout the visual processing hierarchy, from the earliest stage of visual neural processing in the lateral geniculate nucleus (O'Connor et al., 2002), primary visual cortex (Gandhi et al., 1999; Martínez et al., 1999; Somers et al., 1999), up to high-level visual cortices (Murray and Wojciulik, 2004; O'Craven et al., 1999; Serences et al., 2004) and the frontal lobes (Gitelman et al., 1999). However, the nature of attentional modulation remains a topic of debate. A number of studies have reported that attention leads to a multiplicative scaling of neuronal responses (Di Russo et al., 2001; McAdams and Maunsell, 1999; Treue

and Martínez Trujillo, 1999; Treue and Maunsell, 1999), which results in an increase of a neuron's signal to noise ratio. In contrast, other studies reported results that violated the predictions of the multiplication hypothesis, by showing that spatial attention leads to increased neural responses in visual areas in the absence of any visual stimulation (Kastner et al., 1999; Luck et al., 1997; Ress et al., 2000; Silver et al., 2007). According to these studies, attentional modulation involves an unspecific baseline shift of activity.

A common approach to investigate the effects of visual attention is the recording of neural responses across a range of a stimulus parameter (e.g., orientation of motion direction) both in the presence and absence of attention. In this way, previous studies have examined the attentional modulation of single-neuron (McAdams and Maunsell, 1999; Motter, 1993; Treue and Martínez Trujillo, 1999) or voxel (Saproo and Serences, 2010, 2014) tuning profiles. However, a complicating factor for the investigation of attentional modulation in high-level object-coding areas like the human lateral occipital complex (LOC) is the lack of analogous neuronal tuning functions. Similarly, the analysis of contrast response functions – a technique that has been used to study the nature of attentional modulation for low-level visual stimuli (Reynolds et al., 2000; Williford and Maunsell, 2006) – is problematic, because object-related neuronal responses become increasingly invariant to contrast along the visual hierarchy (Avidan et al., 2002; Rolls and

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Baylis, 1986) and this invariance may itself depend on attention (Murray and He, 2006). In the present work we therefore used a different approach by exploiting the fact that the LOC represents objects in a distributed fashion across ensembles of neural populations (Haxby et al., 2001; Rice et al., 2014). At the spatial resolution of fMRI this distributed code is expressed in a differential preference of voxels for a given stimulus, likely representing the cumulative stimulus preference of neurons within these voxels. Thus, if attention causes an amplification of neural activity as opposed to a mere baseline shift, these preferences should be augmented with attention, and as a consequence single- and multi-voxel responses should become more informative about the stimuli encoded in these voxels.

In the present study we presented human participants with objects under conditions of spatial attention and inattention in a functional magnetic resonance imaging (fMRI) experiment. We had two aims. First, we sought to probe the nature of attentional modulation of visual object responses in the LOC as described above, by examining whether attentional modulation increased with a voxel's preference for a given object in the absence of attention, or whether the modulation was independent of object preference. In a second step we investigated whether these local modulatory effects of attention resulted in a more informative and reliable object code. To this end we used a mutual information metric (Sapruo and Serences, 2010; Serences et al., 2009) to assess whether single-voxel responses became more informative about object identity with attention. At the multi-voxel pattern level we examined how these local changes affected the quality of object representations through pattern similarity and classification-based analyses.

2. Materials and methods

2.1. Disclosure

A previous article (Guggenmos et al., 2015) was based on the same fMRI dataset, but pursued a different research question and orthogonal analyses.

2.2. Participants

Eighteen healthy participants (11 female, mean age \pm SEM, 23.4 ± 0.8 years) took part in the experiment for payment after giving written informed consent. The study was conducted according to the declaration of Helsinki, and approved by the local ethics committee.

2.3. Experimental design

Our key experimental manipulation was to direct participants' spatial attention to either an object (attended condition) or a noise stimulus (unattended condition). Overall the experimental design comprised the factors attention (attended, unattended) as a factor of interest, as well as object (camera, watering can, chair), configuration (intact, split) and side of presentation (left, right) as factors of no interest. Configuration was manipulated by minimally scrambling (half-splitting) the objects, but note that the analyses in this article were based on intact objects only. Within each of 8 experimental runs, an object appeared in 4 trials in each attention condition (in 2 trials per side of presentation). The order of presentation was randomized across the 48 trials of each run.

2.4. Experimental procedures

In each trial (Fig. 1A), participants viewed a stimulus display that contained an object and a noise stimulus on either side of a central fixation cross. Spatial attention was manipulated by means of a brightness discrimination task that was performed either on the object (attended condition) or the contralateral noise stimulus (unattended condition). A trial (Fig. 1A) started with a blank fixation screen for $3300 \text{ ms} \pm 2000 \text{ ms}$, after which one half of a central black fixation diamond turned red, indicating the side to which attention should be directed. Following this cue and a short fixed interval (250 ms), four repetitions of the stimulus–response phase appeared. Each stimulus–response phase lasted 1500 ms and comprised the presentation of the stimulus screen (500 ms), a pattern mask (133 ms) and a response screen (867 ms). The object appeared on one side of the fixation cross (offset 3.84° of visual angle) and a noise stimulus at the same offset on the other side of the stimulus screen. All visual stimuli subtended 3.81 by 3.81° of visual angle. A brightness change occurred 283 ms after stimulus onset simultaneously on both the object and the noise stimulus, such that they became independently and randomly either darker or lighter. Participants were instructed to press a button on the response box when the stimulus on the cued side became darker. Responses were counted as valid within a time window of 1000 ms after stimulus offset. In each repetition of the stimulus–response phase, the same object was shown at the same position. The noise stimulus, while also presented at the same position, was randomly generated for each repetition.

To independently identify object-responsive regions of the lateral occipital complex (LOC) in each participant (Malach et al., 1995), we

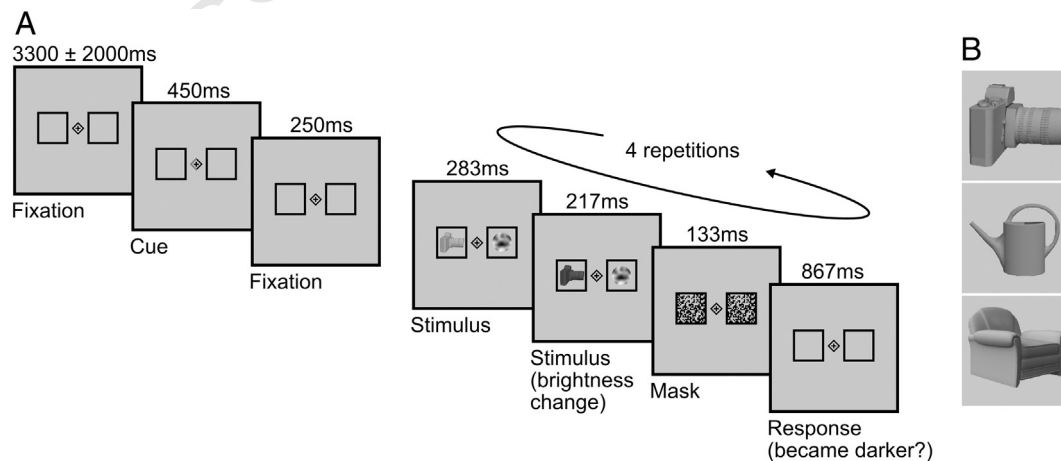


Fig. 1. Experimental procedures and stimuli. A. In each trial a cue indicated the side to which attention should be directed. Subsequently, four repetitions of the stimulus–response phase appeared, during each of which participants had to detect a decrease in brightness of either the object (attended condition) or the noise stimulus (unattended condition). B. The stimulus set consisted of three objects in an intact and half-split configuration.

conducted a localizer run with 5 blocks of intact objects, 5 blocks of split objects and 10 blocks of grid-scrambled versions of the objects in randomized order. Blocks lasted for 15.8 s during which 20 images were presented for 600 ms each, followed by 200 ms blank screen. Pairs of identical objects were shown left and right of fixation, equaling the configuration of the main experiment in eccentricity and size. Participants performed a one-back task on the object pairs, in which they had to indicate via button press whenever the same stimulus display appeared twice in a row.

2.5. Stimuli

Stimuli were generated with Psychophysics Toolbox 3 (<http://psychtoolbox.org>) and projected with a Sanyo LCD projector at 60 Hz. The stimulus set consisted of three grayscale objects (camera, watering can, chair) based on realistic three-dimensional models presented either intact or half-split (Fig. 1B). The objects were selected for representing non-overlapping man-made categories to increase the discriminability of evoked neuronal activation patterns. The noise stimuli matched the objects in terms of spatial extent and complexity to ensure that there would be no performance difference. They were randomly generated for each trial by sampling a 9×9 random binary matrix, scaling the matrix to 216×216 pixels, applying a low-pass filter with a cut-off frequency of 0.02/pixel and cropping pixels outside a circle of 216 pixels diameter. This procedure resulted in circular grayscale stimuli with randomly distributed smooth patches that approximately matched the objects in terms of spatial extent. Both the objects and the noise stimuli were scaled to grayscale RGB values between 50 and 205. To generate these brightness changes, the underlying RGB histograms were shifted up or down by 50 (the image background remained constant with an RGB value of 200). The pattern masks were generated for each trial by sampling an 18×18 random binary matrix and scaling the matrix to 216×216 pixels.

2.6. Eyetracking

Eyetracking data were successfully collected in 16 of 18 subjects using an infrared video eyetracking system (iView XTM MRI 50Hz, SensoMotoric Instruments, Teltow, Germany). For each run, the horizontal eye movement data were low-pass filtered and drift corrections were performed. As a measure of fixation reliability, we computed the percentage of recorded eye gaze positions during stimulus presentation within a 1.93° visual angle circle around the center of the fixation cross. This radius corresponded to the eccentricity of the inner edges of the two stimulus-containing boxes (see Fig. 1A). In addition, we computed the number of saccades to the intact objects and the noise stimuli, separately for the attended and the unattended condition. Saccades were defined as events of at least three consecutive data points in velocity space exceeding a velocity criterion of $30^\circ/\text{s}$. Saccades were counted as object-directed or noise-directed saccades, when their endpoint was located within the object-containing box, or the noise-containing box, respectively.

2.7. fMRI data acquisition and preprocessing

fMRI data were acquired on a 3-Tesla Siemens Trio (Erlangen, Germany) scanner using a gradient echo planar imaging (EPI) sequence and a 12-channel head-coil. We recorded 8 experimental runs of 214 whole-brain volumes each, and one LOC localizer run of 242 volumes ($TR = 2$ s, echo time (TE) 25 ms, flip angle 78° , 33 slices, 3 mm isotropic resolution, interslice gap 0.75 mm). In addition, a high-resolution T1-weighted image was acquired ($TR = 1.9$ s, echo time (TE) 2.51 ms, flip angle 9° , 192 slices, resolution 1 mm isotropic). The data of the experimental runs were realigned using SPM8 (Wellcome Department of Imaging Neuroscience, Institute of Neurology, London). Data analyses for the main experiment were generally performed in native subject

space. An exception was an illustrative display of the whole-brain group-level T-maps for the main effect of attention, for which we generated spatially normalized (MNI) and smoothed (8 mm Gaussian kernel) volumes. Preprocessing of the localizer data included realignment, spatial normalization to an MNI template and smoothing (8 mm Gaussian kernel).

2.8. fMRI data analysis

2.8.1. First-level general linear models (GLMs)

For each participant we estimated a GLM including the stimulus-onset regressors, accounting for the factors attention (attended, unattended), object (camera, can, chair) and configuration (intact, split). The onsets of each experimental regressor were set to the beginning of the stimulus–response phase. In addition, six motion parameters were included as regressors-of-no-interest. All experimental regressors were modeled as stick functions and convolved with a canonical hemodynamic response function.

The GLM for the functional localizer comprised regressors for objects and scrambled objects and six motion parameters. The experimental regressors were modeled as boxcar functions with durations equal to the block lengths (15.8 s) and convolved with a canonical hemodynamic response function as implemented in SPM8.

2.8.2. Region of interest procedures

Our region of interest (ROI) was the LOC, a functionally defined region that responds more to images of objects than their counterparts and stretches from the lateral occipital cortex to posterior fusiform gyrus (Grill-Spector et al., 1999). We anatomically constrained the LOC by a bilateral composite mask of the inferior occipital cortex, middle occipital cortex and the posterior half of the fusiform gyrus (derived from the AAL Atlas, Tzourio-Mazoyer et al., 2002). Then the LOC ROI was defined as the intersection of the anatomical mask and the functional localizer based on the t-contrast *intact objects > scrambled objects* of the functional localizer at a significance level of $p < 0.05$ (family-wise error (FWE) corrected at the whole-brain level). Note that this t-contrast was a group-level t-contrast, because the statistical power in the first-level localizer contrasts was not sufficient to define individual ROIs in all participants at the $p_{\text{FWE}} < 0.05$ level. To ensure a homogenous generation of the LOC ROI for all participants we thus first defined the LOC ROI in group-level (MNI) space and subsequently reverse-normalized the generated ROI to each participant's native space.

2.8.3. Quantifying changes in mean BOLD activity

To estimate neural activity in the LOC ROI and its dependence on attention, we extracted the voxel-wise beta values for attended and unattended objects separately and averaged across objects and voxels. This procedure resulted in single values representing the average BOLD response to attended and unattended objects.

To visualize the spatial extent of the attentional modulation at a whole-brain level, we performed a group-level repeated-measures ANOVA with factors attention and object and computed the post-hoc contrast *attended > unattended*. This analysis was based on normalized and smoothed data. Voxels were considered statistically significant at a level of $p < 0.05$, FWE-corrected at the whole-brain level.

2.8.4. Analyzing attentional modulation as a function of object preference

We next analyzed whether the attentional modulation depended on the preference of a voxel for a given object. We reasoned that if attention leads to an amplification of neural responses, the difference between a voxel's attentional modulation for the preferred object and the modulation for the non-preferred objects should increase as a function of object preference. By contrast, if attention led to an unspecific baseline shift irrespective of a voxel's preference for the presented object, the attentional modulation should not differ between the

279 presentations of the voxel's preferred and non-preferred object. We
280 therefore defined a preference index $PI(i)$ for each object i and each
281 voxel based on the data of the unattended condition:

$$PI(i) = \beta_{\text{unatt}}(i) - \langle \beta_{\text{unatt}}(\setminus i) \rangle,$$

283 where $\beta_{\text{unatt}}(i)$ and $\beta_{\text{unatt}}(\setminus i)$ are the voxel-wise beta values in the unat-
284 tended condition for object i and all objects except i (denoted as "not i ":
285 $\setminus i$) respectively; the symbol $\langle \rangle$ denotes the average operation (here
286 across objects). PI was based on the unattended condition to circumvent
287 the potential issue that the object preference of a voxel in the attended
288 condition might not be independent of the magnitude of the attention
289 effect. To compute the strength of the attentional modulation for an ob-
290 ject i relative to the other objects $\setminus i$, we defined a relative attentional
modulation index $RAI(i)$ as follows:

$$RAI(i) = \beta_{\text{att}}(i) - \beta_{\text{unatt}}(i) - (\beta_{\text{att}}(\setminus i) - \beta_{\text{unatt}}(\setminus i)),$$

292 where $\beta_{\text{att}}(i)$ and $\beta_{\text{att}}(\setminus i)$ are the voxel-wise beta values in the attended
condition for object i and all objects except i respectively.

293 Finally, we quantified the RAI as a function of PI . To preclude a selec-
294 tion bias we used a leave-one-run-out procedure, such that PI and RAI
295 were computed on independent data. The leave-one-run-out procedure
296 was performed for each object i separately as follows. In each fold, we
297 sorted the pooled voxels from the LOC ROI according to $PI(i)$ based on
298 data from all but one experimental runs. We then divided the sorted
299 voxels into 10 equinumerous bins (deciles) according to $PI(i)$ and com-
300 puted the average $RAI(i)$ for the voxels in each bin based on the data of
301 the held-out run. Subsequently, we computed an average RAI across ob-
302 jects for each bin, resulting in a single RAI for each bin.

303 2.8.5. Computing the mutual information between BOLD response and pre- 304 sented objects

305 To investigate whether attention increased object information
306 encoded in the activity of individual voxels, we used a mutual informa-
307 tion (MI) metric. MI estimates the extent to which the uncertainty
308 about one variable Y (here: BOLD response to the object being present-
309 ed) is reduced by measuring another variable X (here: the object being
310 presented) (cf. Saproo and Serences, 2010; Serences et al., 2009). The
311 mutual information (MI) measure is defined as the difference of the
312 total entropy $H(X)$ and the noise entropy $H(X|Y)$:

$$MI(X; Y) = H(X) - H(X|Y) \\ = - \sum_{x \in X} p(x) \log_2 p(x) - \left(- \sum_{y \in Y} p(y) \sum_{x \in X} p(x|y) \log_2 p(x|y) \right).$$

314 Thus we subtract from the total entropy $H(X)$, which corresponds to
315 the overall dynamic range of responses, the noise entropy, which is a
316 measure for the noise in the data conditional on each presented object.
317 The remainder quantifies to what degree the variation in the BOLD sig-
318 nal is informative about the presented object. To compute the total and
319 noise entropies, estimated BOLD responses were transformed into a dis-
320 crete variable (X) by dividing the entire range of responses into a set of
321 10 equinumerous bins (deciles). This discretization was based on the
322 pooled range of responses from all voxels in either the attended or the
323 unattended condition after subtracting out the respective mean activa-
324 tion levels of the attended and the unattended condition. This subtrac-
325 tion was done to avoid errors in the binning process due to additive
326 shifts attributed to attention (Saproo and Serences, 2010). In the
327 above formulation, $p(x)$ corresponds to the frequency with which a re-
328 sponse in a given voxel falls into bin x . The noise entropy term $H(X|Y)$
329 additionally required the computation of the probability $p(y)$ of each
330 object y – 1/3 in our case, given that the experiment consisted of three
331 equally often appearing objects – and $p(x|y)$, which corresponds to the
332 frequency with which a response in a given voxel falls into bin x ,
333 given object y was presented. We normalized the mutual information

for each participant to a range between 0 and 1 by dividing $MI(X; Y)$ 334
by the total entropy $H(X)$ (Kojadinovic, 2005). A normalized MI value 335
of 0 indicates that BOLD response X and object label Y are completely in- 336
dependent, whereas a normalized MI value of 1 indicates that response 337
 X gives complete information about the object label Y . The MI metric 338
was applied to the responses of attended and unattended objects 339
separately. 340

2.8.6. Analyzing the effects of attention at the multi-voxel pattern level 341

342 To assess the effect of attention at the multi-voxel pattern level, we
343 examined object-related activation patterns with and without attention
344 by means of a pattern similarity measure and support vector machine
345 (SVM) classification. The two methods are complementary in the
346 sense that the similarity measure provided a transparent quantification
347 of the reproducibility (*within-object pattern similarity*) across runs,
348 whereas the SVM classification assessed the amount of information
349 that can be read out from these activation patterns. 349

2.8.7. Support vector machine classification 350

351 Support vector machine classification (SVM) was performed using
352 *The Decoding Toolbox* (Hebart et al., 2014) with a linear C-SVM and a
353 fixed cost parameter ($c = 1$). We quantified object information in the
354 LOC for attended and unattended objects. We trained the classifier to
355 discriminate between objects based on multi-voxel activation patterns
356 in the LOC ROI in native subject space (Haynes and Rees, 2005;
357 Kamitani and Tong, 2005). A leave-one-run-out cross-validation proce-
358 dure was used, such that in each of 8 folds the classifier was trained on
359 the beta maps of seven runs and tested on the left out eighth run. We
360 performed pair-wise decoding between the three pairs of objects (cam-
361 era–can, camera–chair, can–chair) separately for the attended and the
362 unattended condition. Subsequently the decoding accuracies were aver-
363 aged across folds and object pairs. 363

2.8.8. Pattern similarity analysis 364

365 The pattern similarity analysis was based on z-transformed correla-
366 tions between activation patterns in the LOC ROI. The *within-object pat-
367 tern similarity* (WPS) measured the correlation between the patterns
368 evoked by the same object across the 8 runs (separately for attended
369 and unattended objects). For each object this led to $8 \cdot (8 - 1) / 2 =$
370 28 correlation coefficients for the pairwise combinations of runs,
371 which were z-transformed and averaged across permutations and ob-
372 jects. This procedure yielded a single within-object pattern similarity
373 value for both the attended and the unattended condition. As a control
374 analysis, we also computed the *between-object pattern similarity* (BPS).
375 BPS was assessed analogously to WPS, except that the correlation coef-
376 ficients were computed between patterns evoked by different objects,
377 resulting in three between-object comparisons (camera–can, camera–
378 chair, can–chair). To avoid an overestimation of pattern similarity due
379 to within-run autocorrelations, we excluded all within-run compari-
380 sons (Mumford et al., 2014). 380

3. Results 381

3.1. Behavioral results and fixation control 382

383 Participants detected and reported brightness changes of the objects
384 and the noise stimuli highly accurately (performance > 98%), indicating
385 focused attention on the correct stimulus. On average, $98.3 \pm 0.8\%$
386 (mean \pm SEM) of recorded eye gaze positions during stimulus presenta-
387 tion were within the fixation area, demonstrating that the participants
388 maintained fixation throughout the experiment. There was no difference
389 in the overall number of saccades between the attended and the unat-
390 tended condition (attended: 3.1 ± 1.6 saccades in the experiment; unat-
391 tended: 3.6 ± 2.2 ; $p = 0.43$, $t(15) = -0.80$, two-tailed t-test), and
392 neither was there a difference with respect to the number of object-
393 directed (attended: 2.9 ± 1.6 ; unattended: 0.9 ± 0.6 ; $p = 0.19$, 393

394 $t(15) = 1.36$) or noise-directed saccades (attended: 0.2 ± 0.2 ; unattended: 2.8 ± 2.0 ; $p = 0.22$, $t(15) = -1.26$). The interaction of saccade direction (object-directed, noise-directed) and attention (attended, unattended) was not significant ($p = 0.21$, $F(1,15) = 1.71$, repeated-measures ANOVA). These results, as well as the low absolute number of object- or noise-directed saccades, indicate that differences between the neural correlates of the attended and the unattended condition are unlikely to ensue from effects of eye movements.

402 3.2. Attention amplifies responses to objects in the lateral occipital complex

403 To examine the influence of covert attention on neural activity, we compared the overall average BOLD response for attended and unattended objects within the LOC averaged over objects and sides of presentation. Attended objects led to a significant increase of neural activation ($p < 0.001$, $t(17) = 5.00$, Cohen's $d = 1.17$; Fig. 2A).

408 In order to test whether the effect of the attention manipulation was confined to object-selective cortex, we quantified the overlap between the thresholded ($p_{\text{FWE}} < 0.05$) whole-brain T-maps of the contrasts *attended > unattended* (main experiment) and *intact > scrambled* (functional localizer). We found that 94.8% of the voxels showing an effect in the attention contrast overlapped with voxels classified as object-selective (Fig. 2B). Thus our focus on the LOC was justified by the spatial extent of the attentional modulation. It should be noted, however, that the attended and the unattended conditions differed only with respect to the attended stimulus type (object vs. noise pattern), but neither systematically with respect to low-level features (likely canceling out effects of attention in earlier visual areas in the contrast *attended > unattended*) nor with respect to task (likely canceling out effects of attention in executive cortices). The spatial restriction of attentional modulation to LOC therefore reflects a deliberate property of our design, rather than the absence of attentional modulation in other brain areas.

424 3.3. Attention modulates neural activity as a function of object preference

425 We reasoned that if attention led to an amplification of neural activity (as opposed to a mere baseline shift), the attentional modulation should be greater for a voxel's preferred object relative to its non-preferred objects. An analysis of a voxel's attentional modulation for a given object in dependence of its preference for the object should thus be informative about the specificity of the attentional modulation. To quantify the difference between the attentional modulation for preferred and non-preferred objects, we computed a relative attentional modulation index (RAI). Further, we determined a preference index (PI) for each voxel based on the mean response to a given object relative to the response of the other objects in the unattended condition. We hypothesized that RAI should increase as a function of PI.

437 To this end, we used a leave-one-run-out procedure, in which we sorted the voxels according to their PI, divided the voxels into 10 equinumerous bins (deciles) and computed the average RAI for each

bin. We found that the RAI increased as a function of PI (linear slope [mean \pm SEM]: 0.066 ± 0.022 , $p = 0.009$, $t(17) = 3.00$, two-tailed t-test against the null hypothesis of a slope of zero; Fig. 3). In direct comparison, the average RAI for preferred objects (PI > 0 [mean \pm SEM]: 0.18 ± 0.06) was greater than the average RAI for non-preferred objects (PI < 0 : -0.17 ± 0.06) ($p = 0.011$, $t(17) = 2.86$, Cohen's $d = 0.67$). These results show that the modulation of neural activity through spatial attention comprises an amplificatory component and is not due to a baseline shift only.

449 3.4. Attention increases the mutual information between BOLD responses and object identity

451 To test whether the increase of neural activity increased a voxel's information about the presented objects, we computed the mutual information for attended and unattended objects. We found that attention increased the mutual information of a voxel's responses about the objects presented ($p < 0.001$, $t(17) = 5.72$, Cohen's $d = 1.35$). The percentage of voxels showing higher mutual information in the attended relative to the unattended condition was $55.1 \pm 0.9\%$ (mean \pm SEM across participants), which was significantly different from the chance level of 50% ($p < 0.001$, $t(17) = 5.81$). Thus, attention reduced the uncertainty of BOLD responses about object identity, implying enhanced object coding at the level of single voxels.

462 3.5. Attention enhances object representations at the pattern level

463 A growing body of evidence suggests that the LOC codes object not by means of individual neurons or neuronal populations, but across multiple distributed neuronal populations (Haxby et al., 2001; Rice et al., 2014). Thus, if attention has an enhancing effect on sensory representations, the above finding of object-specific local modulation by attention should improve the quality of multi-voxel activation patterns.

469 In a first step we assessed the effect of attention on the reproducibility of activation patterns by computing the within-object pattern similarity (WPS) of activation patterns across repeated presentations of the same object, separately for attended and unattended object presentations. We found that attention significantly increased WPS ($p < 0.001$, $t(17) = 10.51$, two-tailed t-test; Fig. 4A), indicating that attention improved the reproducibility of responses at the pattern level. However, in a control analysis we found that attention also led to a considerable increase of the between-object pattern similarity (BPS; $p < 0.001$, $t(17) = 9.73$, two-tailed t-test). If the increase in reproducibility for the same object (WPS) was outweighed by a simultaneous increase of the ambiguity between different objects (BPS), nothing is gained. We therefore directly compared WPS and BPS and found that the increase in WPS was greater than the increase in BPS ($p < 0.001$, $t(17) = 4.22$), indicating that attention led to a functionally relevant improvement of the reproducibility of multi-voxel activation patterns.

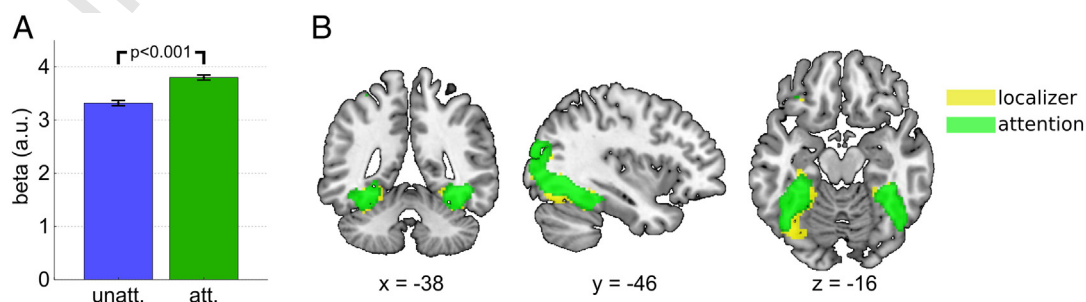


Fig. 2. Modulatory effect of attention. A. LOC ROI. The bars represent average beta values of the LOC ROI for the attended and unattended condition, averaged across objects and sides of presentation. Error bars denote SEM corrected for between-subject variance (Cousineau, 2005). Statistical comparison was based on a two-tailed t-test. B. Whole-brain analysis. Overlay of object-selective voxels (based on the independent functional localizer, *intact > scrambled*, thresholded at $p_{\text{FWE}} < 0.05$, colored in yellow) and voxels showing a significant effect of attention (*attended > unattended*, thresholded at $p_{\text{FWE}} < 0.05$, colored in green).

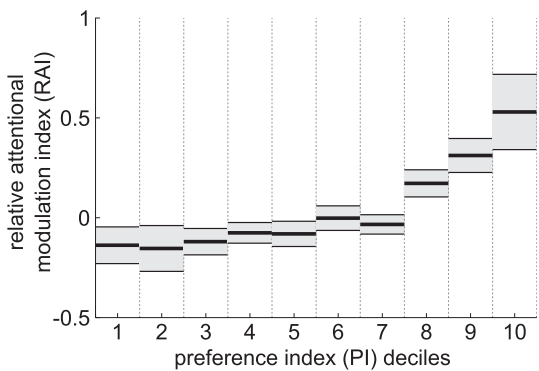


Fig. 3. Relative attentional modulation as a function of object preference. The relative attentional modulation index (RAI) quantifies the attentional modulation for a given object relative to the average modulation of the other objects. For each participant voxels were binned into deciles according to their object preference index (PI). The plot shows the averaged RAI for each preference bin. Error bars denote SEM corrected for between-subject variance (Cousineau, 2005).

In a second step we directly assessed how attention affected the readout of object information from the LOC by performing support vector machine classification between objects. Decoding accuracies were significantly above chance in both the attended ($66.6\% \pm 2.0\%$; $p < 0.001$, $t(17) = 8.36$, two-tailed t-test against the chance decoding accuracy of 50%) and the unattended condition ($54.8\% \pm 1.8\%$; $p = 0.017$, $t(17) = 2.66$; Fig. 4B). Importantly, classification performance was significantly and markedly greater in the attended compared to the unattended condition ($t(17) = 4.74$, $p < 0.001$, Cohen's $d = 1.12$). Thus, the attentional modulation of neuronal responses increased object information in the LOC at the multi-voxel pattern level.

3.6. Enhanced readout at the pattern level is linked to the local increase in mutual information, but not mean activation

Finally, we assessed whether the attentional modulation at the single-voxel level was related to the enhancement of object representations at the pattern level. In the single-voxel-level analyses we found that attention led to an increase of (1) BOLD signal, and (2) the mutual information. We therefore correlated – across participants – both effects with the increase in decoding accuracy. We found that the increase in decoding accuracy correlated with the increase in mutual information (Pearson's $r = 0.59$, $p = 0.009$), but not with the increase in BOLD activation ($r = 0.01$, $p = 0.96$). A direct comparison confirmed that the

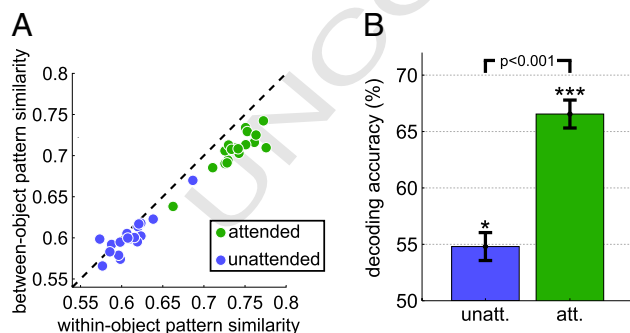


Fig. 4. Pattern level. A, between-object and within-object pattern similarity within the LOC ROI. Each dot represents one participant. The dashed diagonal line indicates identical within- and between-object similarity of activation patterns. Attention leads to a shift of data points below the diagonal line, indicating higher pattern similarity for repeated presentations of the same object compared to the pattern similarity of different objects. Between-subject variance was removed for illustration. B, SVM decoding results based on percent correct classification (decoding accuracy). Error bars denote SEM corrected for between-subject variance (Cousineau, 2005). Statistical comparison was based on a two-tailed t-test.

increase in mutual information explained significantly more variance than the BOLD increase ($p = 0.034$, $z\text{-score} = 2.11$, Steiger's z-test; Steiger, 1980). Although the absence of a significant contribution of the BOLD increase is surprising (possibly caused by ceiling effects of the BOLD increase), the relationship between mutual information and decoding accuracy suggests that the local attentional modulation of neuronal responses increases the information content of object representations at the pattern level.

4. Discussion

We examined tuning-dependent attentional modulation of object representations in the LOC and the resulting enhancement of object representations at the single-voxel level and the multi-voxel pattern level. At the single-voxel level we found that (1) responses in the LOC were considerably stronger when an object was attended relative to when a noise stimulus was attended; (2) the relative attentional modulation (the attentional modulation for a given object relative to the average modulation of other objects) increased as a function of a voxel's preference for the given object; and (3) mutual information between a voxel's responses and object identity increased, demonstrating that responses became more informative about a presented object when the object was attended compared to when it was unattended. All three results provide evidence against a mere baseline-shift effect of attention. Further analyses showed that these local changes resulted in increased object information at the level of multi-voxel patterns and increased similarity of these patterns across multiple presentations, indicating increased reproducibility of distributed neuronal responses.

4.1. Effects of attention at the level of individual voxels

A key goal of this study was to investigate whether the observed increase in activity involved amplificatory attentional modulation, or merely an unspecific baseline shift. Previous neuroimaging studies reported that neural activity increased with attention in high-level visual cortex (Baldauf and Desimone, 2014; Connor et al., 1997; Murray and Wojciulik, 2004; O'Craven et al., 1999; Serences et al., 2004), and showed that the effects of attention were specific to coarse functional modules, such as parahippocampal place area (PPA) or fusiform face area (FFA). However, given that objects are known to be coded across distributed neuronal ensembles in visual cortex (Haxby et al., 2001; Rice et al., 2014), it is desirable to analyze attentional modulation at a more fine-grained level, thereby accounting for the differential tuning of neuronal populations within these areas. Here we provide evidence for voxel-wise object-specific attentional modulation of responses in the LOC by identifying a relationship between attentional modulation and object preference. The consistent increase of the relative attentional modulation across preference levels suggests that subtle difference in preference measured in the absence of attention became amplified as attention was directed to the objects. Our additional information-theoretic analyses indicated that such attentional modulation effectively increased the information of voxel-wise responses about object identity, in line with previous work on orientation coding in V1, which likewise found an increase in mutual information with attention (Saproo and Serences, 2010).

How do these results relate to the multiplicative gain hypothesis of attention derived from neurophysiological recordings in monkeys (McAdams and Maunsell, 1999; Treue and Martínez Trujillo, 1999)? It should be noted that a direct comparison between the BOLD responses in our study and spiking activity in these previous studies is difficult for two reasons: first, BOLD responses are more closely related to the local field potentials and hence synaptic activity than to spiking neuronal activity (Ekstrom, 2010; Logothetis, 2003; Logothetis et al., 2001); and second, efficient event-related fMRI designs such as ours do not permit inferences about the absolute level of stimulus-related BOLD activity, which would be necessary to quantify the ratio between attended and

569 unattended responses analogous to the ratio of firing rates in these previous
 570 neurophysiological studies. Nevertheless, our results do provide
 571 indirect evidence for the multiplicative gain as opposed to a mere baseline
 572 shift hypothesis. Consider the result of increased attentional modulation
 573 with object preference. A voxel's preference for a given object
 574 may indicate that, for a fixed number of neurons tuned to different objects,
 575 the tuning curves of neurons are biased more towards the given object than
 576 to the other objects. Alternatively, it may indicate that for a fixed bias
 577 towards the given object an overall greater number of neurons prefer the
 578 given object. Importantly, in both cases an unspecific baseline shift
 579 would lead to an equal increase of neural activity for preferred and non-
 580 preferred objects, which is at odds with our results. To illustrate why the
 581 increase in MI provides evidence for a multiplicative gain mechanism as
 582 opposed to a pure baseline shift explanation, it is helpful to consider two
 583 objects A and B and a hypothetical voxel consisting of neurons with a
 584 preference for, e.g., object A. In case of a pure baseline shift the voxel
 585 would show increased responses to both objects and neural responses
 586 would therefore not become more informative about whether object A or
 587 B was presented. In contrast, in case of multiplicative scaling, attention
 588 will lead to greater response amplification for object A compared to
 589 object B, increasing the dynamic range of responses and resulting in
 590 increased mutual information between neural responses and presented
 591 objects. Thus, the increase in mutual information by attention provides a
 592 second line of evidence in favor of a multiplicative gain mechanism and
 593 against a pure baseline shift explanation.
 594

595 4.2. Effects of attention at the multi-voxel pattern level

596 At the level of multi-voxel activation patterns we found improved
 597 decodability of attended relative to unattended objects, which is in
 598 accordance with similar reports for early (Jehee et al., 2011; Kamitani
 599 and Tong, 2005) and high-level visual areas (Pratte et al., 2013; Reddy
 600 and Kanwisher, 2007). This result demonstrates that the attentional
 601 modulation increased the information content of distributed object
 602 representations in the LOC, potentially benefitting information readout
 603 from the LOC by high-level executive cortices. An analysis of pattern
 604 similarity showed that attention increased the reproducibility of
 605 activation patterns of the same object. Such an increase in reproducibility
 606 would be expected on the assumption of a multiplicative attentional
 607 scaling mechanism, where neuronal responses become amplified without
 608 an equivalent increase of the noise (which increases as the square-root
 609 of the signal). Another possibility is that the increase in reproducibility
 610 is the result of more discrete neural processing with attention, as
 611 proposed for conscious relative to non-conscious percepts (Sackur
 612 and Dehaene, 2009; Schurger et al., 2010). When discrete decisions
 613 are reached at each (object) processing stage, before they are
 614 dispatched to the next stage, the resulting activation patterns might
 615 become more stereotypical and reproducible.

616 A number of previous fMRI studies have used MVPA to study the effects
 617 of attention on neural responses (Esterman et al., 2009; Jiang et al.,
 618 2013; Pratte et al., 2013; Reddy and Kanwisher, 2007; Reddy et al.,
 619 2009; Tamber-Rosenau et al., 2011). In particular, Reddy and
 620 Kanwisher (2007) and Reddy et al. (2009) investigated the decodability
 621 of complex stimuli in high-level visual cortex when they were presented
 622 alongside a second object and were either attended or unattended.
 623 Reddy and Kanwisher (2007) found that information about object
 624 categories encoded in multi-voxel activation patterns was strongly
 625 reduced to the point of being abolished when attention was diverted.
 626 In the present study we showed that multi-voxel responses were
 627 reduced, but still informative about object categories even when
 628 attention was diverted. This difference may be explained by the fact
 629 that participants in the study by Reddy and Kanwisher (2007) directed
 630 their attention to complex distractor stimuli (which, in addition, were
 631 the relevant stimuli in other trials), whereas participants in our study
 632 viewed noise stimuli in the unattended condition. It is conceivable that
 633 the absence of high-

634 level visual cortex information for unattended objects in Reddy and
 635 Kanwisher (2007) was caused by distractor-related neural responses
 636 interfering with the activation pattern of the unattended target object.
 637 Along similar lines, Reddy et al. (2009) interpreted the informational
 638 gain for attended objects (or loss for unattended objects) in the biased
 639 competition framework. According to this view, attention serves to
 640 disambiguate the overlapping multi-voxel patterns of different objects
 641 through a shift towards the pattern of the currently attended object.
 642 Aside from investigating the effect of attention in sensory cortices,
 643 other studies have successfully used MVPA to study the initiation and
 644 control of attentional shifts. For instance, Esterman et al. (2009) and
 645 Tamber-Rosenau et al. (2011) showed that spatial patterns of brain
 646 activity within the medial superior parietal lobule reliably differentiated
 647 between several domains of cognitive attentional control at a given
 648 moment. Thus, in our and previous studies, MVPA presented a powerful
 649 technique to probe distributed neural underpinnings of different
 650 attentional phenomena, from the initiation of attentional shifts to the
 651 modulation of sensory representations.

652 4.3. Linking the single-voxel and the multi-voxel pattern level

653 Finally, we linked the effects of attention at the single-voxel level
 654 with the effects at the pattern levels by correlating the increase in
 655 decoding accuracy of multi-voxel activation patterns to the increase in
 656 either BOLD signal or mutual information. Unexpectedly, we found
 657 that the increase in mean activation was not related to the increase in
 658 decoding accuracy. This negative finding could indicate that the
 659 attentional manipulation in our paradigm operated in a range, in which
 660 effects at the pattern level were insensitive to the overall magnitude
 661 (e.g., because the BOLD increase was at maximum). Alternatively, as
 662 the overall effect of attention likely involves both a multiplicative
 663 component and a baseline shift, the unspecific baseline shift component
 664 might have masked the effect of the relevant multiplicative component.
 665 In contrast, we found that the increase in mutual information explained
 666 a considerable amount of variance of improvements in pattern-based
 667 decoding. This result demonstrates that the increase of object
 668 information at the single-voxel level substantially translated to an
 669 enhanced object code at the pattern level. This link is informative, as
 670 the information content encoded in the linear combination of voxels
 671 can show strong gains, while information encoded in the individual
 672 voxel may show only small changes (for examples of such scenarios see
 673 Haynes and Rees, 2006). It is currently not clear whether the
 674 distributed object code in LOC represents the immediate neural
 675 correlate of perception, or whether it reflects object processing prior
 676 to perception. In either case our data indicate that the enhancement
 677 of sensory representations through attention – which may directly or
 678 indirectly underlie perceptual improvements – is not a phenomenon
 679 that solely emerges at the level of distributed object fingerprints.
 680 Instead, the improvement in pattern decoding likely represents the
 681 cumulative result of informational gains in multiple local units of
 682 LOC.

683 4.4. Implications for mechanisms of visual attention

684 The results of the present study corroborate the notion that behavioral
 685 benefits of attention are based on an enhanced stimulus processing
 686 in sensory brain areas (Bisley, 2011). Our finding that the magnitude
 687 of attentional modulation increased with object preference suggests a
 688 response gain mechanism that magnifies stimulus-driven responses as
 689 a function of response strength without attention. Importantly, our
 690 information-theoretic analyses demonstrate that the attentional
 691 modulation effectively increases object information encoded in high-
 692 level visual cortex, which may facilitate the readout in executive
 693 cortices and thus benefit perceptual decision making. A unifying
 694 theoretical framework for such attentional modulation of neural
 695 activity is provided by the normalization model of attention
 696 (Reynolds and Heeger, 2009). The model describes the modulation
 697 of attention by two processes: a

695 multiplication of neuronal responses by an attention field and a division
 696 (normalization) by a suppressive drive. Thus, our observed differences
 697 between neural responses to attended and unattended objects may
 698 not only be caused by a boost of neural processes tuned to the attended
 699 object, but also by a suppression of activity related to the unattended
 700 object. Another key aspect of the model is that it makes specific predic-
 701 tions regarding the effect of different attentional strategies on neural ac-
 702 tivity. According to the model, a purely spatial attention strategy causes
 703 a scaling of the entire tuning curves (because the attention field is then
 704 assumed to be constant across feature dimensions), whereas a purely
 705 feature-based attention strategy causes a sharpening of tuning curves.
 706 The fact that our brightness discrimination task emphasized spatial at-
 707 tention strategies over feature-based strategies may thus explain the
 708 strong amplitude modulation of the BOLD response in our study. Future
 709 neuroimaging studies could test whether our findings of tuning-
 710 dependent attentional modulation and information-theoretic gains
 711 through endogenous visual spatial attention generalize to other forms
 712 of attention, e.g. to involuntary (exogenous) shifts of attention or to
 713 other sensory modalities.

714 In conclusion, our results show that visual spatial attention modu-
 715 lates neural activity as a function of voxel-based object preferences.
 716 Through these modulatory processes, attention enhances object coding
 717 both at the single-voxel and pattern level, which may give rise to im-
 718 proved perception and perceptual decisions.

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