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Measuring Neuronal Avalanches to inform Brain-Computer Interfaces

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Abstract

Large-scale interactions among multiple brain regions manifest as bursts of activations called neuronal avalanches, which reconfigure according to the task at hand and, hence, might constitute natural candidates to design brain-computer interfaces (BCI). To test this hypothesis, we used source-reconstructed magneto/electroencephalography, during resting state and a motor imagery task performed within a BCI protocol. To track the probability that an avalanche would spread across any two regions we built an avalanche transition matrix (ATM) and demonstrated that the edges whose transition probabilities significantly differed between conditions hinged selectively on premotor regions in all subjects. Furthermore, we showed that the topology of the ATMs allows task-decoding above the current gold standard. Hence, our results suggest that Neuronal Avalanches might capture interpretable differences between tasks that can be used to inform brain-computer interfaces.

36 Introduction

37 Brain-Computer Interfaces (BCIs) constitute a promising tool for establishing direct
38 communication and control from the brain over external effectors for clinical applications^{1,2}.
39 However, the ideal features to design a BCI are unknown, since the underlying microscopic brain
40 processes, and their reflection on brain signals, are poorly-understood³. As a result, mastering non-
41 invasive BCI systems remains a learned skill that yields suboptimal performance in ~30% of users,
42 referred to as the “BCI inefficiency” phenomenon⁴. Measuring the dynamical features that are
43 relevant to the execution of a task and, as a consequence, may improve BCI performance, remains
44 an open challenge³. Indeed, the current features that are used in the context of BCI rely on local
45 measurements⁵ (mostly frequency band power features and time-point features, depending on the
46 BCI paradigm) disregarding the interconnected nature of brain dynamics. Electromagnetic
47 imaging data is dominated by ‘bursty’ dynamics, with fast, fat-tailed distributed, aperiodic
48 perturbations, called “neuronal avalanches”, traveling across the whole brain⁶⁻⁹, which have been
49 recorded using electro/magnetoencephalography^{10,11}. Neuronal avalanches spread preferentially
50 across the white-matter bundles¹², they are modified by neurodegenerative diseases¹³, and they
51 evolve over a manifold during resting-state, generating rich functional connectivity dynamics¹⁴.
52 Such rich dynamics are a major contributor to time-averaged functional connectivity^{6,15}. Hence,
53 the spreading of neuronal avalanches might be a correlate of the functional interactions among
54 brain areas and, as such, we hypothesize that they could spread differently according to the task at
55 hand, thereby providing a powerful and original marker to differentiate among behaviors. To test
56 our hypothesis, we compared source-reconstructed magnetoencephalography (MEG) signals in
57 resting-state (RS) and while performing a hand motor imagery (MI) task within a BCI protocol, in
58 order to track the dynamical features related to motor imagery as compared to rest. We obtained
59 the probabilities of each pair of regions being recruited sequentially in an avalanche¹², compared
60 these probabilities across MI and RS conditions edge- and subject-wise, and related the differences
61 between the two conditions to the performance in the BCI task, as measured using the BCI
62 classification accuracy. Furthermore, we used these features to decode the tasks from source-
63 reconstructed data.

64

65 Results

66 We used the spatio-temporal spreading of large aperiodic bursts of activations as a proxy for
67 communications between pairs of regions. Within this framework, large-scale, higher-order
68 perturbations are considered to mediate the interactions between brain regions. We tested for
69 differences between the two experimental conditions (i.e. resting-state, RS, and hand motor
70 imagery, MI) in the probabilities of any such perturbation to propagate across two brain regions.
71 To this end, we built an avalanche transition matrix (ATM) for each subject, containing regions in
72 rows and columns, and the probability that region j would activate at time $(t+1)$, given that region
73 i was active at time t , as the ij^{th} entry. Here, we consider the brain as a network, where the nodes
74 represent brain regions, and the edge linking two of them is defined as the probability of the two
75 regions being subsequently recruited by an avalanche. The differences in the probability of being
76 sequentially recruited by an avalanche was used to track (subject- and edge-wise) the spatial
77 propagation of the perturbations across the two experimental conditions. To validate the observed

78 differences, for each subject and each edge, we built a null-model (Figure 1A) randomizing the
79 labels of each trial (i.e. RS or MI) 10000 times, so as to obtain a null distribution of the differences
80 expected by chance. These distributions were used to spot, individually, the edges that differed
81 between the two conditions above chance level. The significances were corrected for multiple
82 comparisons across edges using the Benjamini-Hochberg (BH) correction¹⁶. Following this step,
83 we focused on the edges that were consistently significant across subjects (defined here as
84 “reliable” edges). To achieve this, we randomized 10000 times, in each subject, the statistically
85 significant edges (Figure 1B). This way, we identified the edges which differed significantly
86 between the experimental conditions in a higher number of subjects than expected at chance level
87 ($p < 0.05$, BH corrected across edges). Our results show that there is a set of edges, consistent across
88 most subjects, across which large-scale perturbations propagate differently according to the
89 experimental condition (Figure 2A).

90 We then checked if the significantly different edges would cluster over specific brain regions. To
91 this end, we computed the expected number of significant edges incident on any region, given a
92 random distribution (with a comparable density), and selected those regions with an above-chance
93 number of significant edges clustered upon them (Figure 1B). Statistics were again corrected using
94 BH, this time separately for each region, to avoid inflating the probability of finding significant
95 results by chance. As evident in Figure 2, panel C, to the left, these “reliably different” edges
96 cluster on premotor regions bilaterally and, particularly, on the caudal middle frontal gyri
97 bilaterally ($p < 0.0001$, BH corrected). We replicated the analysis demonstrating the robustness to
98 the choice of arbitrary parameters (see Figure S1), and to the methodology and parcellation used
99 (see Figure S2). We repeated the analyses with 200000 permutations which confirmed the stability
100 of our results (not shown). We have also performed the same pipeline as described above, this time
101 using the power spectra, the ERD/S, and the phase locking-value, all of them in the theta, alpha
102 and beta bands, as features to distinguish the hand motor imagery from the resting-state (see Figure
103 S3). So far, we have classified the trials according to the stimulus presented to the subject.
104 However, if the differences we found were genuinely related to the task execution, one might
105 expect that they would be greater when the trials were successful (i.e. when the subject could
106 control the BCI device), as compared to when the trials were unsuccessful. To test this hypothesis,
107 in each subject, we compared the differences between MI and RS in the successful trials, to the
108 differences between MI and RS in the unsuccessful trials, expecting to see greater differences at
109 the individual level (in the same set of edges) in the former case as compared to the latter. To
110 statistically test this hypothesis, we used a permutation approach, randomizing successful and
111 unsuccessful trials within each subject. Here, we proceeded under the null hypothesis that if the
112 differences in transition probabilities were truly related to the kind of task at end (i.e. MI or resting
113 state) they should be greater when the task is performed correctly, as compared to when the task
114 has been done wrongly. Hence, we have compared the differences between successful MI and
115 successful resting state, to the differences between unsuccessful MI and unsuccessful resting state.
116 Then, we have built the corresponding null-model under the null-hypothesis that the correct
117 execution of the task would not entail greater differences in the transition probabilities. Hence, we

118 have allocated the trials randomly to the successful (hit) and unsuccessful (miss) trials, and we
119 computed the distribution of the differences expected by chance. Finally, we compared the
120 observed differences between hits (i.e. successful rest vs. successful MI) versus the differences
121 between the misses, demonstrating that when tasks are successfully executed the corresponding
122 differences in the edges are greater than what would be expected by chance. As shown in Figure
123 2, panels C, to the right, we could confirm that the transition probabilities across the previously
124 identified reliable edges differed more, in each subject, between conditions, in successful trials as
125 compared to unsuccessful trials, supporting the hypothesis that the relationship between transition
126 probabilities and task performance is valid and measurable at the individual level.

127 MI-based BCI experiments rely on the use of features extracted from power spectra measured in
128 location and frequency bins sensitive to oscillatory changes. More specifically, the system takes
129 advantage of the desynchronization effect associated with a decrease of the power spectra as
130 compared to the rest condition observed within the mu and/or beta band and over the contralateral
131 sensorimotor area when one performs a motor imagery task of the right hand¹⁷. To improve the
132 classification performance based on power spectra, spatial filters relying on the Common Spatial
133 Patterns (CSP) approach^{18,19} have been adopted and widely used in the BCI domain⁵. To take
134 advantage of the interconnected nature of brain functioning, recent work consisted in using
135 functional connectivity estimators, mostly relying on phase-locking value (PLV)²⁰, as alternative
136 features for classification^{20,21}. To explore the performance of neuronal avalanches in the decoding
137 of the task (i.e., resting-state versus hand motor imagery), we compared the ATMs to the CSP
138 approach. In a preliminary analysis, we also explored the performance of the power-spectra and of
139 the phase-locking values which both performed, as expected, worse than the CSP (not shown). The
140 CSP and ATM outputs were classified with a Support Vector Machine (SVM), and the results
141 were compared. As it can be seen in Figure 3A and 3D, the classification performance seemed
142 comparable for both methods with MEG (averaged performance of 0.76 for both CSP+SVM and
143 for ATM+SVM) and greater for ATM+SVM than CSP+SVM with EEG (averaged performance
144 of 0.75 and of 0.80 respectively for CSP+SVM and for ATM+SVM). Furthermore, in both MEG
145 and EEG we observed greater inter-subject variability in the case of CSP+SVM (standard
146 deviation= 0.13 and 0.15, for MEG and EEG, respectively) than with ATM+SVM (standard
147 deviation= 0.11 and 0.10 for MEG and EEG, respectively).

148 Then, we moved on to a subject-specific analysis, to explore the applicability of the ATM method
149 in the context of a BCI training. We aimed to compare the ability of correctly classifying a trial as
150 MI and RS within each subject. Hence, for each subject, we ran t-tests (and confirmed them with
151 Wilcoxon tests) to compare the 50 success rates obtained with CSP+SVM to the 50 success rates
152 obtained using ATM+SVM. This was done under the null hypothesis that CSP+SVM and
153 ATM+SVM would not yield any statistically different performance in trial classification. We
154 repeated this comparison for every subject, and corrected the statistical comparisons for multiple
155 comparisons across subjects using the False Discovery Rate (FDR). We also repeated the analysis
156 for 75 random splits, and the results did not change, showing that our results reached convergence
157 at 50 splits.

158 This analysis showed that for the MEG dataset, ATM+SVM yielded significantly higher
159 classification accuracy than CSP+SVM did for 6 subjects, while the opposite was true for 7
160 subjects. For the remaining 7 subjects, there was not any statistically significant difference between
161 the decoding performances of CSP+SVM and ATM+SVM (Fig. 3, panel B). For the EEG data,
162 ATM+SVM yielded better classification accuracy than CSP+SVM for 12 subjects. In four
163 subjects, CSPs yielded better accuracy than ATMs (Fig. 3, panel E). In 5 subjects, there was not
164 any statistically significant difference between the two approaches.

165 Moreover, we examined the variability of the estimates across the splits. Steady estimates are
166 important to train online algorithms and high variability might be partly responsible for ineffective
167 training. We observed marginally higher intra-subject variability in CSP+SVM (median value of
168 0.07 in both modalities) as compared to ATM+SVM (median value of 0.06 in both modalities). In
169 particular, the standard deviation across the split is smaller for the ATMs for most subjects. In
170 Figure 3, panels C and F for MEG and EEG respectively, we compare the variance (across random
171 splits) of the estimates obtained with the two pipelines (again, ATM on the x-axis, CSP on the y-
172 axis). We have also checked what is the contribution of very small avalanches (given that most
173 avalanches are power-law distributed, and small avalanches are the most frequent). As reported in
174 Figure S7 for the case of the threshold $|z| > 3$, one can observe that extremely small avalanches
175 do not contribute significantly to the performance of the classification, as convergence is reached
176 when including avalanches of size three. We have also investigated the influence of the frequency
177 band (as opposed to broad-band) to the classification performance. As reported in the Figure S8,
178 the broad-band case shows the best performance.

179
180 Finally, we explore the relationship between the magnitude of the differences in the transition
181 probabilities between the two experimental conditions (in each subject, for every edge) to the
182 individual BCI performance (defined as the proportion of trials in which the subject controlled the
183 BCI device) in the MI task, as measured using the BCI score. Figure 4, panel A shows the edges
184 whose differences between conditions correlate the most with the BCI scores (the color code shows
185 the intensities of the correlations, for visualization purposes only edges with correlations with p-
186 values < 0.05 are shown). Firstly, for nearly every edge we observed a positive correlation. To
187 help interpretation, we clustered all the edges according to functional regions (i.e., executive
188 regions, pre/motor areas, parietal areas, temporal areas, occipital areas, (Figure 1C). That is, we
189 computed the average Spearman's correlation over all the edges connecting any two functional
190 regions (also including self-connections, i.e. edges which are comprised within a functional
191 region). To check if the differences in edges transitions which correlated to task performance
192 clustered over certain functional areas above chance-level, we again built a null-model. To this
193 end, for 10000 times, we randomly allocated edges correlation coefficients to functional areas and,
194 each time, we computed the average. We compared the observed average correlation coefficient
195 to the null distribution to obtain a significance value per functional area. Significance values were
196 then corrected for multiple comparisons across all their combinations (i.e., 5×5 , 25 p-values). Our
197 results suggest that edges that significantly relate to BCI task performance hinge pre/motor areas

198 and parietal areas ($p < 0.0001$, See Figure 4, panel B). Since we retrieved nearly exclusively positive
199 correlations, our results capture that perturbations spread more often between premotor/motor
200 areas and parietal areas when the subject is engaged in the motor-imagery task, as compared to the
201 resting-state condition. We replicated these results using different parcellation schemes (see Figure
202 S9).

203 204 **Discussion**

205 In this work, we set out to test if neuronal avalanches can track subject-specific changes induced
206 by the execution of a task (i.e., hand motor imagery) in the large-scale brain dynamics. The
207 working hypothesis was that meaningful communication among regions on the large-scale is
208 intermittent, and it is best understood and measured in terms of aperiodic perturbations. Neuronal
209 avalanches are inherently aperiodic processes with scale-free fluctuations, whose statistical
210 parameters meet theoretical predictions from mean-field theory²²⁻²⁴. In our data, we confirmed that
211 the measured branching ratio is compatible with that of a system operating at criticality or near-
212 criticality²⁵. We went on from there to test the basic idea that brain regions interact differently
213 while performing different tasks. We reasoned that, if avalanches convey interactions occurring
214 between regions, their spreading should also be modified according to the task at hand. Such
215 context-dependent modifications should then be encoded in the avalanche transition matrices and,
216 in turn, might be decoded in order to tailor brain-computer interfaces. More specifically, such
217 information could be considered either as potential predictors of BCI performance, to conceive
218 tailored training programs, or as alternative features, to improve the classification performance.

219
220 With respect to the encoding framework, we identified, in an unsupervised manner, a number of
221 functional links (i.e. edges) that are reliably more likely to be dynamically recruited during a hand
222 motor imagery task as compared to resting state. The edges cluster over regions typically involved
223 in motor planning and attention, as expected from a motor imagery task. In particular, our results
224 demonstrated that the activities spreading across these edges differed mostly when contrasting
225 trials that had been successful, as compared to the trials during which the subject could not control
226 the interface. This finding demonstrates a behavioral readout for the observed changes in the
227 transition probabilities. This is in line with previous evidences demonstrating that premotor areas
228 are involved in the planning of motor actions, in the imagining of actions, in allocating executive
229 attention²⁶, as well as in the selection between competing visual targets²⁷, while parietal areas are
230 notably involved, among other things, with the processing of sensitive input. In line with previous
231 findings²⁸, a premotor-parietal network was found to be specifically implicated with spatial
232 imagery tasks. These results suggest that indeed the localization of the different edges carries a
233 behavioral meaning.

234 The ATMs directly track the spreading of activations as they happen (as opposed to quantifying
235 dependencies over time intervals). Using such straight-forward approach¹², we reliably retrieve
236 functional information related to the execution of a task at the subject-level, which was not possible
237 using classical functional metrics²⁹. Our approach is based on theoretical underpinnings derived

238 from statistical mechanics, which posits that higher-order, long-range correlations would appear
239 in a near-critical dynamical regime^{22,25}. In fact, it is important to notice that, by z-scoring each
240 region and using a high-threshold we selected only very strong coherent activity, which is unlikely
241 to be generated by a linear process and that, instead, refers to a higher-order phenomenon. In doing
242 so, we discarded most of the available signals. In practice, we have discarded roughly 90% of the
243 data, applying a “spatio-temporal” filter, and only selecting those points in time and space where
244 large-scale aperiodic perturbations were found. To provide a comparison with more standards
245 techniques, we have used the same pipeline based on techniques that assume stationarity (and take
246 the whole data into account), namely the power-spectra and the event-related
247 desynchronization/synchronization (ERD/S) effects (both containing local information) and the
248 phase-locking value (estimating bivariate synchronization between brain regions). Importantly, all
249 these techniques failed to reproduce any pattern of differences between the two conditions that
250 was replicable at the individual level (see Figure S3). However, in the same dataset, a previous
251 work showed that the power-spectra shows differences at the group-level²⁹ and the grand average
252 of the ERD/S over the cohort showed a clear desynchronization within the beta band in the
253 contralateral sensorimotor area in the MI condition (see Figures S4 and S5) in line with previous
254 studies³⁰⁻³³. The fact that we could find robust individual differences while discarding most data
255 and that we failed to do so when taking the whole data into account suggests that focusing on
256 higher-order perturbations might be useful to capture functionally-relevant processes and, in turn,
257 to apply them to the design of BCIs.

258 We replicated our results using different thresholds and binnings showing that they are resilient to
259 these choices. Also, they can be replicated using different parcellation schemes, and using EEG
260 signals, which is more widely available than MEG for BCI applications, thereby making our
261 methodology suitable in a wide variety of settings. All in all, extensive replications make it
262 unlikely that our results could be due to arbitrary choices or limited to a specific methodology.

263
264 Within the decoding framework, we compared the offline classification performance resulting
265 from the use of the ATM to the gold-standard approach, which relies on spatial filters (i.e., the
266 Common Spatial Patterns). Our results suggest that the integration of periodic and aperiodic
267 features would be a straightforward way to improve task classification. Indeed, the information
268 captured by the two types of feature extraction (namely CSPs and ATMs) and the two modalities
269 (MEG and EEG) are complementary. The ATMs maintain a fairly straightforward interpretability
270 as opposed to CSPs, which operate on large-scale components of the signal that are not as readily
271 interpretable. In particular, the ATMs focus on the strong coherent interactions that intermittently
272 occur on the large-scale. The good performance of the ATMs on the EEG data is relevant to
273 translate our methodology to real-world scenarios. In this configuration, the classification of
274 ATMs leads to a significant improvement of the decoding performance with respect to the
275 benchmark in the majority of subjects. Importantly, in both modalities, we observed a reduced
276 intra and inter-subject variability with our approach as compared to CSP+SVM. This might help,
277 in real-life experiments, to reduce the BCI inefficiency phenomenon. To evaluate the feasibility in

278 online applications, we estimated that for an epoch of 5s the time necessary to extract the features,
279 and to perform the classification, was approximately 25ms for ATM+SVM and 27ms for
280 CSP+SVM. This value is actually compatible with current on-line settings which use similar time
281 windows and update the feedback every 28 ms. Further investigations are needed to explore the
282 performance in the context of online classification with shorter time windows. Nevertheless, it is
283 worthwhile mentioning that this is a first proof-of-concept study of the use of neuronal avalanches
284 as complementary/alternative features for the design of BCI.

285 Identifying neural markers associated with BCI performance is crucial to design optimized and
286 tailored BCI systems³⁴. In turn, the most informative markers provide insight into the processes
287 that underpin the execution of a given task.

288 Neurophysiological predictors of BCI scores are most commonly associated with power spectra.
289 Indeed, sensorimotor μ - and α -rhythms or, more recently, time-averaged brain interactions in these
290 frequency bands have been considered as potential markers³³. These findings were mainly
291 empirical and, in this oscillatory perspective, features such as power spectra and/or (static)
292 synchronization measures have been widely explored to inform the interfaces^{21,33}. Furthermore,
293 regional connectivity strength²⁹ and the M/EEG multiplex core-periphery³⁵ of specific associative
294 and somatosensory areas held predictive power over BCI performance in the same session.
295 However, between 15% and 30% of the subjects do not learn to control the effector despite
296 extensive training. This might mean that the typical features only partly capture the processes that
297 lead to the execution of the task. Hence, different markers might be exploited. Our study
298 contributes, on a practical level, by achieving a differentiation between tasks at the individual level.
299 From a more theoretical perspective, our results suggest that the spreading of local synchronization
300 on the large-scale might be intermittent and aperiodic, and that such spreading carries behavioral
301 relevance. The fact that neuronal avalanches are relevant to the execution of a task might also have
302 implications on the underlying microscopic dynamics. As such, this would allow the deployment
303 of complex and solid mathematical tools derived from statistical mechanics to test the presence of
304 specific microscopic physiological processes.

305 When relating the differences between MI and RS in the probability of an avalanche consecutively
306 recruiting two regions to the magnitude of BCI performance we find mostly positive correlations,
307 indicating that the more avalanches spread between premotor/motor and parietal regions during
308 the task, the better the control of the BCI. This might suggest that the interactions between
309 pre/motor regions and parietal ones underpin the execution of the task. These findings are in line
310 with previous studies relying on MI-based BCI paradigms. In particular, Buch et al³⁶ showed that
311 the structural integrity of the frontoparietal networks predict the ability of stroke patients to control
312 a brain computer interface in a motor imagery task. Using fMRI, Halder et al. showed that the
313 premotor areas participate in executing voluntary modulation of brain rhythms through a MI-based
314 BCI³⁷.

315 Importantly, when interpreting the results in cognitive terms, one should consider that a (BCI) task
316 likely recruits multiple cognitive processes, beyond those exploited by the BCI classification itself.
317 As such, a psychophysiological interpretation of the areas involved in the BCI classification is not

318 straightforward. For example, the right fronto-parietal network dynamics also reflects the
319 allocation of attentional resources, which are typically engaged in cognitive/motor tasks. It is also
320 known that fronto-medial activities are one of the main correlates of sustained attention³⁸. Thus,
321 although the clustering of the edges that we found in the fronto-parietal network is consistent with
322 the prominent involvement of this network in motor imagery tasks, it cannot be mapped uniquely
323 onto one cognitive process. A different perspective is provided by the analysis of cognitive
324 profiles, since it was shown that spatial abilities influence BCI performance³⁹, and in particular
325 mental rotation⁴⁰. As such, training strategies might be tailored over a subject-specific assessment
326 of such abilities. Intriguingly, mental rotation abilities were related in turn to increased activity of
327 the premotor cortex, the superior-parietal and the intra-parietal cortices^{41,42}. Furthermore,
328 activations in the right middle frontal gyrus correlated with BCI performance, which might be
329 interpreted in the light of the role that this region plays in the processing of an observed
330 movement³⁷.

331 In conclusion, in a real-world scenario, multiple mechanisms might be in place. As such, our
332 approach is not expected to be the only useful framework. However, it might capture part of the
333 processes that were typically overlooked in a more oscillatory perspective. Our work paves the
334 way to use aperiodic activities to improve classification performance and tailor BCI training
335 programs.

336

337 **Limitations of the study**

338 This first proof-of-concept study aimed at assessing to which extent neuronal avalanches could be
339 relevant to identify potential markers of BCI performance and alternative features to detect the
340 subjects' intent. However, to explore scalability and deployability, studies will need to involve
341 different types of motor imagery tasks (e.g. feet motor imagery, tongue motor imagery etc..), the
342 assess the sensibility of ATMs towards the discrimination of tasks that involve areas close to each
343 other. Furthermore, we have only assessed the performance of the ATMs in controlling 1 degree
344 of freedom. However, the performance of ATMs in controlling more degrees of freedom will have
345 to be assessed to study the use of ATMs in richer frameworks (i.e. instead of considering only the
346 vertical position of the moving cursor, the horizontal position might also be considered).

347

348

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355

356

357 **Author contributions**

358 Conceptualization: MCC & PS
359 Methodology: MCC & PS
360 Investigation: MCC & PS
361 Visualization: MCC & PS
362 Supervision: FDVF & VJ
363 Data collection and curation: MCC, DS, LH
364 Data processing: MCC, PS, AEK
365 Writing—original draft: MCC & PS
366 Writing—review & editing: MCC, PS, DS, NG, LG, SC, LH, AEK, SD, DSB, VJ, FDVF

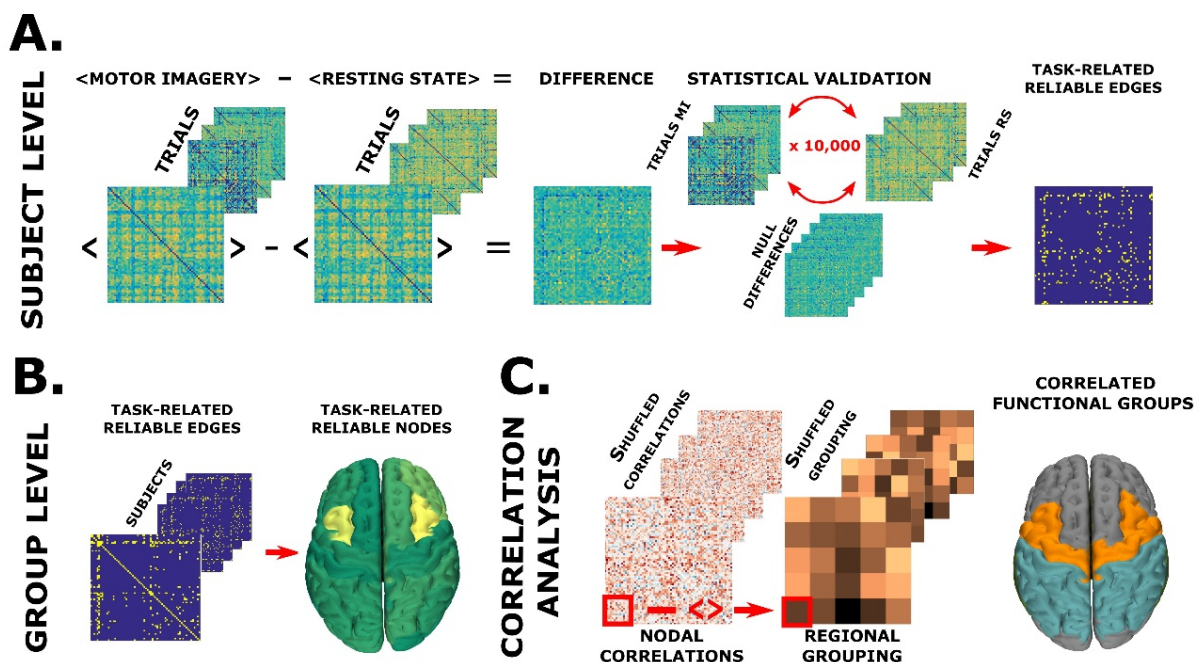
368 **Declaration of interests**

369 The authors declare no competing interests.

370

371

372 **Figures and Tables**



373

374 **Fig. 1 Overview of the analysis. A. Subject-level analysis:** to identify, for each subject, the edges that

375 show a significant condition effect. The average of all RS trials was subtracted, edge-wise, from the average

376 of the MI trials. The differences were validated by shuffling the labels (i.e. MI and RS) 10000 times. This

377 way, significantly different edges were identified for each patient. **B. Group level analysis:** we identified

378 the edges that were significantly different in a large number of subjects (as compared to what would be

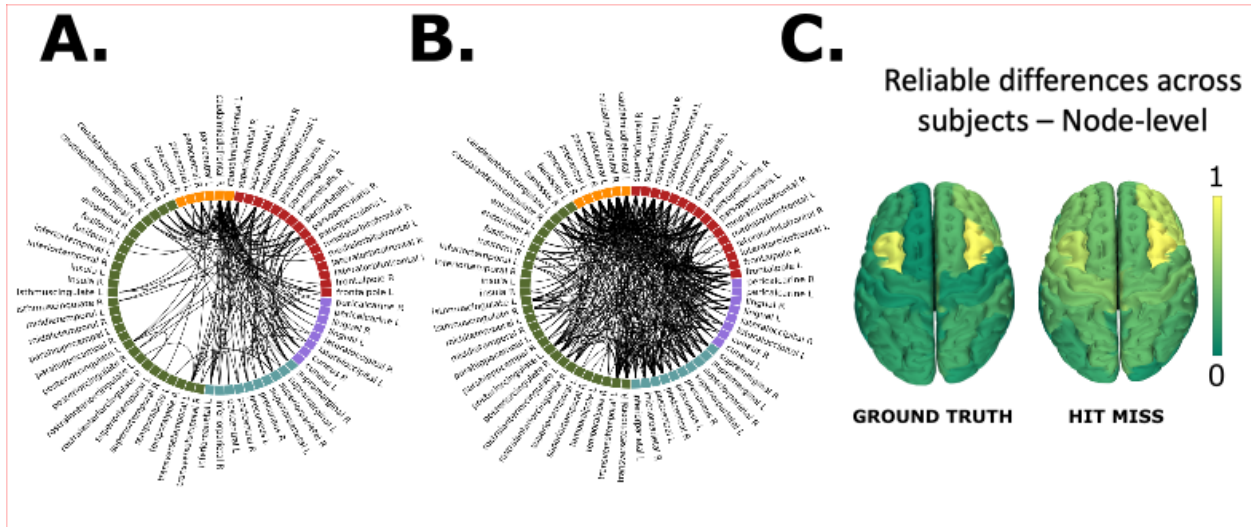
379 expected by chance) and then performed nodal analysis to identify the regions over which significant

380 differences were clustered. **C. Correlation analysis:** correlation coefficients between individual

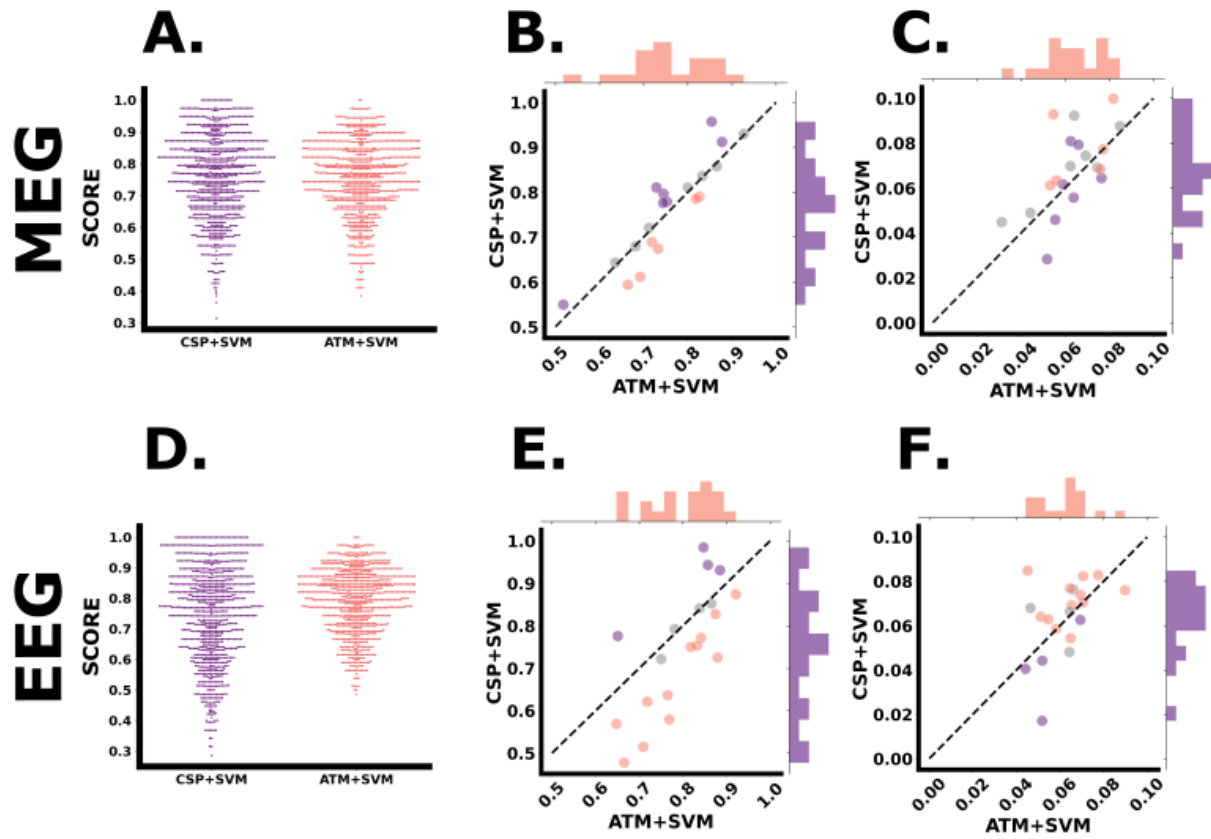
381 differences (for each edge) and individual BCI scores were averaged over 5 regions, namely, executive,

382 pre/motor, parietal, temporal and occipital, obtaining one mean correlation between functional areas (i.e. 5

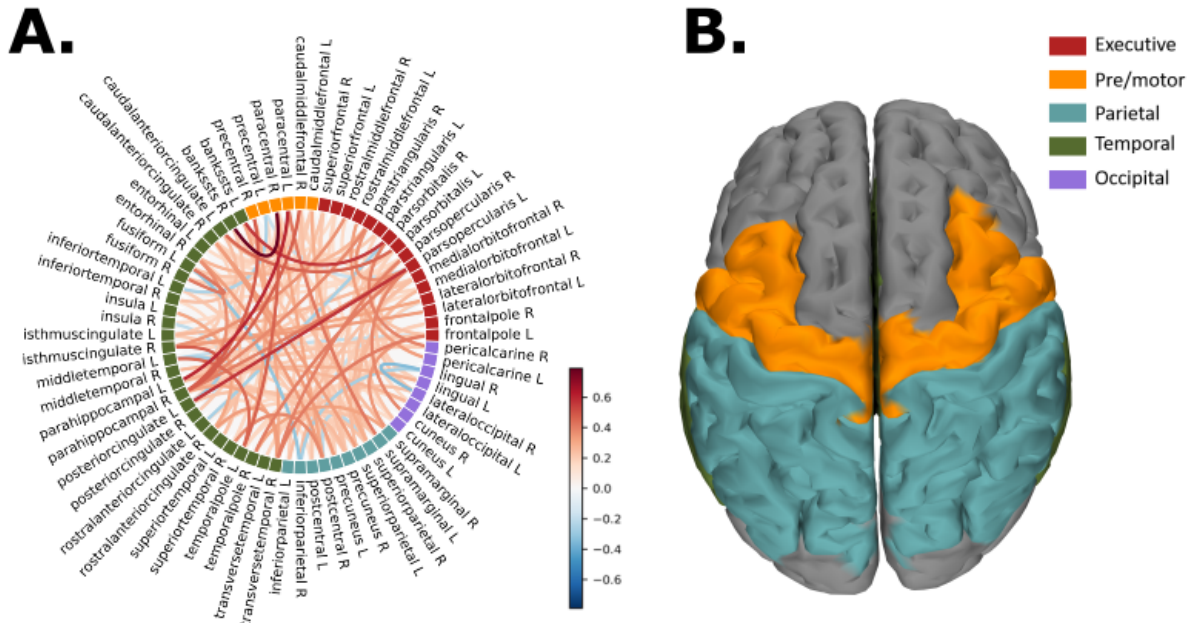
383 x 5 = 25 values). Then, the correlation coefficients were shuffled 10000 times, and each time surrogate
 384 average coefficients were obtained for each group of edges. These nulls were used to check if the edges
 385 with differences in transition probabilities that related to task performance clustered in any specific area.
 386 All statistical analyses were BH corrected for multiple comparisons, as appropriate.
 387



388 **Fig. 2 Reliability analysis. A. Edge-wise differences in transition probability from the ground truth:**
 389 Reliably different task-based interactions over the subjects ($p < 0.05$, after correction for multiple
 390 comparison). **B. Edge-wise differences in transition probability between hit/miss trials:** Reliably
 391 different task-based interactions over the subjects ($p < 0.05$, after correction for multiple
 392 comparison). The reported edges are the ones where the difference observed between MI and Rest in the “hit” trials was
 393 greater than that found in the “miss” trials. **C. Node-wise differences in transition probability - on the**
 394 **left: computed from the trials according to the stimulus presented to the subject (“ground truth”);**
 395 **on the right: from the “hit/miss trials”:** the color scale is proportional to the nodal degree derived from
 396 the matrix with the group-significant differences (the brighter the color, the more edges that differ between
 397 tasks are incident upon that node).
 398



399
400 **Fig. 3 - Classification analysis.** A & D. **Group-level classification performance obtained from MEG**
401 **and EEG data:** for each classification tool (respectively, in purple to the left, CSP+SVM and in salmon
402 to the right, ATM+SVM) each dot corresponds to the accuracy obtained for a given subject and a given
403 split. B & E. **Individual-level classification performance from MEG data and EEG data:** each dot
404 corresponds to the accuracy averaged over the 50 splits obtained from a given subject. The x-axis refers to
405 the accuracy of ATM+SVM, while the y-axis refers to the accuracy of CSP+SVM. The dashed black line
406 represents equal accuracy for both methods. Therefore, the dots below (resp. above) the line represents the
407 subjects for which ATM+SVM performed better (resp. worse) than CSP+SVM. Dots have been color coded
408 accordingly: in salmon, the subjects for whom ATM+SVM were statistically more accurate than the
409 CSP+SVM; in violet, the subjects for whom CSP+SVM were statistically more accurate than the
410 ATM+SVM, and in gray, the subjects where the two methods did not yield statistically different
411 performances. C & F. **Individual-level classification performance variability from MEG data and**
412 **EEG data:** each dot corresponds to the standard deviation over the 50 splits obtained from a given subject.
413 The dashed black line represents equal variability for both methods. The x- and y-axis have been coded in
414 descending value order so that the dot distribution can be read similarly as in the previous plots, with dots
415 below (resp. above) the dashed line representing subjects for whom ATM+SVM led smaller (resp. greater)
416 variability than CSP+SVM. The color code is identical to the plots B and E, so that salmon (resp. violet)
417 dots represent the subjects for whom ATM+SVM *accuracy* was significantly better (resp. worse) than the
418 *accuracy* of CSP+SVM. We chose to keep the color code constant to allow for more direct comparison of
419 the performance (accuracy and variability) of both methods.



420
 421 **Fig. 4 Correlation analysis.** **A. Edge-wise correlations:** edge-wise correlation with BCI scores. For
 422 visualization purposes, only the edges with p -values < 0.05 are visualized. The color of the edges is
 423 proportional to the correlation coefficient. **B. Node-wise differences in transition probabilities:** the
 424 picture shows the functional-areas averaged correlation coefficients. In orange the pre/motor areas, in
 425 turquoise the parietal lobe.
 426

427 STAR Methods

428 Key-resources table

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
Code used for the analysis	https://github.com/mccorsi/NeuronalAvalanches4BCI.git	N/A
Brainstorm	https://github.com/brainstorm-tools/brainstorm3	Article: http://www.hindawi.com/journals/cin/2011/879716/
MNE-python	https://github.com/mne-tools/mne-python	Article: 10.1016/j.neuroimage.2013.10.027
Scikit-learn	https://github.com/scikit-learn/scikit-learn	Article: https://jmlr.csail.mit.edu/papers/v12/pedregosa11a.html
MOABB	https://github.com/NeuroTechX/moabb	Article: https://iopscience.iop.org/article/10.1088/1741-2552/aadea0

429 Resource availability

430 Materials availability

431 Given the personal nature of the data, it is not possible to make it public now. However, the data
432 is available upon request to the corresponding authors for the purpose of replication.

433

434 Data and code availability

435 • The conception of the protocol was done before changes in the French legislation regarding
436 the data sharing process. Therefore, there is a substantial number of requirements to be met
437 before being allowed to share the data. At this point, it is not possible to make the data
438 public now. However, the data is available upon request to the corresponding authors for
439 the purpose of replication.

- 440 • The code is publicly available at <https://github.com/mccorsi/NeuronalAvalanches4BCI.git>.
- 441 • Any additional information required to reanalyze the data reported in this work paper is
442 available from the lead contact upon request.

443

444 Experimental model and study participant details

445 The research was conducted in accordance with the Declaration of Helsinki. A written informed
446 consent was obtained from subjects after explanation of the study, which was approved by the
447 ethical committee CPP-IDF-VI of Paris. All participants received financial compensation at the
448 end of their participation. Twenty healthy subjects (27.5 ± 4.0 years old, 12 men), with no medical
449 or psychological disorder, were recruited. They participated in a BCI experiment where MEG and
450 EEG were simultaneously recorded. A description of the participants characteristics is provided in
451 the Table S1. In the French legislation is not allowed to register the ancestry, race, or ethnicity of

452 the participants unless the main aim of the protocol is the assessment of the effect of such
453 information on the observations. Therefore, the authors cannot provide such participant
454 information.

455

456 **Method Details**

457 **BCI experiment**

458 We used the dataset from Corsi et al²⁹. The BCI task consisted of a standard two-target box task⁴³,
459 where the subjects were instructed to modulate their alpha and/or beta band brain activity to control
460 the vertical position of a moving cursor to hit a gray vertical bar, referred as the target, displayed
461 on the right part of the screen. To hit the “up-target” the subjects had to perform a sustained hand
462 motor imagery (MI) of the right-hand grasping and to hit the “down-target”, the subjects were
463 instructed to remain at rest. Each run was composed of 32 trials each with either up and down
464 targets, respectively associated with MI and Rest instructions, equally and randomly distributed
465 across trials. The online BCI experiment was composed of two phases (see Figure S10):

466 i) the training phase, divided in five consecutive runs without providing any feedback, meaning
467 that the gray target was the only element displayed on the screen. Each trial consisted of 1s of
468 inter-stimulus interval (ISI) followed by 5s of target presentation. At the end of the training phase,
469 offline analysis consisted of extracting R-square maps from the power spectra computed from the
470 collected data to plot contrast maps between conditions to elicit the most relevant information,
471 namely the (channel; frequency bins) couples of interest that best discriminate the subjects’ intent,
472 to train the classifier.

473 ii) the testing phase was made of six runs where the feedback, consisting of a moving cursor, was
474 provided. Each trial consisted of 1s of ISI, followed by 5s of target presentation. The feedback was
475 provided from $t=3s$ to $t=6s$. It consists of a cursor that starts from the left to the right part of the
476 screen with a fixed velocity. Experimenters instructed the subjects to start to either remain at rest
477 or to perform a sustained MI task as soon as they saw the target, i.e. at $t=1s$. The online features
478 were obtained from the estimation of the power spectra via an autoregressive model that relied on
479 the maximum entropy method⁴⁴ every 28ms on a time window of 0.5s. These features were
480 classified using the Linear Discriminant Analysis (LDA) method. The feedback provided to the
481 subject, namely the vertical position of the moving cursor, relied on the linear combination of the
482 computed features via the moving average method⁴⁵. The BCI performance used in this study
483 refers to the proportion of trials in which the subjects could control the vertical position of the
484 moving cursor to hit the target. In this work, the analysis relied on the data obtained from the
485 testing phase.

486

487 **M/EEG data acquisition and preprocessing**

488 EEG signals were recorded with a 74 EEG-channel system, with Ag/AgCl passive sensors
489 (Easycap, Germany) placed according to the standard 10-10 montage, with the references placed
490 at the mastoids, and the ground electrode located at the left scapula. MEG signals were recorded
491 via a system composed of 102 magnetometers and 204 gradiometers (MEGIN Neuromag TRIUX

492 MEG system). M/EEG signals were simultaneously recorded in a magnetic shielding room with a
 493 bandwidth of 0.01-300Hz and a sampling frequency of 1kHz. Head positions were digitized via
 494 the Polhemus Fastrak digitizer (Polhemus, Colchester, VT). Three points were used as landmarks
 495 to provide co-registration with the individual anatomical MRI: nasion, left and right pre-auricular
 496 points. Individual T1 sequences (256 sagittal slices, TR=2.40ms, TE=2.22ms, 0.80mm isotropic
 497 voxels, 300x320 matrix; flip angle=9°) were acquired with a 3T Siemens Magnetom PRISMA
 498 after the BCI experiments. Subjects were instructed to remain at rest for 15 minutes. Images were
 499 preprocessed with the FreeSurfer toolbox⁴⁶ and imported to the Brainstorm toolbox⁴⁷ where the
 500 digitized locations of the landmarks, and of the EEG electrodes were aligned with the MRI.

501 To remove the environmental noise in MEG signals, we applied the temporal extension of the
 502 Signal Space Separation (tSSS) with MaxFilter⁴⁸. To remove ocular and cardiac artifacts, we
 503 performed an Independent Components Analysis (ICA) via the Infomax approach with the
 504 Fieldtrip toolbox^{49,50}. Only the components that contained physiological artifacts were removed
 505 through a visual inspection of the signals. Once the data was preprocessed, we cut the recordings
 506 into epochs of 7 seconds.

507 Source reconstruction was performed by the computation of individual head models with the
 508 Boundary Element Method (BEM)^{51,52} where the surfaces were obtained from three layers related
 509 to the individual MRI (scalp, inner skull, outer skull) that contained 1922 vertices each. Sources
 510 were estimated via the weighted Minimum Norm Estimate (wMNE)^{53,54}. In this work, we used the
 511 Desikan parcellation scheme⁵⁵. The list of the regions of interest is available in the Table S2.

512 For a complete description of the preprocessing steps, please refer to Corsi et al²⁹.

513

514 **Data pipeline**

515 Each source-reconstructed signal was z-scored (over time), thresholded, and set to 1 when above
 516 threshold, and to zero otherwise (threshold: $z = |3|^{10}$). Note that each region was z-scored
 517 independently (over time). Then, an avalanche was defined as starting when at least one region is
 518 above threshold, and as finishing when no region is active. For each avalanche, we estimated a
 519 transition matrix, structured with regions in rows and columns, and the ij-th edge is defined as the
 520 probability that regions j would be active at time t+1, given region i was active at time t^{13,56}. To
 521 consider the intra-regional dynamics, the main diagonal of the transition matrix contains the
 522 probability that if a region is recruited by an avalanche, it will keep being active at the successive
 523 time step. For each subject, we obtained an average transition matrix (i.e. averaging edge-wise
 524 over all avalanches) for the baseline condition, and an average transition matrix for the hand motor
 525 imagery task. To ensure appropriate sampling⁵⁷, we have binned the data with bins ranging from
 526 1 to 3 (stopping at three to avoid aliasing). To select the optimal binning, we looked at the
 527 branching ratio, since a branching ratio ~ 1 typically indicates a process operating near a critical
 528 regime. The branching ratio is calculated as the geometrically averaged (over all the time bins)
 529 ratio of the number of events (activations) between the subsequent time bin (descendants) and that
 530 in the current time bin (ancestors) - eq.1, as:

$$531 \quad \sigma_i = \prod_{j=1}^{N_{bin}-1} \left(\frac{n_{events}(j+1)}{n_{events}(j)} \right)^{\frac{1}{N_{bin}-1}} \quad (1)$$

532 and then geometrically averaging it over all the avalanches - eq.2²².

$$533 \quad \sigma = \prod_{i=1}^{N_{aval}} (\sigma_i)^{\frac{1}{N_{aval}}} \quad (2)$$

534 where σ_i is the branching parameter of the i -th avalanche in the dataset, N_{bin} is the total amount of
535 bins in the i -th avalanche, $n_{events}(j)$ is the total number of events active in the j -th bin, and N_{aval} is
536 the total number of avalanches in each participant's recording.

537 In branching processes, a branching ratio of $\sigma = 1$ indicates critical processes with activity that is
538 highly variable and nearly sustained, $\sigma < 1$ indicates subcritical processes in which the activity
539 quickly dies out, and $\sigma > 1$ indicates supercritical processes in which the activity increases as
540 runaway excitation. The bin length equal to one sample yielded a $\sigma = 1$, hinting at the avalanches
541 as occurring in the context of a dynamical regime near operating near criticality, was chosen for
542 subsequent analyses. Importantly, the other binnings also yielded branching ratios extremely close
543 to 1 (0.995, and 0.978 for binnings 2 and 3, respectively), and the results of the analyses remain
544 unchanged, showing resilience to the details of the pipeline. However, one should notice that this
545 particular dataset entails rather short epochs and, as such, it is not best suited for the evaluation of
546 a long tail. This is all the more true considering that a stimulus was being delivered and, as such,
547 the dynamics was not evolving unperturbed.

548 In order to compare how the trials are encoded in the data, we provide a comparison with standard
549 feature extraction techniques, we computed the power spectra, via the Welch method with a
550 window length of 1 s and a window overlap ratio of 50%, the event-related
551 desynchronization/synchronization (ERD/S) effects via Morlet wavelets with a central frequency
552 of 1Hz and a time resolution of 3s between 3 and 40Hz^{58,59}, and the phase-locking value, as in
553 Lachaux et al⁶⁰. The PLV was chosen for its straight-forward interpretation, and for its theoretical
554 assumptions (i.e. stationarity of the signal), which is different from the one of the ATMs. Even
555 though working in the source space may mitigate the volume conduction effects⁶¹, it is important
556 to mention that the PLV method is influenced by zero-lag interactions, which might be either true
557 interactions or spurious correlations induced by the field-spread.

558 For these analyses, the classification of the trials as MI or RS was based on the outcome of the
559 experiment. To explore the robustness of our results to different classification algorithms, we also
560 classified the trials as MI/RS based on either Linear Discriminant Analysis or a Support Vector
561 Machine. The results showed that our conclusions are robust to the classification algorithm (see
562 Figure S6).

563

564 **Classification analysis**

565 To assess the extent to which the ATMs might be considered as an alternative feature for BCIs,
566 we compared the classification performance resulting from a feature extraction approach based
567 respectively on the ATMs and on spatial filters, namely Common Spatial Patterns (CSP)^{18,19}. In
568 addition, as a preliminary study, we also tested the classification performance associated with other
569 features such as the power-spectra (of the source-reconstructed time-series) and the phase-locking
570 values. All the considered features were classified with two different techniques, namely linear
571 discriminant analysis (LDA) and support vector machines (SVM). We obtained the best

572 classification performance using CSP followed by the Support Vector Machine (SVM) classifier.
573 Therefore, we selected this framework as the benchmark against which ATMs were compared.
574 For each subject, we divided the dataset to include 80% of the trials in the train split and 20% of
575 the trials in the test split. The classification scores for all pipelines were evaluated with an accuracy
576 measurement using a random permutation cross-validator. 50 re-shuffling and splitting iterations
577 were performed. The SVM was trained using either the CSPs or the ATMs. For each subject, the
578 CSP method decomposes the source-reconstructed signals using spatial filters, and then selects the
579 n modes that capture most inter-class variance. Here, we selected eight spatial modes (since they
580 yielded the best classification accuracy) and returned the average power of each. As for the ATMs,
581 for each subject we found the optimal z-score threshold for identifiability. Then, we fed an SVM
582 classifier with either feature (CSP-filtered data or ATM). Finally, we compared the classification
583 performance (i.e. the proportion of correctly labeled trials) for CSP+SVM and ATM+SVM, over
584 50 random splits of the data. For each subject, we ran t-tests (and confirmed them with Wilcoxon)
585 under the null hypothesis that CSP+SVM and ATM+SVM would not yield a statistically different
586 performance in trial classification. We repeated this comparison for all the subjects and corrected
587 the statistical comparisons for multiple comparisons across subjects using the False Discovery
588 Rate (FDR). To calculate the inter-subject variability, we used the standard deviation of the
589 classification performance across splits and subjects. As per the intra-subject variability, we
590 calculated the standard deviation of the classification accuracy across the 50 splits for each subject.
591 To estimate the computational time required to extract and to classify the features, we used a built-
592 in function in python.

593

594 **Quantification and statistical analysis**

595 For each subject, we computed the difference in the probability of a perturbation running across a
596 given edge during resting-state and during the MI task. To statistically validate this, for each
597 individual, we randomly shuffled the labels of the individual avalanches (i.e. each trial-specific
598 transition matrix was randomly allocated to either resting-state and hand motor imagery). We
599 performed this procedure 10000 times, obtaining, for each edge, the distribution of the differences
600 given the null-hypothesis that the transition matrices would not capture any difference between the
601 two conditions. Note that this approach does not require normality of the original distributions.
602 We used the null distribution to obtain a statistical significance for each edge. The retrieved
603 significances were Benjamini-Hochberg-corrected for multiple comparisons across edges¹⁶.
604 Following this procedure, we obtained for each patient, a matrix with the edges that significantly
605 differed from the two conditions. We then looked at the concordance of such matrices across
606 subjects, as to only focus on the edges that are reliably related to the task at hand. We have only
607 selected those edges that were significant in a higher-than-chance number of subjects. Finally, we
608 selected only those nodes that had more significantly different edges incident upon them, as
609 compared to chance level. This way, we selected the areas whose involvement in large-scale
610 dynamics is qualitatively different, in multiple subjects, between the two conditions (i.e. RS vs.
611 MI task), and refer to these as the “task-specific” areas.

612 Then, we moved on to check what edges differed related to the BCI performance. To this end, we
613 related, for each edge, the individual differences in the transition probabilities in the two
614 experimental conditions to the individual BCI performances. We then grouped the edges according
615 to functional areas, namely: executive areas, pre/motor areas, parietal areas, temporal areas, and
616 occipital areas. To statistically validate this approach, for 10000 we have randomly allocated the
617 edges to these groups and computed the average correlation coefficient at each iteration for each
618 group of edges. We used these averages to build a null-distribution for each functional area, and
619 used to have a statistical significance. Finally, these significances were corrected across functional
620 regions using the BH correction for multiple comparison. We have repeated the correlation
621 analysis without grouping the regions into functional areas but carrying out the correlation analysis
622 for each region separately. In this case, no single region survived the BH correction (not shown).
623 Finally, we replicated our results using the Destrieux parcellation scheme⁶² (the associated list of
624 the regions of interest is available in the Table S2) and using the electroencephalogram.
625 Furthermore, we repeated the analysis changing the threshold to define active regions.

626

627

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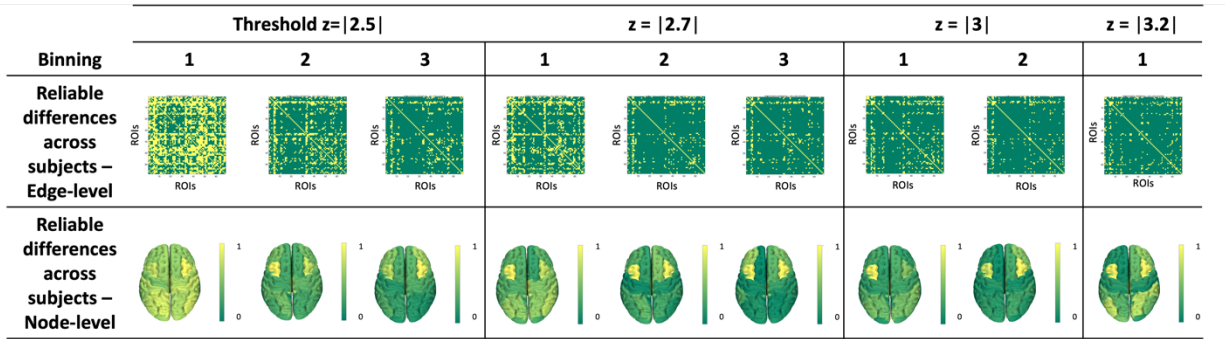
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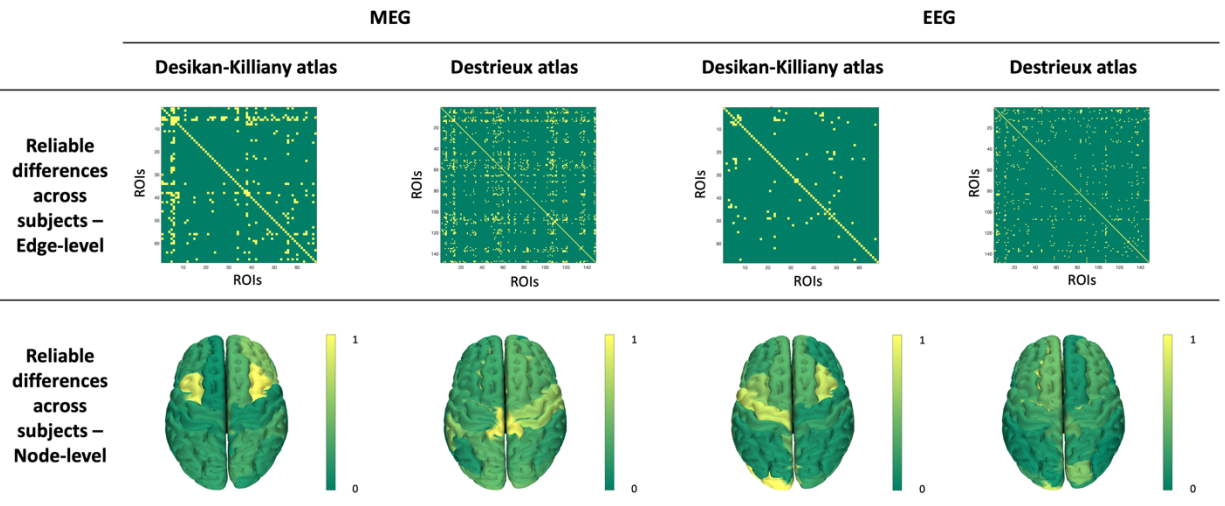
786 **Supplementary materials**



787

788 **Figure S1. Replication analysis across thresholds and binnings, related to Figure 2.**

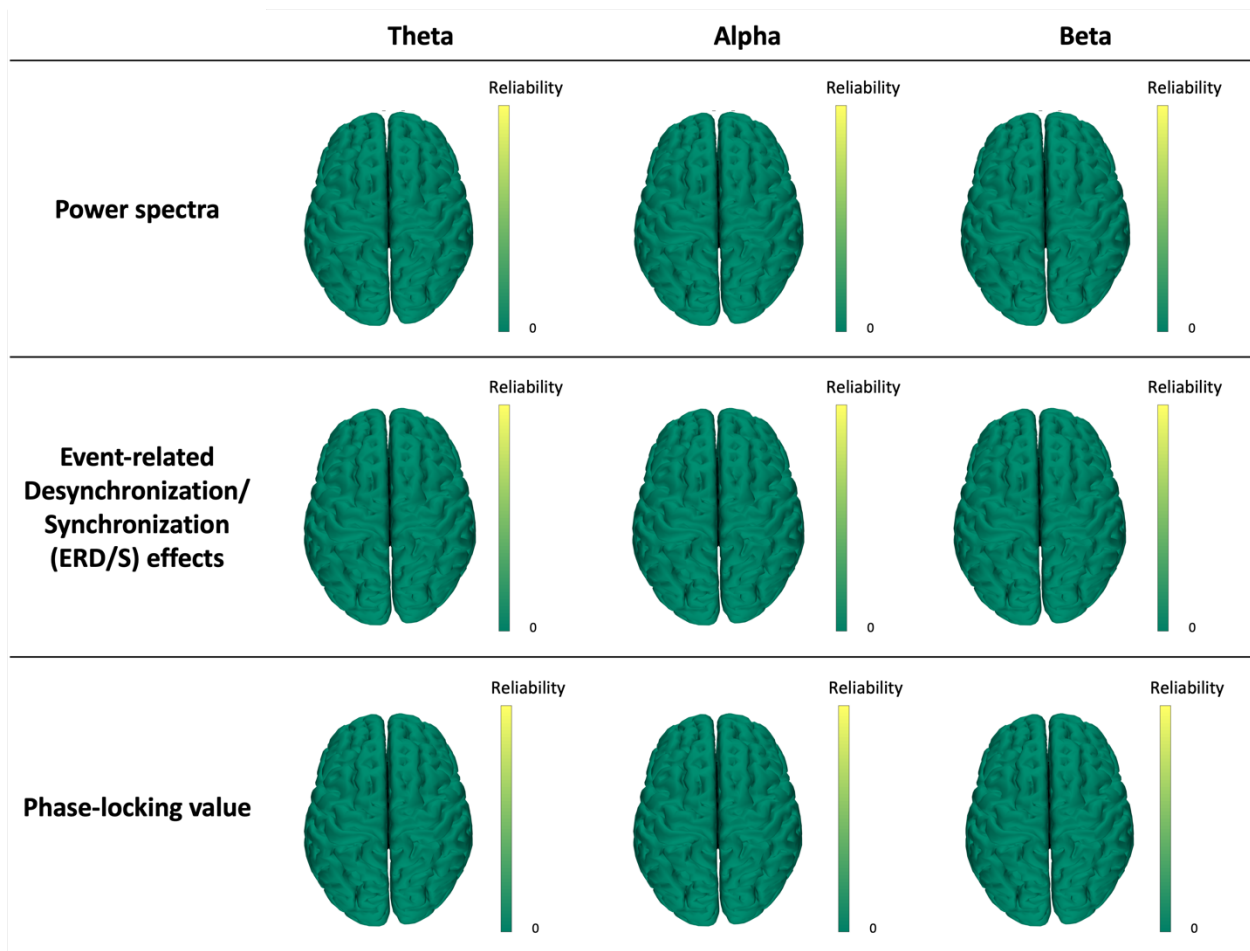
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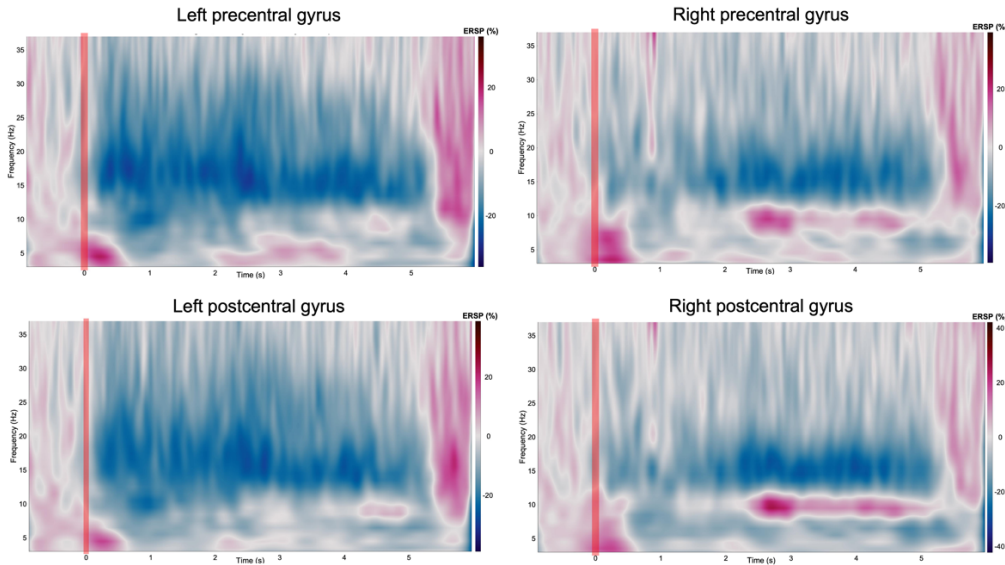
791 **Figure S2. Replication analysis using EEG and the Destrieux atlas, related to Figure 2.**

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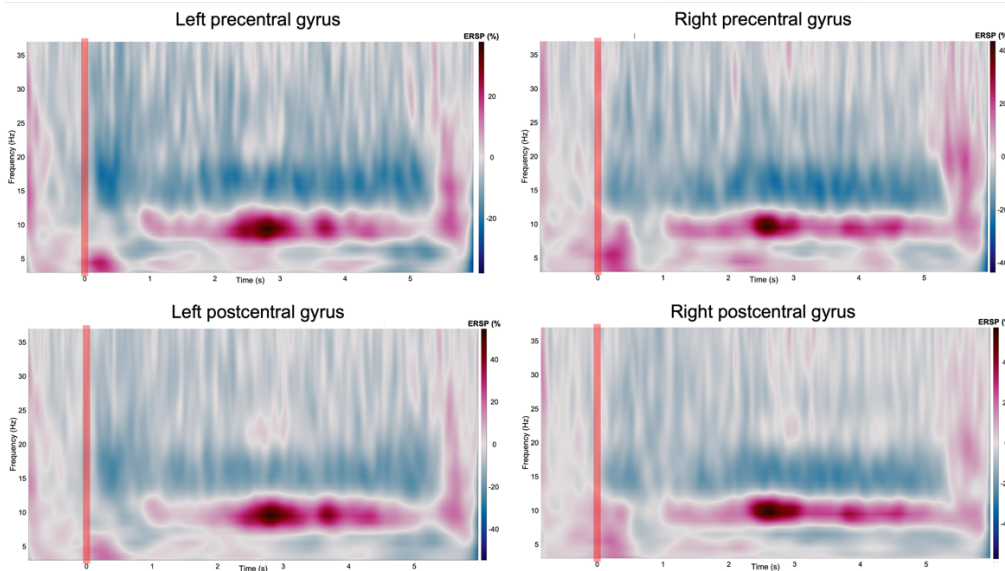
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Figure S3. Reliability analysis performed on MEG data on features extracted respectively via power spectra, event-related desynchronization/synchronization (ERD/S) effects, and phase-locking value estimators, related to Figure 2.



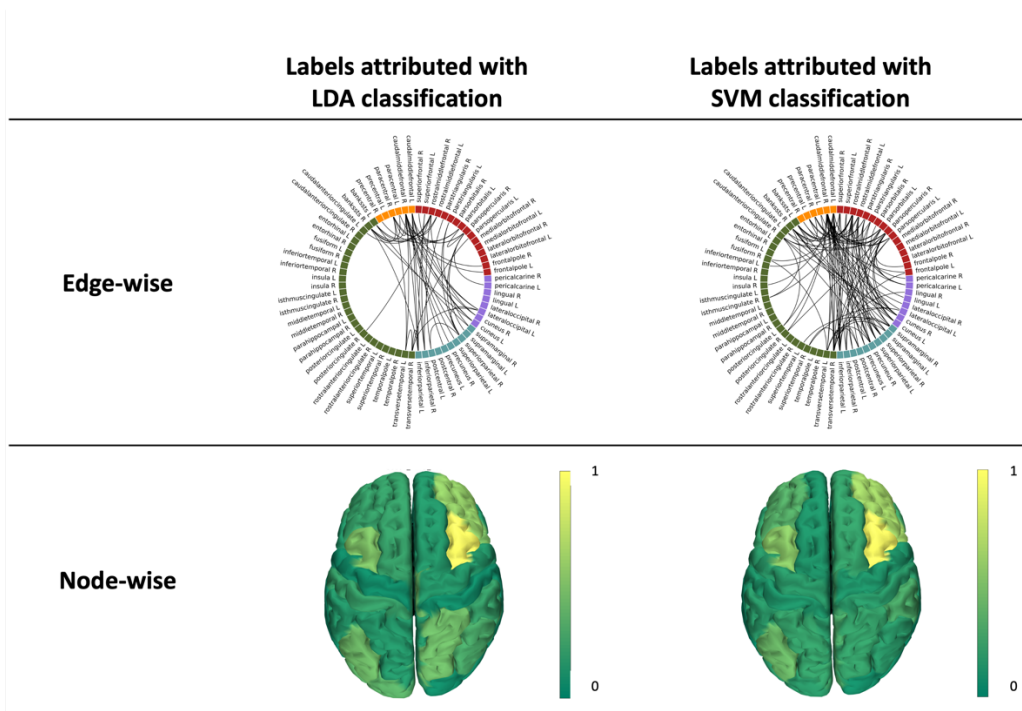
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799 **Figure S4. Grand average time-frequency analysis in Motor Imagery condition (n=20, MEG, Desikan-**
 800 **Kiliany) with ERD/S within the left and the right precentral gyri (first line) and the left and the right**
 801 **postcentral gyri (second line), related to Figure 2. t=0s corresponds to the moment when the target is**
 802 **displayed on the screen. t=5s corresponds to the moment when the result (ie hit/miss) is provided to the**
 803 **subjects.**
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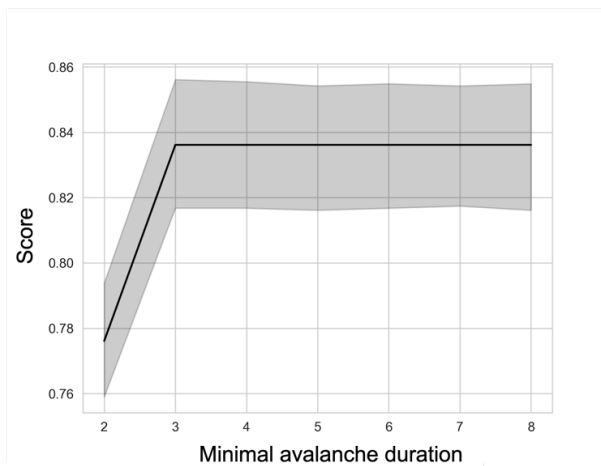
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806 **Figure S5. Grand average time-frequency analysis in the Rest condition (n=20, MEG, Desikan-**
 807 **Kiliany) with ERD/S within the left and the right precentral gyri (first line) and the left and the right**
 808 **postcentral gyri (second line), related to Figure 2. t=0s corresponds to the moment when the target is**
 809 **displayed on the screen. t=5s corresponds to the moment when the result (ie hit/miss) is provided to the**
 810 **subjects.**

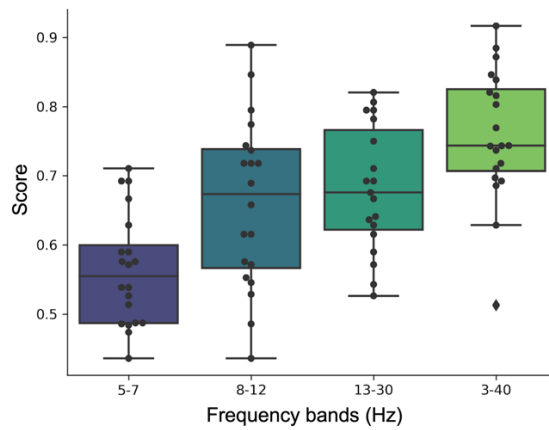


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812 **Figure S6. Influence of the classification tool on the reliability patterns edge and node-wise ($p < 0.05$,**
 813 **BH corrected), related to Figure 2. On the left, the differences are derived from trial classification based**
 814 **on linear discriminant analysis (LDA), while on the right, the differences are derived from trial classification**
 815 **based on support vector machine (SVM).**
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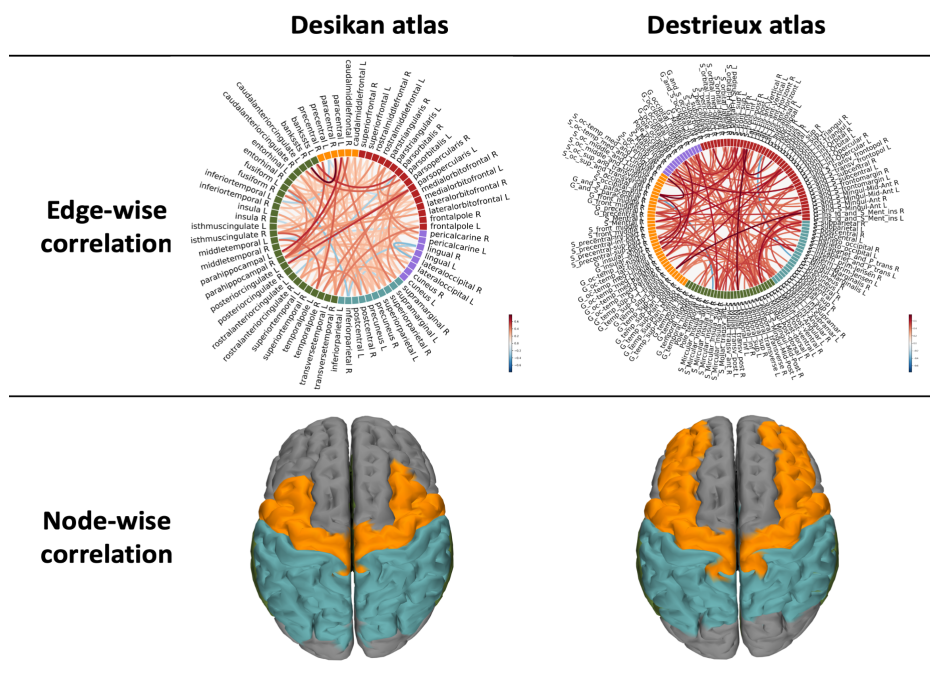


817 **Figure S7. Influence of the minimal duration of the avalanches used to compute the ATM on the**
 818 **classification performance (with $|z| = 3$), related to Figure 3.**
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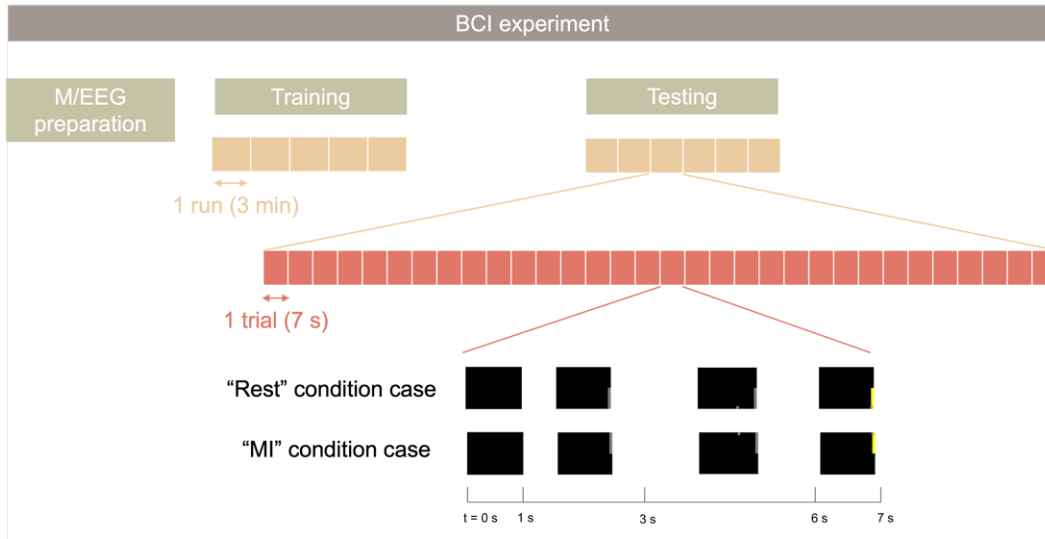
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Figure S8. Influence of the frequency band on the classification performance with ATMs, related to Figure 3. For each frequency band, we plotted the distribution of the individual performance. Each dot represents the median of the scores obtained over the splits for each subject.



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Figure S9. Replication analysis on MEG data using the Desikan and the Destrieux atlases, related to Figure 4. For visualization purposes, only the edges with $|r| > 0.6$ are visualized. The color of the edges is proportional to the correlation coefficient.



831

832 **Figure S10. Online BCI experiment, related to STAR Methods.**

833

834 **Table S1. Participants characteristics, related to STAR Methods.**

#Subject	Age	Gender (Male/Female)	BCI Score (%)
1	19	M	89.3
2	30	M	38.1
3	29	M	86.1
4	31	M	73.1
5	33	M	63.9
6	26	M	88.9
7	27	F	56.7
8	27	F	70.0
9	22	F	60.0
10	27	F	66.1
11	35	F	63.3
12	29	F	53.9
13	26	M	77.2
14	33	F	69.2
15	22	M	80.0
16	30	F	61.1
17	27	M	71.0
18	28	M	73.0
19	28	M	68.3
20	23	M	56.7

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836 **Table S2. List of regions of interests used in the study associated respectively with the Desikan-**
837 **Killiany and the Destrieux atlases, related to STAR Methods.**
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#ROI	Desikan-Killiany atlas	Destrieux atlas
#1	bankssts L	G_Ins_Ig_and_S_cent_ins L
#2	bankssts R	G_Ins_Ig_and_S_cent_ins R
#3	caudalanteriorcingulate L	G_and_S_cingul-Ant L
#4	caudalanteriorcingulate R	G_and_S_cingul-Ant R
#5	caudalmiddlefrontal L	G_and_S_cingul-Mid-Ant L
#6	caudalmiddlefrontal R	G_and_S_cingul-Mid-Ant R
#7	cuneus L	G_and_S_cingul-Mid-Post L
#8	cuneus R	G_and_S_cingul-Mid-Post R
#9	entorhinal L	G_and_S_frontomargin L
#10	entorhinal R	G_and_S_frontomargin R
#11	frontalpole L	G_and_S_occipital_inf L
#12	frontalpole R	G_and_S_occipital_inf R
#13	fusiform L	G_and_S_paracentral L
#14	fusiform R	G_and_S_paracentral R
#15	inferiorparietal L	G_and_S_subcentral L
#16	inferiorparietal R	G_and_S_subcentral R
#17	inferiortemporal L	G_and_S_transv_frontopol L
#18	inferiortemporal R	G_and_S_transv_frontopol R
#19	insula L	G_cingul-Post-dorsal L
#20	insula R	G_cingul-Post-dorsal R
#21	isthmuscingulate L	G_cingul-Post-ventral L
#22	isthmuscingulate R	G_cingul-Post-ventral R
#23	lateraloccipital L	G_cuneus L
#24	lateraloccipital R	G_cuneus R
#25	lateralorbitofrontal L	G_front_inf-Opercular L
#26	lateralorbitofrontal R	G_front_inf-Opercular R
#27	lingual L	G_front_inf-Orbital L
#28	lingual R	G_front_inf-Orbital R
#29	medialorbitofrontal L	G_front_inf-Triangul L
#30	medialorbitofrontal R	G_front_inf-Triangul R
#31	middletemporal L	G_front_middle L
#32	middletemporal R	G_front_middle R
#33	paracentral L	G_front_sup L
#34	paracentral R	G_front_sup R
#35	parahippocampal L	G_insular_short L
#36	parahippocampal R	G_insular_short R
#37	parsopercularis L	G_oc-temp_lat-fusifor L
#38	parsopercularis R	G_oc-temp_lat-fusifor R
#39	parsorbitalis L	G_oc-temp_med-Lingual L
#40	parsorbitalis R	G_oc-temp_med-Lingual R
#41	parstriangularis L	G_oc-temp_med-Parahip L
#42	parstriangularis R	G_oc-temp_med-Parahip R
#43	pericalcarine L	G_occipital_middle L
#44	pericalcarine R	G_occipital_middle R
#45	postcentral L	G_occipital_sup L
#46	postcentral R	G_occipital_sup R
#47	posteriorcingulate L	G_orbital L
#48	posteriorcingulate R	G_orbital R
#49	precentral L	G_pariet_inf-Angular L
#50	precentral R	G_pariet_inf-Angular R
#51	precuneus L	G_pariet_inf-Supramar L
#52	precuneus R	G_pariet_inf-Supramar R

#53	rostralanteriorcingulate L	G_parietal_sup L
#54	rostralanteriorcingulate R	G_parietal_sup R
#55	rostralmiddlefrontal L	G_postcentral L
#56	rostralmiddlefrontal R	G_postcentral R
#57	superiorfrontal L	G_precentral L
#58	superiorfrontal R	G_precentral R
#59	superiorparietal L	G_precuneus L
#60	superiorparietal R	G_precuneus R
#61	superiortemporal L	G_rectus L
#62	superiortemporal R	G_rectus R
#63	supramarginal L	G_subcallosal L
#64	supramarginal R	G_subcallosal R
#65	temporalpole L	G_temp_sup-G_T_transv L
#66	temporalpole R	G_temp_sup-G_T_transv R
#67	transversetemporal L	G_temp_sup-Lateral L
#68	transversetemporal R	G_temp_sup-Lateral R
#69		G_temp_sup-Plan_polar L
#70		G_temp_sup-Plan_polar R
#71		G_temp_sup-Plan_tempo L
#72		G_temp_sup-Plan_tempo R
#73		G_temporal_inf L
#74		G_temporal_inf R
#75		G_temporal_middle L
#76		G_temporal_middle R
#77		Lat_Fis-ant-Horizont L
#78		Lat_Fis-ant-Horizont R
#79		Lat_Fis-ant-Vertical L
#80		Lat_Fis-ant-Vertical R
#81		Lat_Fis-post L
#82		Lat_Fis-post R
#83		Pole_occipital L
#84		Pole_occipital R
#85		Pole_temporal L
#86		Pole_temporal R
#87		S_calcarine L
#88		S_calcarine R
#89		S_central L
#90		S_central R
#91		S_cingul-Marginalis L
#92		S_cingul-Marginalis R
#93		S_circular_insula_ant L
#94		S_circular_insula_ant R
#95		S_circular_insula_inf L
#96		S_circular_insula_inf R
#97		S_circular_insula_sup L
#98		S_circular_insula_sup R
#99		S_collat_transv_ant L
#100		S_collat_transv_ant R
#101		S_collat_transv_post L
#102		S_collat_transv_post R
#103		S_front_inf L
#104		S_front_inf R
#105		S_front_middle L
#106		S_front_middle R
#107		S_front_sup L
#108		S_front_sup R

#109	S_interm_prim-Jensen L
#110	S_interm_prim-Jensen R
#111	S_intrapariet_and_P_trans L
#112	S_intrapariet_and_P_trans R
#113	S_oc-temp_lat L
#114	S_oc-temp_lat R
#115	S_oc-temp_med_and_Lingual L
#116	S_oc-temp_med_and_Lingual R
#117	S_oc_middle_and_Lunatus L
#118	S_oc_middle_and_Lunatus R
#119	S_oc_sup_and_transversal L
#120	S_oc_sup_and_transversal R
#121	S_occipital_ant L
#122	S_occipital_ant R
#123	S_orbital-H_Shaped L
#124	S_orbital-H_Shaped R
#125	S_orbital_lateral L
#126	S_orbital_lateral R
#127	S_orbital_med-olfact L
#128	S_orbital_med-olfact R
#129	S_parieto_occipital L
#130	S_parieto_occipital R
#131	S_pericallosal L
#132	S_pericallosal R
#133	S_postcentral L
#134	S_postcentral R
#135	S_precentral-inf-part L
#136	S_precentral-inf-part R
#137	S_precentral-sup-part L
#138	S_precentral-sup-part R
#139	S_suborbital L
#140	S_suborbital R
#141	S_subparietal L
#142	S_subparietal R
#143	S_temporal_inf L
#144	S_temporal_inf R
#145	S_temporal_sup L
#146	S_temporal_sup R
#147	S_temporal_transverse L
#148	S_temporal_transverse R

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