

1 **Prestimulus alpha power is related to the strength of** 2 **stimulus representation**

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13 **Abbreviated title:** Alpha power relates to representation strength

14 **Number of pages:** 17

15 **Author contributions statement:** L.C.B., F.P. L. and A.M.C. conceived the experiment. L.C.B. performed
16 the experiments and analysed the data. All the authors wrote and reviewed the manuscript.

17 **Funding:** L.C.B was supported by grants #2016/04258-0, São Paulo Research Foundation (FAPESP) and
18 #2018/08844-7, São Paulo Research Foundation (FAPESP). AMC was supported by grants #2017/25161-8,
19 São Paulo Research Foundation (FAPESP). The funders had no role in study design, data collection and
20 analysis, decision to publish, or preparation of the manuscript.

21 **Abstract**

22 Spatial attention can modulate behavioural performance and is associated with several electrophysiological
23 markers. In this study, we used multivariate pattern analysis in electrophysiology data to investigate the effects
24 of covert spatial attention on the quality of stimulus processing and underlying mechanisms. Our results show
25 that covert spatial attention led to (i) an anticipatory alpha power desynchronization; (ii) enhanced stimuli
26 identity information. Moreover, we found that alpha power fluctuations in anticipation of the relevant stimuli
27 boosted and prolonged the coding of stimulus identity.

28 **Keywords:** spatial attention, alpha oscillations, multivariate pattern analysis, EEG

29 Introduction

30 Attention is essential to select and process sensory stimuli in the environment. One of the main difficulties
31 in studying attentional selection in humans is assessing the quality of processing of attended and ignored
32 stimuli. Measures such as the amplitude of electrophysiological evoked responses (i.e. N1, P1) have been
33 used as a reflection of this processing. However, a recent study has questioned this view since the amplitude
34 of the evoked response was not correlated with a boost in the target representation.¹ Moreover, how well the
35 unattended stimulus is processed is particularly hard to assess, given that participants are typically asked not
36 to respond to these events.

37 One possibility is to use methods which evaluate neural processing without necessarily requiring a
38 behavioural response. Recent studies have relied on multivariate pattern analysis (MVPA) techniques to
39 analyse EEG/MEG responses.²⁻⁴ In general, these methods are based on the theoretical basis that the
40 MEG/EEG signal reflects coupled dipoles activity in the underlying neural circuitry. Although the specific
41 dipole activity may not be identified, their summation would result in different patterns of activity across
42 MEG/EEG sensors²⁻⁴. These MVPA methods have been increasingly used to understand the effects of
43 attention and its underlying mechanisms. Several studies have shown that spatial attention modulates stimulus
44 representation in working memory⁵⁻⁷ and sensory information input⁸. Moreover, temporal attention seems to
45 enhance relevant sensory information input, creating a temporal protection window against distractors¹, and
46 boosting its representational content.

47 Another pre-activating mechanism commonly described in the literature of spatial attention is the mod-
48 ulations in the spectral characteristics of the alpha (8-16 Hz) band⁹. This oscillatory activity is associated
49 with cognitive functions such as visual attention¹⁰, working memory¹¹ and cognitive load¹². For example,
50 anticipatory lateralized desynchronisation of alpha power is correlated with spatial expectations of relevant
51 upcoming stimuli in a particular hemifield^{10,13}. Studies suggest that alpha oscillations can play a role in
52 information processing by suppressing the activity of particular neural populations involved with the irrelevant
53 stimuli feature/spatial location processing, and by selecting the inhibition release of task-related neural popu-
54 lations^{14,15}. These anticipatory states reflected by the prestimulus power of low-frequency oscillations are
55 also related to modulations in the amplitude of sensory event-related potentials^{16,17}. The general relationship

56 between oscillatory activity and evoked responses is still not clear, and different explanations have been
57 proposed on how these two relate^{17,18}. In the specific case of anticipatory alpha power and evoked responses,
58 there is evidence for both positive and negative correlations. Moreover, the mechanisms by which alpha
59 oscillations modulate perception is also unknown. Recent studies have challenged the view that alpha power
60 modulates perceptual precision and have suggested that it increases perceptual¹⁹ or decision bias^{20,21}.

61 In the present work, we combined frequency and multivariate pattern analyses to investigate: (1) how
62 covert spatial attention modulates stimulus representation; (2) whether and how different EEG markers are
63 modulated. We adapted previous tasks that presented targets of different modalities rhythmically^{22,23} to
64 investigate whether spatial attention induces generic anticipatory mechanisms. Critically, we combined both
65 analyses to investigate how anticipatory mechanisms of spatial attention can influence stimulus processing.
66 We found that anticipatory alpha can modulate performance by modulating baseline excitability and improving
67 the precision of stimulus representation.

68 **Materials & Methods**

69 **Data and script availability**

70 Data (raw and analysed), presentation and analysis scripts are publicly available at (<https://osf.io/wbhc8/>).
71 The procedures and analysis were not pre-registered prior to the research being conducted

72 **Participants**

73 Twenty participants (age range, 18-27 years; 11 female) gave informed consent to participate in this study.
74 The sample size was based on previous EEG studies^{6,8,24}. Data from one participant was excluded from the
75 final analysis due to excessive noise in the EEG signal. All participants had normal or corrected-to-normal
76 vision and were free from psychological or neurological diseases (self-reported). The experimental protocol
77 was approved by the Research Ethics Committee of the Federal University of ABC.

78 **Apparatus**

79 Stimuli were presented using the Psychtoolbox v.3.0 package for MATLAB on a 20-inch CRT monitor with a
80 vertical refresh rate of 60 Hz, placed 50 cm in front of the participant. EEG was recorded continuously from
81 64 ActiCap Electrodes (Brain Products) at 1000 Hz by a QuickAmp amplifier (BrainProducts). All sites were

82 referenced to FCz and grounded to AFz. The electrodes were positioned according to the International 10-10
83 system. Additional bipolar electrodes registered the electrooculogram (EOG).

84 **Procedure**

85 Each block began with the presentation of a central fixation point (white, 0.4°) and two circles (horizontal
86 eccentricity of 5° , size of 3°), one at the left and the other at the right side of the fixation point (Figure
87 1A). Each experimental block consisted of two streams of stimuli, presented inside the circles in one of the
88 visual hemifields. Stimuli presentation was one at a time, alternating between visual hemifields, always
89 starting at the left side, with an SOA of 500 ms between them (2Hz frequency). Participants had to identify
90 the oddball stimuli within a stream of standard stimuli presented at a specific side by pressing a button
91 with their right index finger. Standard visual stimuli were vertical/horizontal oriented Gabor patches (3
92 degrees of visual angle) with a spatial frequency of 2 cycles per degree (cpd). The oddball stimuli (target)
93 were vertical/horizontal oriented Gabor patches (3°) with a higher spatial frequency defined by an adaptive
94 procedure. There were 70% of standards (half vertical and half horizontal) and 30% of targets. All stimuli
95 lasted 0.1 s.

96 Each block was preceded with an instruction screen indicating in which visual hemifield (right or left) the
97 participant had to detect targets, thus resulting in two main experimental situations: attend to the right or left
98 hemifield. Volunteers were instructed to fixate at the fixation point, but also to allocate their covert attention
99 to the indicated side. Each block consisted of 120 stimuli, 60 for each location, with 18 targets. Therefore,
100 for each location, there were 21 vertical and 21 horizontal oriented standard and 9 horizontal and 9 vertical
101 oriented oddball patches. The order was pseudo-randomized considering no two consecutive oddball stimuli.
102 There were 36 blocks (18 blocks for each condition). Block types were presented in a pseudorandom order
103 (not more than three same attended side blocks in a row).

104 The session began with volunteers performing a training session, which consisted of one block of the
105 experimental procedure followed by a weighted up-down staircase procedure²⁵. The staircase block was
106 shorter, with 80 stimuli. After every 12 attended side stimuli presentation, the spatial frequency value was
107 recalculated based on accuracy. A psychometric function was fitted to the data to obtain the spatial frequency
108 corresponding to 75% of correct responses.

109 Interleaved with the experimental blocks, participants performed a localizer task. The task was to detect
110 a colour change in the fixation point (from white to yellow) while the standard stimuli were presented
111 sequentially (SOA of 500 ms) and randomly at left and right sides. Five blocks were presented after every
112 nine main experimental blocks, totalling 15 localizer blocks and 900 standards (50% vertically oriented)
113 presented at each side in total. The localizer was initially designed to be used as a training set to the
114 classification procedure in the main experiment. However, this procedure did not work well, and scores were
115 not above chance within the localizer blocks. For this reason, we have decided not to include this analysis in
116 the paper. Data, analysis and a brief discussion of the localizer data can be seen at <https://osf.io/ca2fd/>.

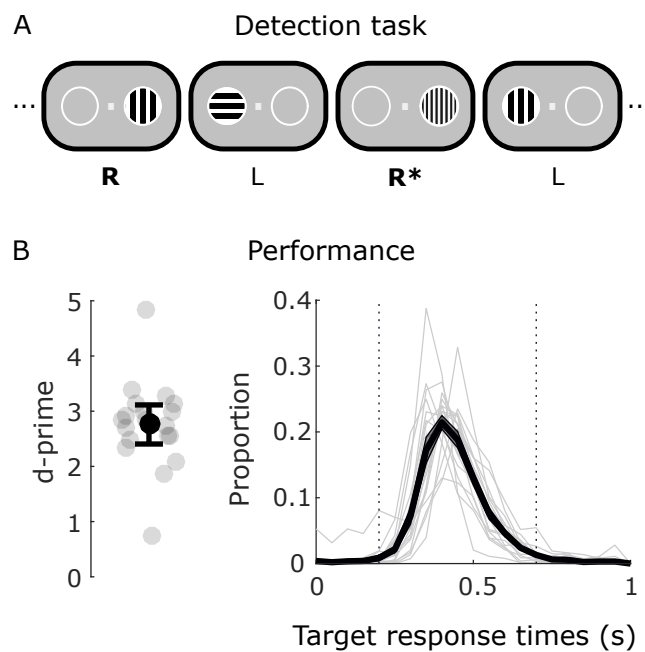


Figure 1. A) Each experimental block began with the presentation of a fixation point. Visual stimuli appeared in sequence, in alternated sides, separated by a stimulus onset interval of 0.5 s. In different blocks, participants had to respond to the oddball target either on the right or left stream. The oddball stimuli (target) were Gabor patches with a higher spatial frequency defined by a staircase procedure. There were 70% of standards and 30% of targets. All stimuli lasted 0.1 s. B) Left: Distribution of participants' d-primes (circles) and its respective errorbar (mean, S.E.M). Right: Reaction times for targets (mean, S.E.M). Dashed lines represent the interval that was considered as hits. Lighter lines represent individual response times.

117 EEG pre-processing

118 EEG pre-processing was carried out using BrainVision Analyzer (Brain Products). All data were down-
119 sampled to 250 Hz and re-referenced to ear electrodes. For eye movement artifact rejection, an independent
120 component analysis (ICA) was performed on filtered (Butterworth Zero Phase Filter between 1 Hz to 30 Hz)

121 data. Eye related components were identified by comparing individual ICA components with EOG channels
122 and by visual inspection.

123 **EEG analysis**

124 EEG analyses were based only on standard stimuli to avoid contamination from motor responses. Standard
125 stimuli presented 500 ms before or 200 ms after a motor action were also excluded from further analyses.
126 Stimuli were separated, in different analyses, based on Attention (attended/ignored), stimuli hemifield
127 occurrence (right/left), and stimuli orientation (vertical/horizontal).

128 ERP consisted of a filtered (Butterworth Zero Phase Filter between 0.05 Hz to 30 Hz) segmented (-0.25
129 to 0.495 s, where 0 is the onset of the stimulus) and baselined (-0.25 to 0 s) data. For the frequency analysis,
130 no-filters were used and data were segmented between -1.95 and 1.95 s relative to stimulus onset. Time-
131 frequency analysis was based on a short-time Fourier transform of Hanning tapered data. We estimated
132 frequencies between 4 and 40 Hz, using a frequency dependent time window of 5 cycles that was advanced
133 over the data in 20-ms steps. Power was logarithmically transformed in the end. Analyses were performed
134 using FieldTrip toolbox²⁶ (<http://fieldtriptoolbox.org>).

135 For the MVPA analysis, ERP data from all conditions and all electrodes were exported from MATLAB to
136 Python 3 Jupyter Notebook (5.0.0) to decode stimulus orientation using Scikit-learn library. Classification of
137 grating orientation (vertical or horizontal) was performed separately for each attention condition and side
138 (attended stimulus presented at the left hemifield, ignored stimulus at the left hemifield, attended stimulus at
139 the right hemifield, ignored stimulus at the right hemifield). All EEG channels were used as features for the
140 classification procedure. The classification pipeline consisted of a leave-one-block-out cross-validation (18
141 blocks) procedure. Training and test data were normalised between 0 and 1 based on the training data, and a
142 logistic classifier with a L2 regularisation was used with all parameters set to the default in Scikit. For each
143 participant, time point and model, the logistic regression pipeline returned labels' probabilities of the trials
144 and the area under the receiver operating characteristic curve (AUC) was calculated as performance score.
145 Afterwards, left and right scores were averaged with respect to attended and ignored conditions.

146 Critically, the experiment was designed so that the: i) feature that defined whether the stimulus was a
147 target or not (spatial frequency) was orthogonal to the feature to be decoded (orientation); ii) both features

148 (spatial frequency and orientation) shared a common a similar neural mechanism, meaning that participants
149 would not be able to ignore the feature to be decoded while trying to perform the task.

150 **Statistics**

151 **Relation between reaction times and pre-stimulus alpha power**

152 We ran two generalised linear mixed-effects models in MATLAB (glme), a linear model using log-transformed
153 reaction times as the dependent variable and a second binomial one considering hits as the dependent variable.
154 Pre-stimulus alpha power was the fixed factor, and participants' slope and intercept in alpha power were the
155 random factors.

156 **EEG**

157 Statistics of one-dimensional classification scores were performed non-parametrically²⁷ with sign-permutation
158 tests. For each time-point, the decoding value of each participant was randomly multiplied by 1 or -1. The
159 resulting distribution was used to calculate the p-value of the null-hypothesis that the mean discrimination-
160 value was equal to 0.5. Cluster-based permutation tests were then used to correct for multiple comparisons
161 across time using 1000 permutations, with a cluster-forming threshold of $p < 0.05$. The significance threshold
162 was set at $p < 0.05$ and all tests were two-sided. Similar results were obtained when performing univariate
163 t-tests and using an FDR based correction on the estimated p-values. These statistical analyses were
164 performed for the ERP, time-frequency and Fourier Transform analysis in MATLAB. Moreover, cluster-based
165 analysis implemented in the MNE library (version 0.18.2, default parameters) was performed to calculate
166 whether decoding scores were statistically different from the null-hypothesis ($AUC = 0.5$), and to calculate
167 whether attended and ignored decoding scores were more likely drawn from different probability distributions
168 (function: `permutation_cluster_1samp_test`).

169 **Results**

170 **Behavioural results**

171 Participants' performance were computed considering hits as responses between 200 ms to 700 ms after a
172 target was presented at the attended side (Figure 1B, right). All other responses were considered false alarms.
173 Participants were able to perform the detection task (Hit Rate: mean = 0.75, SEM = 0.033, min = 0.344, max

174 = 0.976; and d' : mean = 2.759, SEM = 0.181, min = 0.727, max = 4.84, Figure 1 B, left). Additionally, there
175 was no significant effect of side on d -prime (mean \pm SEM, left: 2.824 ± 0.219 ; right: 2.733 ± 0.167 ; $t(18) =$
176 1.023 , $p = 0.32$).

177 Event related potentials

178 To investigate the effects of attention on event-related potentials, we focused on contralateral electrodes
179 relative to the visual hemifield of the standards stimuli. Specifically, we focused on parieto-occipital electrodes
180 (Right hemifield conditions: PO9/PO7/ PO3/O1; Left hemifield conditions: PO10/PO8/PO4/O2), baselined
181 between -50 to 50 ms. Although attended stimuli evoked a stronger negative peak around 180 ms (Figure 2,
182 left), there was no significant difference between attended and ignored conditions (highest negative cluster-stat
183 = 51.3833, $p = 0.18$, time = 0.172 to 0.2, highest positive cluster-stat = 51.3833, $p = 0.068$, time = 0.42 to
184 0.5). Although we did not find significant differences between conditions, it is important to notice it is hard
185 to disentangle attended and ignored ERP due to the fixed SOA design and possible component overlapping.
186 However, there was clear activity lateralization due to attention (Figure 2, right).

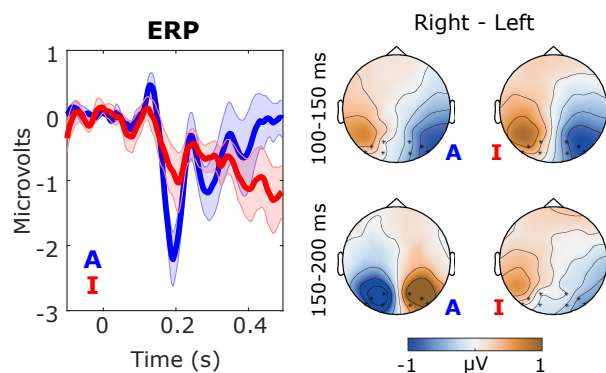


Figure 2. Event related potentials. Left: Activity evoked by attended (blue) and ignored (red) standards. Time point zero corresponds to the onset of stimuli. Right: Topographic plots showing the difference between the average activity of the standard stimuli presented at right and left hemifields when attended and ignored during P1 and N1 time windows (100-150ms and 150-200 ms). Asterisks represent used parieto-occipital channels.

187 Alpha-band oscillations

188 Alpha band desynchronization is a key marker of attention. Therefore, we compared the power spectrum
189 of attended and ignored conditions. Similar to the ERP analysis, we focused on the same parieto-occipital
190 contralateral electrodes to stimulus presentation when that stream was to be attended or ignored(Figure 3

191 A). There was a difference in power evoked by attended and ignored stimuli (positive cluster-stats = 1203.6,
192 1269.2, 1791.6, all $p < 0.01$; negative cluster-stats = 774.26, $p < 0.004$; stats = 502.33, $p = 0.027$). The clusters'
193 time period coincides with stimuli occurrence, which is in line with previous work showing that attention
194 modulates the post-stimulus induced responses as the power of low-frequency bands (alpha/beta)^{28,29}.
195 Additionally, there was a significant alpha (9 - 15 Hz) power attenuation when attended standard stimuli were
196 about to be presented compared to ignored ones.

197 In a second step, we restricted our analysis on prestimulus anticipatory alpha power. We ran a Fast Fourier
198 Transform with a Hanning taper on a shorter epoch (-0.3 to 0 s relative to stimulus onset). We targeted
199 frequencies around the previous significant band. Given the window duration and frequency resolution (from
200 2 to 6 cycles), we were able to compare the prestimulus power for attended and ignored stimuli of five
201 frequencies: 6.58, 9.87, 13.16, 16.45 and 19.74 Hz. Alpha band frequency of 9.87 Hz showed a significant
202 anticipatory attentional effect (Figure 3 B, 6.58 Hz: attended = 0.473 ± 0.049 , ignored = 0.494 ± 0.045 , $t(18)$
203 = -2.827, $d = -0.649$, $p = 0.055$; 9.87 Hz: attended = 0.550 ± 0.069 , ignored = 0.595 ± 0.069 , $t(18) = -2.922$,
204 $d = -0.670$, $p = 0.045$; 13.16 Hz: attended = 0.356 ± 0.073 , ignored = 0.394 ± 0.073 , $t(18) = -2.449$, $d =$
205 -0.562 , $p = 0.125$; 16.45 Hz: attended = 0.070 ± 0.075 , ignored = 0.067 ± 0.073 , $t(18) = 0.287$, $d = 0.066$,
206 $p > 0.9$; 19.74 Hz: attended = -0.084 ± 0.064 , ignored = -0.091 ± 0.064 , $t(18) = 0.696$, $d = 0.160$, $p > 0.9$,
207 p -values corrected for multiple comparisons using Bonferroni).

208 To evaluate whether prestimulus alpha power was correlated with performance, we ran two separate
209 mixed-models: one investigating how alpha power modulated reaction times to correct target detection and
210 one investigating how alpha power modulated target detection (hit rate) for 9.87 Hz and for 13.16 Hz (Figure
211 3 C). We did not find a significant effect of alpha power on reaction time (9.87 Hz: alpha fixed effect, $t =$
212 0.404 , $p = 0.686$, 13.16 Hz model: alpha fixed effect, $t = -0.179$, $p = 0.858$), nor hit rate (9.87 Hz model:
213 alpha fixed effect $t = -1.76$, $p = 0.078$, 13.16 Hz model: $t = -1.903$, $p = 0.057$).

214 **Multivariate pattern analyses**

215 We used an L2-regularised logistic regression to test whether orientation information could be decoded in
216 different conditions. We trained and tested separately for each attention and side and, subsequently, we
217 averaged the scores separately for attended and ignored conditions (Figure 4 A). We found that classification

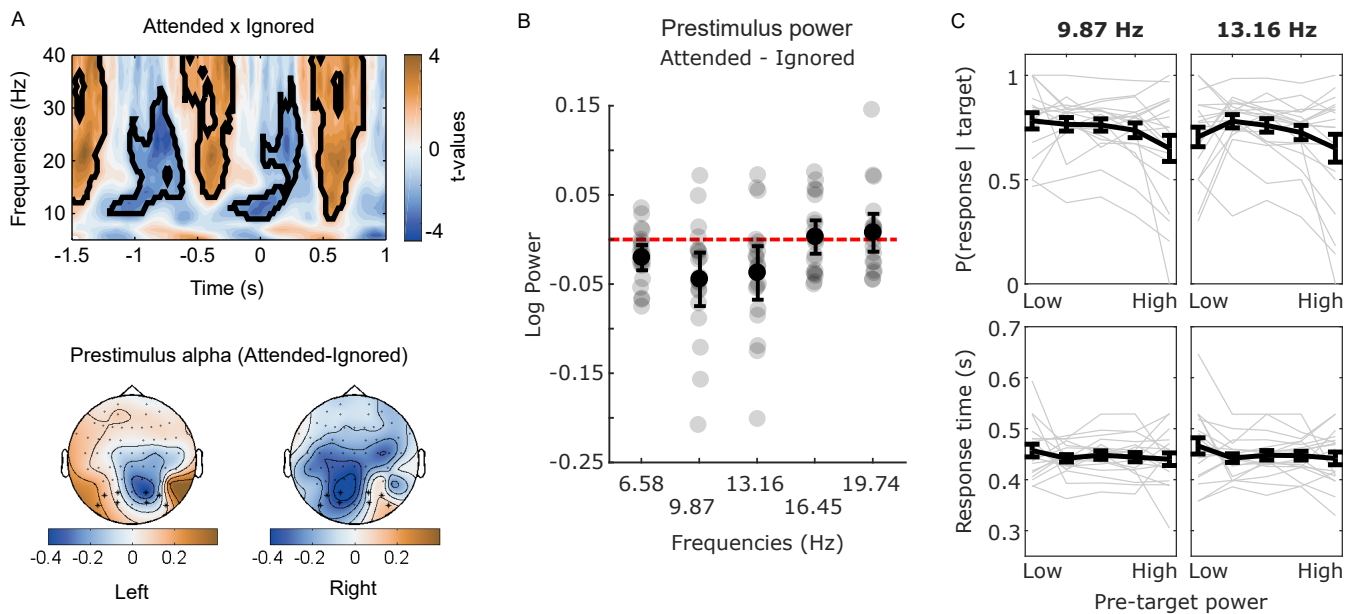


Figure 3. A) Top: Power spectrum paired t-test comparison between attended and ignored stimuli. Black contours indicate significant clusters. Bottom: Alpha power (dB) topography from the difference between attended and ignored stimuli at a prestimuli time period (-0.5 to 0 s). Asterisks represent used parieto-occipital channels. B) Error bars (mean, S.E.M) showing the difference in prestimulus power between attended and ignored conditions at frequencies around the previous significant band. Individual differences are represented as dots in the background. B) Error bars (mean, S.E.M) illustrating hits and reaction times for the pre-target alpha power bins. For graphical purposes, alpha power was binned in five bins (with a similar number of trials) based on prestimulus alpha power and the behavioural output was calculated for each bin. Individual responses for different bins are represented in the background.

218 was above chance levels for attended stimuli (Attended right: time = 0.184 to 0.224, cluster-stat = 41.351, $p =$
 219 0.031; Attended left: time = 0.144 to 0.18 and 0.384 to 0.408, cluster-stats = 41.19 and 26.72, $p = 0.006$ and
 220 $p = 0.034$; Attended [mean], time: 0.148 to 0.224, 0.26 to 0.324, 0.356 to 0.428, cluster-stats = 81.23, 63.11,
 221 and 71.11, $p = 0.002, 0.002, 0.002$). There were no significant clusters in the Ignored condition. A second
 222 cluster-based analysis comparing Attended and Ignored scores was performed and showed that attended
 223 stimuli had higher classification scores than ignored stimuli (time: 0.144 to 0.22 s, cluster-stat = 211.332, $p =$
 224 0.018).

225 To investigate whether higher differences between attended and unattended representations lead to better
 226 performances, we computed a across participants ($n=19$) correlation between d-prime and the difference
 227 between attended and ignored decoding scores. We found that attentional manipulation on decoding scores
 228 was correlated with participants' d-prime values (Spearman correlation = 0.57, $p = 0.010$, Figure 4 B. Similar
 229 correlation results were obtained using other methods such as Kendall's Tau, Sheppard's Pi and percentage

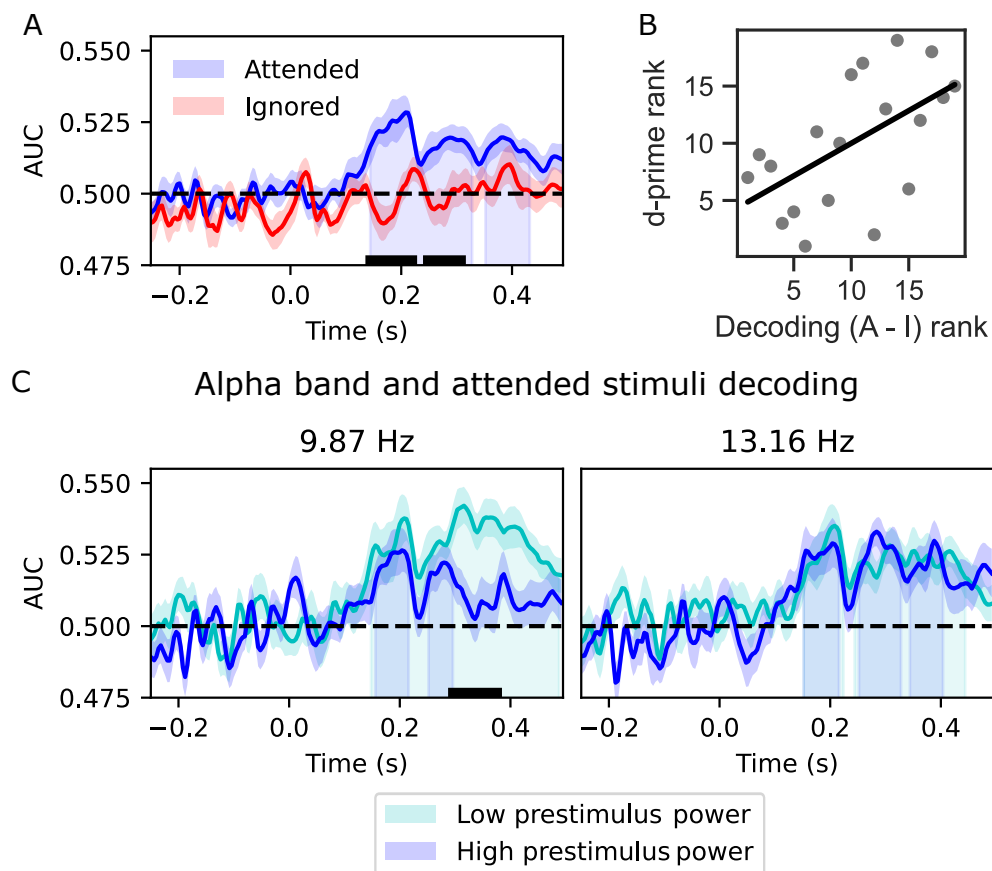


Figure 4. A) Decoding scores across different experimental conditions. Red (ignored) and blue (attended) lines represent mean and error bars represent standard error of the mean. Time zero is the moment in which a standard was presented. Shadows under the curve represent clusters where classification was better than chance. The black line at the left panel shows the cluster period in which classification was higher in attended than in ignored conditions. B) Scatterplot showing the cross-subject correlation between d-prime and the difference in decoding scores between attended and ignored conditions. C) Decoding scores for attended stimuli (mean, S.E.M) grouped into low (cyan) and high (darker blue) prestimuli alpha power. Grouping was performed for both frequencies at alpha band: 9.87 Hz and 13.16 Hz. The black line shows the cluster period in which classification was higher in low alpha power trials than in high alpha power trials, and shadows under the curve represent the statistical clusters different from scores at chance.

230 bend correlation).

231 Given that attention modulated both alpha power (stronger effect at 9.87 Hz) and classification accuracy,
232 we tested whether prestimulus alpha desynchronisation was correlated with an increased classification. To
233 test this hypothesis, we performed a median split on attended stimuli based on their prestimulus alpha power
234 (9.87 Hz and 13.16 Hz) and recalculated the decoding score (AUC) for each participant and time point (Figure
235 4 C). For the low alpha band (9.87 Hz), a direct comparison between prestimulus power conditions showed
236 a higher decoding score for stimuli preceded by low alpha power (cluster-stat = 63.209, $p = 0.008$, time =

237 0.30 to 0.376). Results for the higher frequency of alpha band (13.16 Hz), however, showed no modulation
238 (highest cluster-stat = 10.617, $p = 0.495$, time = -0.192 to -0.18). Taken together, our results suggest that the
239 frequency in which there was a stronger modulation of attention (9.87 Hz) was also correlated with higher
240 classification scores.

241 Discussion

242 In the present study, we investigated the effects of covert spatial attention on sensory information and related
243 mechanisms. Attention resulted in a pre-stimulus alpha desynchronization on contralateral sensors. Using
244 a multivariate decoding approach, we found that spatial attention enhanced stimulus identity coding at the
245 relevant location. Moreover, we found that that stronger alpha desynchronisation boosted the representation
246 of target identity.

247 Several studies have shown that visual-spatial attention elicits larger P1 and N1 components for attended
248 than for ignored-stimuli³⁰. However, P1 and N1 effects seem to indicate distinct attentional mechanisms:
249 while P1 modulation suggests a suppressing mechanism, it has been suggested that N1 modulation represents
250 a sensory gain mechanism³¹. In this study, we did not find a significant effect of attention on event-related
251 potentials. One crucial difference in our study is that events were presented sequentially in a stream. This
252 type of presentation leads to overlaps of event-related potentials which, in turn, might have made it harder to
253 find effects on early components. Moreover, it has been recently suggested that stronger response amplitudes
254 (i.e. ERP, BOLD response) do not necessarily imply enhancement in information about stimulus identity³².
255 A recent study investigating temporal attention found a modulation in N1, but no correlation between N1
256 amplitude and the decoding scores¹. Therefore, it seems that an increase in signal-noise-ratio is not necessarily
257 linked to boosting information about stimulus identity.

258 We observed a stronger contralateral alpha decrease in anticipation of attended targets. Our results
259 are in agreement with several studies that have shown that alpha oscillations are correlated with spatial
260 attention^{6,33-37}. There has been an increasing discussion as to whether alpha oscillations are associated with
261 an increase in perceptual processing or if it modulates performance by biasing perceptual¹⁹ or decisional
262 mechanisms^{20,21}. In recent studies, it has been suggested that decreased alpha power does not improve
263 perceptual acuity, but biases perception by increasing baseline excitability¹⁹⁻²¹. This proposal is based

264 on findings that show that: (1) decreased alpha power was associated with a higher tendency to report
265 the presence of a stimulus, even when a target is absent; (2) alpha power did not affect performance on
266 discrimination tasks^{19–21}. In our experiment, the behavioural task was to detect the presence of a target,
267 marked by an increase in the spatial frequency of the Gabor. Although not significant, there was a tendency
268 of higher reportability rates when alpha power decreased, making our results compatible with the perceptual
269 bias proposal.

270 Our decoding results showed that spatial attention enhanced target identity coding. Even though the
271 decoded feature (stimulus orientation) and the task-relevant feature (spatial frequency) are independent, they
272 share common mechanisms and attending to one of them seems to affect the other. Within the attended field,
273 decoding was increased in trials with decreased alpha power. Although this finding appears to be more easily
274 explained with the idea of alpha being associated with perceptual precision, it is worth to point out that the
275 increase in decoding was in a later period. This result is consistent with a previous report that found that
276 lower alpha can reduce the immediate interference by a distractor¹. Given that participants did not make
277 judgements about the orientation of the target, it is not possible, with our current experiment, to be sure
278 whether an increase in decoding would be translated into an increase in the behavioural discrimination.

279 We conclude that stimulus identity processing is modulated by covert spatial attention and that anticipatory
280 alpha power is associated with such processing.

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