Supplementary Material: Direct evidence for encoding of motion streaks in human visual cortex

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Supplementary data

Univariate analysis

Differences in percent signal change between 45 and 135 degree conditions.

It is important to show that none of the conditions produced differences in activation at the univariate level, as this would render any multi-voxel pattern analysis redundant. Here we compared the percent signal change in each individually defined region of interest for 45 and 135 degree conditions for faster and slower motions and static stimuli. Although there were some weak biases evident, none of the differences were statistically significant (see Figure S1 and Table S1).
Figure S 1. Percent signal change in each region of interest averaged across participants for 45° vs. 135° stimuli. Error bars show +/- 1 standard error. None of these differences were significant in any area (see Table S1)
<table>
<thead>
<tr>
<th></th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>hMT+/V5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Orientations</strong></td>
<td>2.47 (0.17)</td>
<td>1.92 (0.38)</td>
<td>0.40 (&gt; .5)</td>
<td>0.94 (&gt; .5)</td>
</tr>
<tr>
<td><strong>Fast</strong></td>
<td>1.77 (0.48)</td>
<td>2.21 (0.25)</td>
<td>1.95 (0.36)</td>
<td>0.10 (&gt; .5)</td>
</tr>
<tr>
<td><strong>Slow</strong></td>
<td>0.55 (&gt; .5)</td>
<td>0.74 (&gt; .5)</td>
<td>0.96 (&gt; .5)</td>
<td>0.67 (&gt; .5)</td>
</tr>
</tbody>
</table>

**Table S 1.** *T*-values for paired t-tests between 45 and 135 degree conditions for each condition in each region of interest, averaged across 8 subjects. *P*-values are shown in brackets, corrected within each condition for multiple comparisons.

**Time series analysis.**

As an additional check on the univariate data, we plotted the time course of the BOLD signal for each block for all participants. A single representative participant’s time series is shown in Figure S2. It should be noted that this is presented here purely for illustrative purposes, as additional inferences from data already selected by a statistical test (as here) would represent an example of circular analysis or “double-dipping” [1]. The plots of time course (Figure S2) show the average BOLD response for a single representative participant, collapsed across all 10 runs and aligned to the start of each block. Each panel refers to one functionally defined Region of Interest (ROI) and different colours correspond to different conditions. The error bars show the standard errors of
mean across runs. Similar patterns were seen for all participants, confirming stimulus-specific activity in all visual regions.

**Figure S2.** Time course plots for a single representative participant for each ROI, collapsed across all 10 runs for each condition and aligned to the start of each block. Each panel represents a single visual region, and different colours represent different conditions (static, slow and fast motion). Error bars show +/- 1 standard error.

**Eye movements.**

Eye movements were measured in the scanner using a video eye tracker (ASL 504LRO Eye Tracking System), although reliable data could only be obtained for five of the eight participants. We measured eye movements and pupil dilation during scanning, and results were analyzed using custom code in MATLAB Version 7.8 to determine whether
there were any significant differences between the conditions (for instance, observers might have tracked fast motion more than slow) that might account for the results. Eye tracking data for each of these participants were preprocessed by excluding all the data points where the signal was lost and removing slow drifts in the position data. Analysis of eye position showed no significant differences at the group level between any of the experimental conditions (horizontal: $F(2,6)=0.34$, $p=0.726$; vertical: $F(2,6)=0.31$, $p=0.745$); nor was there a difference between 45 and 135 degree conditions for any of the stimuli (horizontal: $F(1,3)=0.22$, $p=0.67$; vertical: $F(1,3)=0.74$, $p=0.452$) or any interaction (horizontal: $F(2,6)=0.71$, $p=0.531$; vertical: $F(2,6)=1.32$, $p=0.335$). More importantly, we also analyzed the variability (standard deviation) of the eye position data for each condition as this indicates the magnitude of eye movements participants made. There were also no significant differences in variability between stimulus conditions (horizontal: $F(2,6)=2.55$, $p=0.158$; vertical: $F(2,6)=1.33$, $p=0.331$) or between the orientations/directions (horizontal: $F(1,3)=0$, $p=0.996$; vertical: $F(1,3)=0$, $p=0.99$), and no interaction of these factors (horizontal: $F(2,6)=0.35$, $p=0.72$; vertical: $F(2,6)=0.64$, $p=0.558$). Finally, there was also no difference in pupil diameter between conditions ($F(2,6)=1.32$, $p=0.335$) or orientations/directions ($F(1,3)=0$, $p=0.99$) and no interaction ($F(2,6)=1.02$, $p=0.415$).

**Behavioural performance.**

Behavioural performance on the fixation dimming task was recorded for each participant and analyzed to determine whether attentional or arousal differences between
conditions could have accounted for any of the results. A one-way repeated measures ANOVA comparing hit rates for the task across conditions showed there were no significant differences between any of the conditions, \( F(6,7) = 1.07, p = 0.398 \).

**Multivariate pattern analysis**

**Support vector machine (SVM) analysis.**

As described in the main methods, in order to decode the stimulus orientation/direction of motion we used pattern classification with a leave-one-run-out cross-validation procedure. Time series from each scanning run were first z-score normalized to correct for differences between runs. Data were then divided into independent data sets, with data from one scanning run forming the test set and data from all remaining runs being assigned to the training set. Before the actual analysis, we performed a feature-selection step in which we ranked the voxels in each pattern (vector containing the response of voxels in a stimulus block) by the univariate difference (absolute value of the t-statistic) between the two conditions of interest *in the training set only*. The same ordering was then applied to the test set and both data sets were then truncated at 100 voxels. This effectively selects the voxels showing the largest bias between conditions and tests whether these voxel biases are consistent in the *independent* test data. For the actual classification, we trained a linear support vector machine (SVM; [2, 3]) using the freely available LIBSVM package for MATLAB (http://www.csie.ntu.edu.tw/~cjlin/libsvm/). Like other linear classifiers, the SVM algorithm finds a decision hyperplane in a multidimensional space (where each
dimension corresponds to the activity measured for a particular voxel) to optimally separate the sample patterns from two categories in the training data. This optimal decision boundary is chosen to maximize the margin between patterns on either side of the hyperplane. These training patterns are referred to as `support vectors'. Since many data sets cannot be separated perfectly, a SVM decision boundary is generally chosen that permits a small number of incorrect classifications. This is handled through a parameter C which defines the penalty for incorrect classification and which was fixed at C=1 for all our analyses. While it is also possible to use a cross-validation procedure to find the optimal value for this parameter when the data sets are large, in our experience this does not result in great improvements of classification performance.

**Simple pattern-correlation classifier analysis**

In addition, we also conducted a classification analysis using a simple pattern-correlation classifier. As in the SVM analysis, a leave-one-run-out cross-validation procedure was used. Instead of finding a decision boundary, the training step involved calculating the mean voxel pattern across all training observations separately for each condition. Classification entailed calculating a Pearson correlation between each of the test patterns and the mean pattern for each condition. The test pattern was then assigned to the condition that produced the greater correlation coefficient. This method is arguably a more direct test for pattern information associated with one orientation is similar to that produced by the parallel direction of motion. Moreover, as it is based on linear correlation this method implicitly corrects for differences in the mean across
voxels in each condition and thus directly tests for information conveyed by the pattern of activity across voxels. Decoding accuracies obtained through this method are shown in Fig. S3. It is evident that the results are qualitatively very consistent with those from the SVM, although there are some differences, such as the increased significance in V3 rather than V2 and the below-chance decoding for slow motion in V2. Since this is the only instance of below-chance decoding, it is likely to be a result of Type 1 error, and it should be noted that this method of classification is overall less powerful than the SVM.

**Figure S3.** Results from the simple pattern correlation classifier. Decoding accuracy for a) orientation, b) fast and c) slow motion; d)-i) Decoding accuracy for all generalization
conditions. Double asterisks denote accuracies significantly (p<0.01) above chance, while single asterisks denote accuracies at p < 0.05 significance.
Supplementary references

