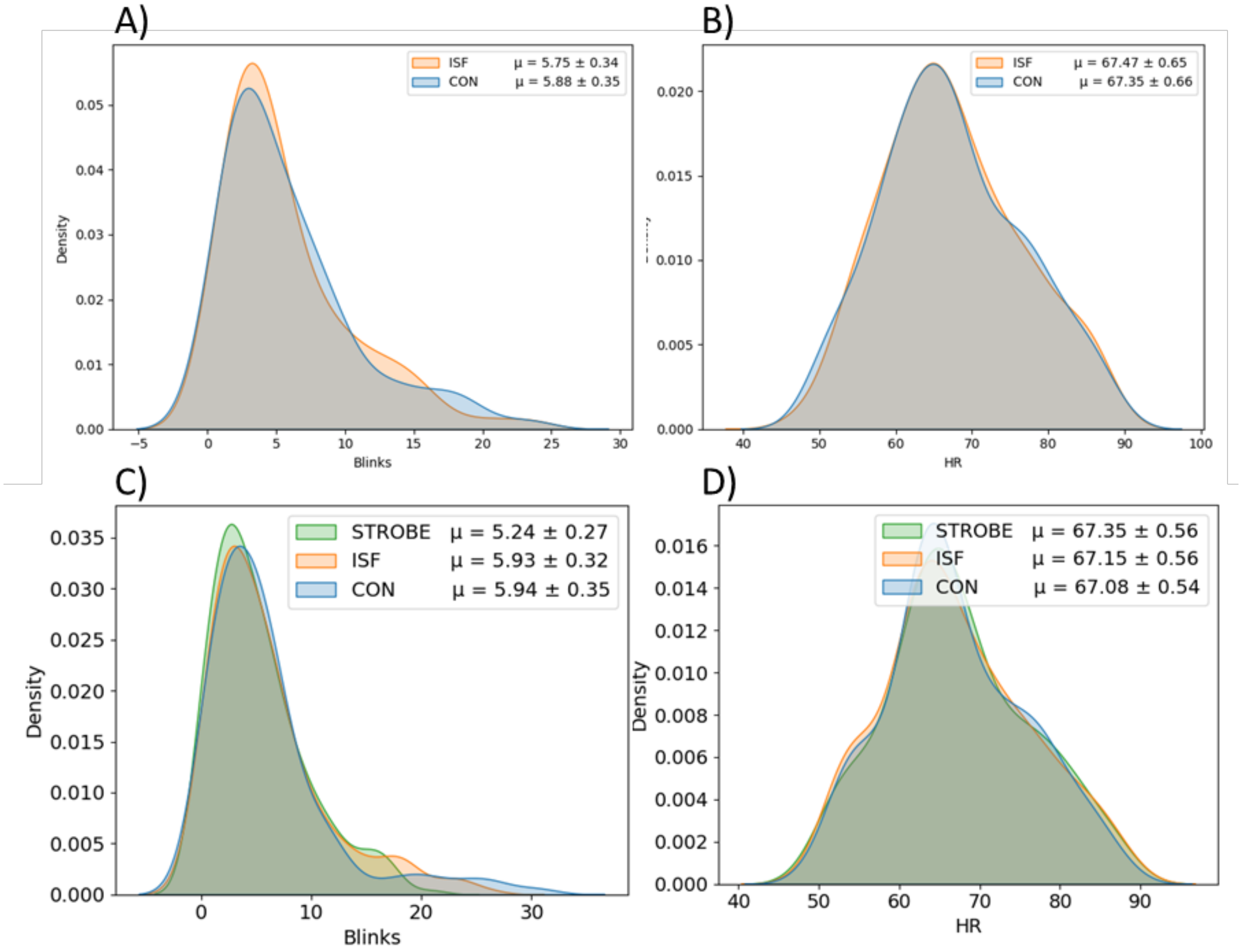
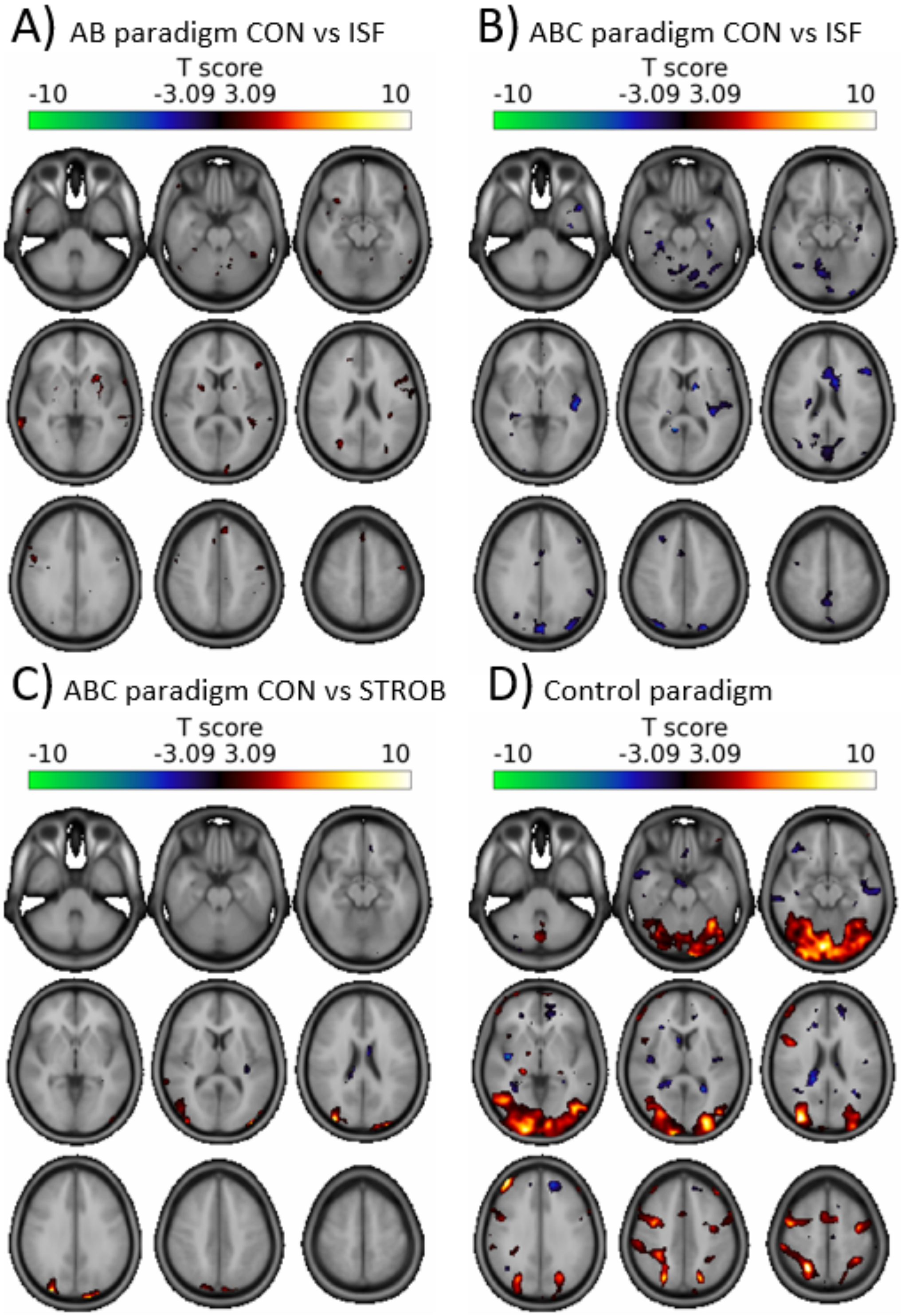
Supplementary Material

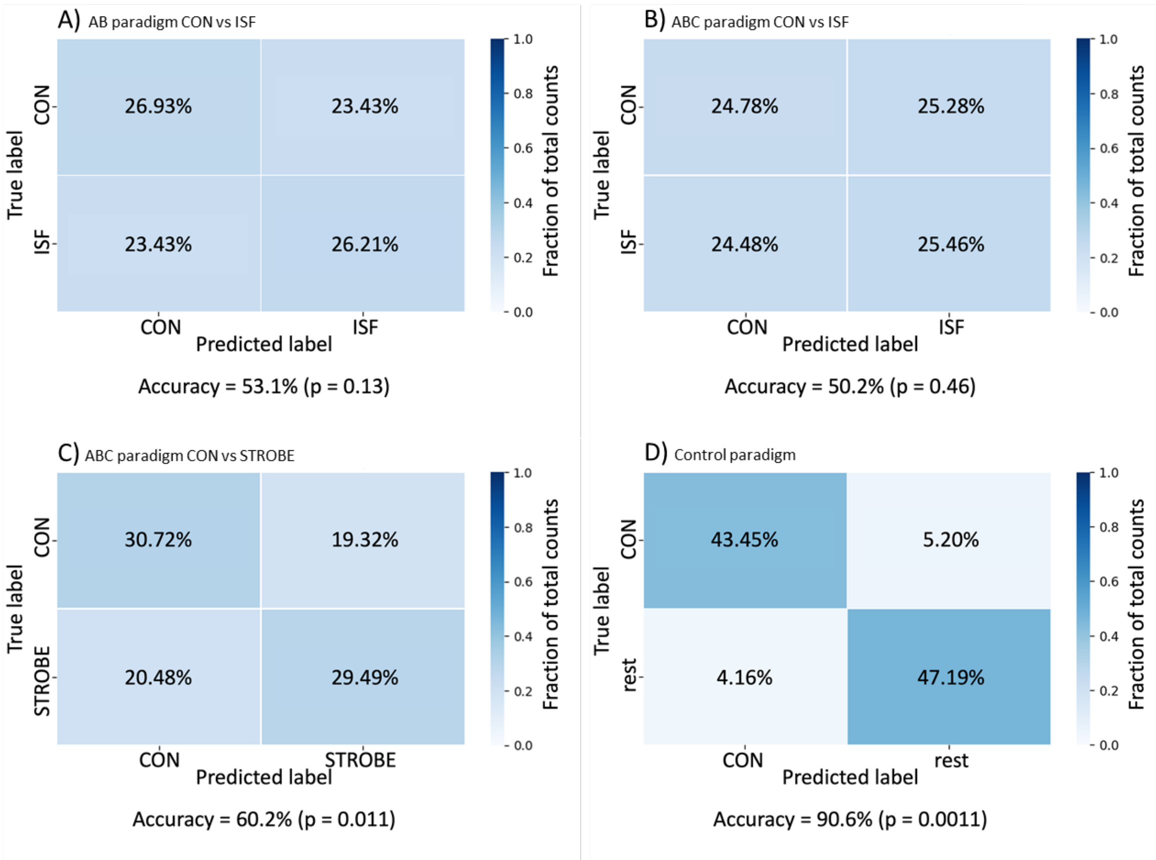
Novel Invisible Spectral Flicker Induces 40 Hz Neural Entrainment with Similar Spatial Distribution as 40 Hz Stroboscopic Light



Supplementary Figure 1. Histograms of heart rate (HR) and blinks during each condition. Presented as mean (μ) ± Standard error of mean.



Supplementary Figure 2. Mass univariate pattern analysis of the fMRI data. A) Data from the AB paradigm testing continuous non-flickering light (CON) versus 40 Hz ISF. B) Data from the ABC paradigm testing CON versus ISF with the 40 Hz stroboscopic light left out. C) Data from the ABC paradigm testing CON versus 40 Hz stroboscopic light with the 40 Hz ISF left out. D) Data from the control paradigm testing no light (darkness) versus continuous non-flickering light. Note how small the difference is between the different conditions of light in A, B and C while the difference in BOLD activity seen in the control paradigm testing no light versus continuous non-flickering light is much larger.



Supplementary Figure 3. Confusion matrices of the multivariate pattern analysis of between-subject comparison with 100 permutations. A) AB paradigm comparing non-flickering continuous light to 40 Hz ISF. B) ABC paradigm comparing non-flickering continuous light to 40 Hz ISF. C) ABC paradigm comparing non-flickering continuous light to 40 Hz Stroboscopic light. D) Control paradigm testing no light stimulus against non-flickering lights.

<table>
<tr><th colspan="5">MVPA model- and training specifications</th></tr>
<tr><td rowspan="2">Model parameters</td><td>Classifier</td><td>C</td><td>Kernel</td><td>Classification by</td></tr>
<tr><td>Support vector classifier</td><td>1</td><td>Linear</td><td>Single observation (TR)</td></tr>
<tr><td colspan="5"></td></tr>
<tr><td rowspan="2">Cross-validation scheme</td><td colspan="2">Within subject</td><td colspan="2">Between subject</td></tr>
<tr><td colspan="2">Stratified k-fold CV</td><td colspan="2">Leave-one-subject-out CV</td></tr>
<tr><td colspan="5"></td></tr>
<tr><td rowspan="2">Number of folds in k-fold</td><td>Control</td><td colspan="2">AB</td><td>ABC</td></tr>
<tr><td>5</td><td colspan="2">8</td><td>12</td></tr>
<tr><td colspan="5"></td></tr>
<tr><td>Permutation scheme</td><td colspan="2">Test data</td><td colspan="2">Training data</td></tr>
<tr><td>Within subject</td><td colspan="2">50 % probability of inverting labels.</td><td colspan="2">Labels of each block are independently and with 50 % probability inverted.</td></tr>
<tr><td>Between subjects</td><td colspan="2">50 % probability of inverting subject labels.</td><td colspan="2">Labels of each subject are independently and with 50 % probability inverted.</td></tr>
<tr><td colspan="5"></td></tr>
<tr><td>Number of permutations</td><td>Control</td><td>AB</td><td>ABC (ISF versus CON)</td><td>ABC (STROBE versus CON)</td></tr>
<tr><td>Within subject</td><td>1000</td><td>1000</td><td>1000</td><td>1000</td></tr>
<tr><td>Between subjects</td><td>1000</td><td>1000</td><td>200</td><td>100</td></tr>
</table>

Supplementary Table 1. Specifications for MVPA. The binary classifications were done on the level of single observations using a support vector classifier with a linear kernel and a slack variable, $C = 1$. Training and testing of the classifier were done both within- and between subjects. Within subject, it was done by stratified, *k*-fold CV with data splits of consecutive data. Between subjects, CV was done by iteratively leaving one subject out for testing and training the classifier on the rest. Classifier performance was evaluated by accuracy ($\frac{TP+TN}{TP+TN+FP+FN}$), and the significance of the obtained accuracy established based on non-parametric permutation tests [1], in which the labels of the data were permuted in a number of repetitions (varying by analysis) to obtain a null-distribution of random accuracies. From this, the *p*-value was estimated as the fraction of accuracies at least as high as the classifier performance (including the classifier performance value itself). According to [2], a good Monte Carlo approximation for the null-distribution can be obtained from 1000 repetitions; however, this was not feasible for all analysis due to the large amount of data. Thus, for the ABC paradigm between subjects, fever repetitions were used, rendering the *p*-value less trusted.

REFERENCES

[1] Ojala M, Garriga GC (2009) Permutation tests for studying classifier performance. In *2009 Ninth IEEE International Conference on Data Mining IEEE*, Miami Beach, FL, USA, pp. 908–913.

[2] Nichols TE, Holmes AP (2002) Nonparametric permutation tests for functional neuroimaging: A primer with examples. *Hum Brain Mapp* **15**, 1–25.