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1 Cortical sensorimotor activity in the execution and suppression of 2 discrete and rhythmic movements

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16 **Competing interests**

17 The author(s) declare no competing interests.

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19 Author Contributions

M.H., PG.Z., JC.B. and R.H. are responsible for the study concept and design.
M.H. acquired the data. The analysis and interpretation of data were carried

22 out by M.H., PG.Z. and R.H. The manuscript was drafted by M.H., PG.Z. and

23 R.H. All authors gave approval of the final submitted version.

24 Abstract

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25 Although the engagement of sensorimotor cortices in movement is well documented, the functional relevance of brain activity patterns remains ambigu-26 27 ous. Especially, the cortical engagement specific to the pre-, within-, and post-movement periods is poorly understood. The present study addressed 28 this issue by examining sensorimotor EEG activity during the performance as 29 well as STOP-signal cued suppression of movements pertaining to two distinct 30 classes, namely, discrete vs. ongoing rhythmic movements. Our findings indi-31 cate that the lateralized readiness potential (LRP), which is classically used as 32 33 a marker of pre-movement processing, indexes multiple pre- and in- movement-related brain dynamics in a movement-class dependent fashion. In- and 34 35 post-movement event-related (de)synchronization (ERD/ERS) observed in the Mu (8-13 Hz) and Beta (15-30 Hz) frequency ranges were associated with es-36 37 timated brain sources in both motor and somatosensory cortical areas. Notwithstanding, Beta ERS occurred earlier following cancelled than actually per-38 formed movements. In contrast, Mu power did not vary. Whereas Beta power 39 40 may reflect the evaluation of the sensory predicted outcome, Mu power 41 might engage in linking perception to action. Additionally, the rhythmic movement forced stop (only) showed a post-movement Mu/Beta rebound, 42 which might reflect an active "clearing-out" of the motor plan and its feed-43 44 back-based online control. Overall, the present study supports the notion that sensorimotor EEG modulations are key markers to investigate control or ex-45 ecutive processes, here initiation and inhibition, which are exerted when per-46 47 forming distinct movement classes.

48 Keywords

49 PMBR, inhibitory control, oscillations, time-frequency, source localization

Introduction 50

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51 It has long been known that when performing a voluntary action, cortical sensorimotor areas are engaged in movement planning, execution and 52 online control ¹. Most corresponding accumulated knowledge has been ac-53 quired in the context of the generation of discrete movement, which consti-54 tute an important, but not sole class of movements that humans can perform 55 ². Consequently, two aspects of action control and its neural sensorimotor un-56 derpinnings are strongly under-represented. On the one hand, we know little 57 58 about cortical sensorimotor engagement related to movement suppression, 59 even though both movement generation and suppression are commonplace in our interaction with the environment ³. On the other hand, previous investi-60 gations of neural activity when suppressing movements have focused exclu-61 sively on short-lived discrete movements and have then ignored the case of 62 63 ongoing-rhythmic movement suppression, which is also crucial in action control 4-7. The few studies at hand on sensorimotor activity related to action sup-64 pression have dealt with prepared discrete movements ⁸⁻¹¹, discrete move-65 ments sequence ^{12,13} or isometric force exertion ^{14,15}. Kinematically, discrete 66 67 actions are delimited by moments without movement (i.e., with zero velocity and acceleration), such as grasping an object. In contrast, continuous actions, 68 such as walking, lack recognizable endpoints and are typically considered 69 rhythmic if they constitute (periodic) repetitions of particular events². Motor 70 control encompasses both action classes, which differ not only regarding their 71 kinematics ¹⁶ but also in terms of movement dynamics and control processes 72 73 ^{17,18}, as well as of corresponding brain engagement ¹⁹. Indeed, the neural structures associated with controlling discrete and rhythmic actions differ 74 75 considerably ¹⁹⁻²¹, due to different timing and initiation mechanisms ^{17,20}. Additionally, integrating in- and post-movement sensory information shows dis-76 tinct dynamics between discrete and rhythmic action classes ^{22,23}, which may 77 involve open- and closed-loop control, respectively. As sensorimotor EEG ac-78 tivity has been linked to movement-related sensory integration in the frame-79 80 work of forward internal models of motor control (see below), its investigation 81 and comparison in both movement classes appears to be crucial.

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82 The present study aims to help providing a more complete picture of 83 the cortical sensorimotor activity underlying action control through the study of both the performance and suppression of movements belonging to two 84 fundamentally distinct classes, discrete and rhythmic movements. EEG activ-85 ity over sensorimotor areas was analyzed in terms of the lateralized readi-86 ness potential (LRP) and event-related (de)synchronization (ERS/D) of Mu (8 -87 13 Hz) and Beta (15 - 30 Hz) cortical oscillations. In addition, a second objec-88 tive was to provide new insights into understanding the functional relevance 89 90 of these movement-related neural sensorimotor activities with regard to ac-91 tion executive control.

92 Prior work has established standard non-invasive methods to explore movement-related brain activity. When recording scalp EEG, the LRP is be-93 lieved to reflect the central response preparation within the primary motor 94 95 cortex (M1) that control the movement ²⁴. As for brain oscillations, a well-defined pattern of activity has been described during and after movement exe-96 cution in Mu and Beta rhythms. This pattern is characterized by an ERD asso-97 98 ciated with the movement's execution, followed by an ERS subsequent to the 99 movement stop ²⁵. This ERD/ERS pattern has been recorded over sensorimotor areas for several (contrasting) movement conditions, including self-paced 100 and stimulus-triggered movements ^{26,27}, real and imagined movements ²⁸, as 101 well as discrete short responses and lasting rhythmic movements ^{29,30}. Espe-102 103 cially, the cortical ERD/ERS dynamics were clearly observed for each movement cycle in the case of low-frequency movement repetition (< 1 Hz), that 104 is, when the repetition was most likely due to a concatenation of discrete 105 106 movements. In contrast, it transformed into a sustained ERD during higher-107 frequency movement repetition, that is, when the movements were truly rhythmic ³⁰⁻³². 108

Despite the large number of studies reporting these movement-related neurophysiological modulations, their functional relevance remains debated. The LRP is thought to reflect the pre-movement M1 engagement as a final pathway for the central generation of movement, that is, the downstream specification of commands to the peripheral motor structures ³³. Accordingly, LRP is massively used as an index of movement initiation when triggering dis-

crete movement across multiple simple and choice reaction time tasks ^{34,35}. In 115 116 this context, LRP may follow a fixed-threshold dynamics, that is, the reaching a threshold activation amplitude determines whether the response will be 117 triggered or not ^{36,37}. Based on the assumption that the reach of this threshold 118 discriminates successfully from failed cancellations of a prepared discrete 119 movement ³³, LRP has become a popular tool for investigating discrete action 120 inhibition ³⁸⁻⁴¹. When performing a continuous action, an external signal may 121 indicate the performer to speed up 42 , continue 43 or stop 6,12,42 the ongoing ac-122 tion. In such cases, a new command specification might engage in the build-123 124 ing up of the motor activity. However, the purported assignment of LRP to 125 pre-movement processing has led to its dereliction for investigating the vol-126 untary modulation or suppression of an ongoing rhythmic movement. Indeed, 127 the very possibility of an LRP reduction has been ignored by the few studies exploring rhythmic movement stopping ^{7,43}. 128

129 The Mu/Beta ERD reflects the desynchronization of an ensemble of cortical neurons over sensorimotor brain areas. In contrast, the post-movement 130 131 Mu/Beta ERS reflects its neural resynchronization ⁴⁴. The Mu/Beta activity has 132 been initially suggested to echo a cortical idling state during "mental inactivity" ⁴⁵ or a "status guo" in maintaining the current sensorimotor or cognitive 133 state ⁴⁶. Although Mu and Beta tend to follow a similar pattern of activity and 134 135 can be mapped to a single dipole due to an overlap in their cortical sources, recent evidence showed that they index distinct neurological functions ⁴⁷. 136 These functions, which are still debated, have been proposed in the frame-137 work of forward internal models of motor control ⁴⁸, in which the sensory con-138 139 sequences of movement are predicted (through forward models) and com-140 pared to the actual sensory outcome. Indeed, the Mu rhythm has been considered as an alpha-like oscillation engaged in a "diffuse and distributed al-141 pha system", in reference to the multiple ~ 10 Hz rhythms originating from in-142 dependent brain sources ⁴⁹. Within this broad alpha system, the Mu rhythm 143 might reflect a perception-to-action translation ^{47,50}. Accordingly, Mu syn-144 chronicity occurs when visual and auditory representations are converted into 145 146 action-based representations. The potential distinction between sub-frequencies bands ⁴⁷ and the Mu involvement in inverse models ⁵¹ is still examined. 147

At any rate, the Mu rhythm is generally viewed as a correlate of the reciprocal interaction between motor and sensory cortices, this interaction being crucial in the internal models controlling the action.

According to recent reviews ^{47,52}, the Beta ERD reflects movement 151 preparation, including the adjustments of motor commands and the anticipa-152 tion of errors ⁵³. The Beta ERD modulation by movement uncertainty ⁵⁴ also 153 suggests that it plays a role in predicting the sensory consequences of the ac-154 155 tion. The observation of an above-baseline ERS following movement, known 156 as the post-movement Beta rebound (PMBR), led to multiple hypotheses. 157 Beta oscillations could reflect the post-movement processing of sensory reafference ⁵⁵. Indeed, the occurrence of PMBR after passive movements ⁵⁶ or 158 when accompanying peripheral nerve stimulation ⁵⁷ is consistent with the 159 idea that PMBR originates in sensory feedback to the motor cortices. More 160 specifically, the PMBR was proposed to index the integration of sensory feed-161 back to evaluate movement outcome, with any deviation from the forward-162 predicted outcome leading to an update of the motor plan⁴⁷. Alternatively, 163 164 PMBR could reflect the active inhibition of the motor cortex to terminate a 165 movement ⁵⁸. The observation of a single PMBR following a sequence of discrete movements ^{13,59} and its association to movement parameters such as 166 accuracy, variability, and rate of force development ^{60,61} have been taken as 167 168 an argument for its involvement in the active inhibition of the motor cortex 169 following movement termination.

170 All in all, multiple interpretations have been put forth to explain neural 171 sensorimotor activity before, during and after a movement. Additionally, in 172 relation to the ERD/ERS pattern, the brain activation found over both pre-(motor) and post-Rolandic (somatosensory) areas ^{50,52,62} contributes to blur 173 the numerous functional hypotheses. Still, experiments requiring both initia-174 175 tion and suppression of movement have tried to provide new insight into the 176 functionality of the sensorimotor ERD/ERS by showing that its occurrence depends on whether a movement is actually performed versus withheld ¹¹. The 177 cortical activity also differed between normal movement completion and 178 forced suppression ¹² and between guick and slow movement termination ¹⁴. 179 180 However, the characterization of the movement-related sensorimotor activity

suffers from large variation in the task parameters employed across studies (e.g., task duration and movement amplitude), which alters the corresponding neural activity, and has hampered the establishment of convincing functional interpretations ¹⁵.

185 To complement our understanding of the movement-related neural sensorimotor activity, the present study examined EEG activity when per-186 forming a movement and suppressing it. EEG was recorded in the context of 187 two fundamental classes of movement: discrete and rhythmic ones. Using a 188 189 graphic tablet, we asked participants to initiate a discrete movement after a 190 GO stimulus and pursue a rhythmic movement after a CONTINUE stimulus. In-191 frequently, a STOP signal following the primary stimulus indicated partici-192 pants to cancel the prepared-discrete movement or to stop the ongoingrhythmic one. Firstly, in line with the interpretation of LRP as a sign of move-193 194 ment preparation, we hypothesized its large amplitude following a GO stimulus to contrast with its absence following a CONTINUE stimulus, and the STOP 195 signal occurrence to reduce its amplitude in the discrete experiment only. 196 197 Secondly, following the assumption that Mu and Beta rhythms encode recip-198 rocal interactions between motor and sensory cortices to enable monitoring of movement, we expected to observe a sustained Mu ERD during ongoing 199 rhythmic movement ³⁰, reflecting the closed-loop processing of sensory infor-200 mation in the CONTINUE condition, and it to be aborted by movement sup-201 202 pression in the STOP condition. In contrast, we expected to indifferently observe a transient Mu ERD/ERS in discrete completed, successfully cancelled, 203 and unsuccessfully cancelled actions, as the movement is controlled in an 204 205 open-loop fashion, and to observe a transient and sustained Beta ERD, re-206 flecting motor activation, in the discrete and rhythmic condition, respectively. 207 Third, we anticipated a PMBR, reflecting the post-movement sensory "check", to be visible after movement suppression in the rhythmic STOP ¹⁴ and the dis-208 crete conditions, with differences between the discrete completed, success-209 fully cancelled, and unsuccessfully cancelled actions, for the movement out-210 come differs in each case ¹¹. 211

212 Method

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213 **Participants**

Fifteen healthy individuals (9 males, mean age 25 years, SD = 2.2) 214 served as voluntary participants. All were right-handed, as assessed by the 215 Edinburgh Handedness Inventory ⁶³, and had a normal or corrected-to-normal 216 217 vision. None of the participants reported a history of psychiatric or 218 neurological disorders. The study was conducted with the informed consent 219 of all participants according to the principles stated in the Declaration of 220 Helsinki, and the procedures were approved by the local research ethics committee (Comité de Protection des Personnes Sud-Ouest et Outre-Mer II; 221 ID-RCB: 2020-A03215-34). 222

223 **Procedures**

224 Experimental procedures

225 Participants performed two experiments that have been previously de-226 scribed ⁴³, and for which details are provided in Appendix A. Briefly, both ex-227 periments required participants to perform voluntary right-hand movements 228 on a graphic tablet using a stylus. In both experiments, the participants completed one practice block and 30 experimental blocks, each consisting of 20 229 230 trials. In the first experiment, visual GO stimuli called for the quick initiation of discrete-swipe movements (GO_D condition). Following the primary GO stim-231 232 ulus, a STOP signal was presented infrequently (in 25 % of trials, STOP_D con-233 dition), indicating the participants to cancel the prepared movement, leading to successful-STOP_D or fail-STOP_D trials. The experiment was designed follow-234 ing the recent guideline for stop-signal tasks ⁶⁴. In the second experiment, 235 236 participants executed self-paced rhythmic movements; a visual CONTINUE 237 stimulus called for the continuation of a rhythmic movement (CONTINUE condition). As in the first (discrete) experiment, infrequently (in 25 % of trials, 238 239 STOP_R condition), a STOP signal followed the primary CONTINUE stimulus to 240 order participants to stop the ongoing movement quickly. Following such 241 STOP trials, a rhythmic GO_R trial was added to reengage participants in the

242 rhythmic movement. In these GO_R trials, participants were instructed to tran-243 sit from a static position to an oscillating movement as soon as the GO stimulus (green or blue) was presented. In both the discrete and rhythmic experi-244 ment, the minimal delay between two trials was 3500ms and the primary 245 stimulus occurrence varied randomly in a 500 ms window. As such, the two 246 experiments are close in design in terms of the stimuli properties and the ef-247 fectors engaged in the movement production; their main difference consisted 248 249 in the movement type to perform and stop, namely prepared-discrete versus 250 ongoing-rhythmic movements.

251 *EEG recording and preprocessing*

252 Scalp EEG was recorded using an ActiveTwo system (BioSemi Instrumentation, 64 electrodes) with a sampling rate of 2048 Hz. The EEG 253 254 electrodes were cautiously positioned based on four anatomical landmarks 255 (i.e., nasion, inion, and preauricular points) in accordance with the 5 % 10/20 international system ⁶⁵. Additional electrodes were placed below and above 256 257 each eye. The data were online referenced to the BioSemi CMS-DRL 258 reference. All offsets from the reference were kept below 15 mV. The EEG data were filtered online with a frequency bandpass filter of 0.5-150 Hz. The 259 participant's arm was fixed on the table to restrain the movement to wrist 260 261 articulation and avoid muscular noise in the EEG signal due to substantial 262 contraction of the biceps and deltoid muscles. Continuous EEG data were 263 imported and preprocessed in bespoke scripts using functions from the 264 EEGLAB Matlab plugin ⁶⁶ :

- Visual inspection was used to remove channels with prominent
 artifacts in the continuous EEG.
- 267

The EEG data were then re-referenced to a common average.

- The data were partitioned into epochs of 3 s (locked to the primary stimulus onset; 1000 ms to 2000 ms).
- Those epochs containing values exceeding the average across the data segments by 5 SD were rejected.
- Scalp EEG data typically represent a mixture of activities originating from brain sources that are not separable based on channel data

solely. Independent component analysis (ICA) ⁶⁷ can be applied to 274 275 identify statistically independent signal components (ICs) spatially filtered from the 64 channels data. An ICA was applied to continuous 276 EEG data (concatenation of the EEG epochs) to identify 63 neural ICs 277 contributing to the observed scalp data. Using the ICLABEL classifier 278 ⁶⁸ over the 30 first ICs, components with less than 10% chance to 279 account for neural activity were considered as artifacts, and removed 280 281 from the EEG data structure, thus removing their contributions to the 282 observed EEG. The rejection was systematically verified by visual 283 inspection of component properties (time series, spectra, topography) 284 according to ICLABEL guidelines 68.

Across all participants, these procedures led to the omission of 8.6 % of the STOP trials in the discrete task (SD = 1.4 %) and 4.1 % of the rhythmic STOP trials (SD = 1.9 %).

288 Measures

289 *Reaction times (RT)*

The behavioral results of these experiments have been published separately ⁴³. Here and in the results section (below) we shortly present the behavioral measures that are essential to appreciate the main (EEG) results.

293 In the discrete experiment, RT_{GO} was calculated in the GO_D trials as the time between the primary stimulus onset and the response onset; the latter 294 was defined as the moment the reach had exceeded 5 % of the Euclidean dis-295 296 tance between the initial and furthest (i.e., end) position of the discretemovement response. As an inhibitory RT, each participant's RT_{STOP-D} was esti-297 mated using the integrative method for stop-signal tasks ^{64,69}. In the rhythmic 298 299 experiment, the movement-related StopTime was calculated as the time elapsed between the STOP signal onset and the end of the movement (i.e., 300 301 null velocity). Each participant's RT_{STOP-R} , that is, the time between the STOP 302 signal onset and the onset of movement alteration, was computed by identifying, within the StopTime, the first time point that the movement statistically 303 deviated from the set of uninterrupted movements in the phase space ⁴. 304

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305 Lateralized readiness potentials

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306 In each condition LRPs were computed (using customized scripts written on Matlab) to assess the build-up of cortical motor activity following the 307 primary stimulus (GO or CONTINUE). To this end, the EEG time series locked 308 to the primary stimulus onset were averaged following the subtraction of a 309 -200 to 0 ms pre-stimulus period as a baseline. The LRP was then derived 310 from the difference between electrodes C3 (the electrode over the contralat-311 312 eral motor cortex) and C4 (its ipsilateral counterpart). This was done for GO_{D} , 313 successful-STOP_D and fail-STOP_D trials in the discrete task and CONTINUE and 314 STOP_R trials in the rhythmic one. As LRP is classically characterized by a neg-315 ative deflection underlying motor preparation, LRP peak amplitude was defined in each condition by looking for the minimum peak value following stim-316 ulus onset (LRPs were 15 Hz low-pass filtered for the peak detection). A simi-317 318 lar subtraction, that is, contralateral activity minus ipsilateral activity and vice versa, was performed for each pair of scalp electrodes (e.g., F3 minus 319 F4, CP3 minus CP4 ...) in order to display the lateralized part of the EEG activ-320 321 ity as a topography (Fig. 1).

322 *Mu and Beta time-frequency analysis*

First, a time-frequency decomposition was performed according to the procedure described below, using the preprocessed EEG data from the C3 channel ^{44,70,71}. The resulting time-frequency maps are shown for each experimental condition in Appendix B to provide a classical view of our data.

327 Second, a time-frequency analysis was performed with a focus on the 328 Mu and Beta frequency bands. Thereto, the preprocessed EEG data were 329 band-pass filtered in the 8 to 30 Hz frequency range. We then computed an ICA to this filtered data. This procedure of applying an ICA decomposition to a 330 specific frequency-band is able to outperform the traditional wide-band ICA 331 332 both in terms of signal-to-noise ratio of the separated sources and in terms 333 of the number of the identified independent components ⁷². On the basis of 334 the ICs resulting from the ICA algorithm, equivalent current dipoles were 335 fitted using a four-shell spherical head model and standard electrode 336 positions (DIPFIT toolbox ^{73,74}). Then, to cluster ICs across participants, feature

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vectors were created combining differences in spectra (8-30 Hz), dipole 337 338 location, and scalp topography. Clusters were next identified using a k-means clustering algorithm (k = 12) in EEGLAB. Among the resulting clusters, a 339 single sensorimotor cluster was visually identified in each experiment (i.e., 340 discrete and rhythmic) based on a centroparietal lateralized topography and 341 a time-frequency map showing a clear ERD/ERS pattern. 342

In order to analyze the ERD/ERS activity of the MU and Beta bands, 343 each IC of the two obtained clusters (i.e., discrete and rhythmic) was 344 345 subjected to a time-frequency decomposition (using customized scripts 346 written on Matlab) as follows: The EEG signals locked to the primary stimulus were convolved with complex 3-to-8 cycle-long Morlet's wavelets. Their 347 central frequencies were changed from 8 to 30 Hz in 0.5 Hz steps (and from 348 0.5 to 50 Hz for the C3 channel analysis in Appendix B). From the wavelet 349 transformed signal, $w_k(t, f)$, of trial k at time t (3.5 ms time resolution) and 350 with frequency f, the instantaneous 351 power spectrum $p_k(t, f) = R(w_k(t, f))^2 + I(w_k(t, f))^2$ was extracted (R and I symbolize the real and 352 imaginary parts of a complex number, respectively). The mean power 353 spectrum (i.e., averaged across trials) was then computed for each 354 participant in the GO_D, CONTINUE, STOP_D, STOP_R and GO_R conditions as follow: 355

356 Power =
$$\frac{1}{N} \cdot \sum_{k=1}^{N} p_k(t, f), (N = number of trials).$$

The power spectrum was then normalized with respect to a -400 to -100 ms 357 358 pre-stimulus baseline and transformed to decibel scale (10 · log10 of the sig-359 nal). In the rhythmic experiment, the baseline was extracted from the aver-360 aged GO_R trials (as in CONTINUE and STOP_R conditions, the pre-stimulus period includes movement). This mean power (time \times frequency \times power) was 361 362 next averaged along the frequency dimension in an 8 Hz - 13 Hz window to compute the Mu power and a 15 Hz - 30 Hz window for the Beta power time 363 364 series (time \times power).

365 To detect significant ERD and ERS, the resulting Mu and Beta power time series of each condition was compared against the mean value of the 366

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367 power in the baseline time range (-400 to -100 ms). These comparisons were 368 performed based on a non-parametric permutation procedure (see below). Thus, each time-period for which the power values were significantly below 369 the baseline level was indexed as an ERD. Each time-period subsequent to an 370 ERD and for which power did not significantly differ from the baseline level 371 was indexed as an ERS. Each time-period including power values that were 372 significantly above the baseline level was indexed as a power-rebound. To 373 compare Mu and Beta dynamics between conditions, power time series were 374 375 pairwise compared using the same non-parametric permutation procedure 376 (see below).

377 Brain sources reconstruction

378 To estimate the brain structures pertaining to the clustered ICs, a brain-source reconstruction procedure was applied. For each clustered IC, the 379 inverse ICA weight projections onto the original EEG channels were exported 380 to the sLORETA (standardized low-resolution brain electromagnetic tomogra-381 382 phy) data processing module ⁷⁵. sLORETA provides a unique solution to the inverse problem 75-77. For sLORETA, the intracerebral volume is partitioned into 383 6239 voxels with a 5 mm spatial resolution. Then, the standardized current 384 density at each voxel is calculated in a realistic head model ⁷⁸ based on the 385 386 MNI152 template.

387 Statistical analysis

388 To compare LRP time series between conditions at the group level, the 389 LRPs were subjected to a nonparametric permutation procedure ⁷⁹. Specifi-390 cally, the 15 participants' LRPs were pooled over the two compared condi-391 tions (15 per condition). Two sets of 15 LRPs were then drawn randomly (un-392 paired) from this pool, and the differential grand-average LRP was computed 393 between the two sets. This procedure was repeated 10 000 times, thus pro-394 ducing a LRP distribution based on shuffled data under the null hypothesis. 395 For each time point, a p value was computed as the proportion of these 396 pseudo-differential LRPs that exceeded the observed participants' average 397 differential LRP. This p value indicates whether the observed power distribution for the two conditions diverged more than expected for random data (p 398

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= .05 threshold). To correct for multiple comparisons, we analyzed the result-399 400 ing distributions of p values to compute p thresholds corresponding to the 401 2.5th percentile of the smallest, and the 97.5th percentile of the largest p values distribution ⁸⁰. The same procedure was applied to the averaged Mu and 402 403 Beta power time series to, first, assess ERD and ERS significance by compar-404 ing power time series against baseline values and, second, to asses power 405 difference significance between conditions. In the case of the Mu and Beta power time series, the between-experiment comparison included an unequal 406 number of ICs (20 discrete vs. 19 rhythmic ICs, respectively, see Results sec-407 408 tion). This variation was accounted for in the random-permutation stage of 409 the statistical procedure by randomly selecting a pool of 19 ICs from each experimentation at each iteration. 410

Additionally, the study included measures of self-reported impulsivity, which were correlated with the EEG measures. This exploratory analysis was delegated to Appendix C for reasons of focus.

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414 **Results**

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415 Behavior

In the discrete experiment, the RT_{GO} (M = 472 ms, SD = 64 ms) and re-416 sponse probability (M = .54, SD = .08) permitted the estimation of individ-417 ual's RT_{STOP-D} (M = 269 ms, SD = 45 ms). The average <u>STOP-signal delay</u> 418 419 (SSD) for participants was 203 ms (SD = 79 ms). In the rhythmic experiment, 420 the spontaneous oscillation frequency was 1.65 Hz on average (SD = 0.54421 Hz) and the analysis of the obtained StopTimes (M = 399, SD = 34 ms) en-422 abled the computation of individual's RT_{STOP-R} (M = 268, SD = 24 ms). Importantly, the RT_{STOP-D} and the RT_{STOP-R} values did not differ (t = .03, p > .05) and 423 were unrelated across participants (r = .02, p > .05), suggesting independent 424 425 but comparable timing of inhibition processing between the two experiments.

426 Lateralized readiness potentials

427 In every condition, the LRP computation resulted in a typical negative deflection as portrayed in Fig. 1. In the discrete experiment, the permutation 428 analysis identified a significant difference in the 381 - 556 ms time window (p 429 < .05, corrected) between GO_D and successful-STOP_D conditions (Fig. 1.A) and 430 431 in the 419 - 493 ms window between GO_D and fail-STOP_D conditions. In the rhythmic experiment, the same procedure identified a significant difference 432 433 in the 377 - 434 ms time window (p < .05, corrected) between CONTINUE and $STOP_{R}$ conditions (Fig. 1.B). To compare the "inhibitory effect" between the 434 435 LRPs from the two experiments, differential LRPs were computed based on 436 the GO_D minus successful-STOP_D difference for the discrete one and the CON-437 TINUE minus STOP_R difference for the rhythmic one. The two differential LRPs 438 were next compared through the same nonparametric permutation proce-439 dure, which revealed that the LRP reduction was significantly larger in the discrete experiment than in the rhythmic one in the 402 - 1,243 ms time win-440 441 dow (p < .05, corrected; Fig. 1.C). Still, the peak amplitude of the differential LRP was significantly correlated between discrete and rhythmic experiments 442 443 (*Pearson* r = .96, p < .001). Additionally, the exploratory analysis of individ-

- 444 ual's motor impulsivity indicated a significantly lower LRP peak amplitude for
- $\,$ the more impulsive participants in the GO_{D} and fail-STOP_{\text{D}} conditions (details
- 446 in Appendix C.).





C. Discrete vs. Rhythmic inhibitory effect



Fig.1: LRP analysis

Panel A: LRP (grand-average) computed in the discrete GO_D , success-STOP_D, and fail-STOP_D conditions. GO_D LRP differed significantly from success-STOP_D and fail-STOP_D conditions. In grey, the region of significant difference (according to the nonparametric permutation analysis) between GO_D and success-STOP_D conditions (p < .05, corrected).

Panel B: LRP (grand-average) computed in the rhythmic CONTINUE and STOP_R conditions. In grey, the region of significant difference between the two conditions (p < .05, corrected).

Topographies are presented in panels A and B as the lateralized topographies computed at each condition LRP peak latency (see Method section).

Panel C: LRP inhibitory effect computed in the discrete (GO_D minus success-STOP_D LRP) and the rhythmic (CONTINUE minus STOP_R LRP) experiments. In grey, the region of significant difference between these two differential LRPs (p < .05, corrected).

The represented SSD, RT_{GO} and RT_{STOP} latencies are based on the average of the obtained latencies over all the participants. LRPs were 15 Hz low-pass filtered for graphical purpose.

449 **Mu and Beta oscillations**

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The power maps resulting from the time-frequency decomposition applied to the preprocessed EEG data of the C3 channel (0.5 to 50 Hz) are shown for the different conditions in Appendix B.

453 In both experiments, only one sensorimotor cluster could be identified. Thus, a single sensorimotor cluster of 20 ICs (contribution of 15 participants) 454 was retained for the discrete experiment. Another single cluster of 19 ICs was 455 456 retained (15 participants) for the rhythmic experiment (Fig. 2.A). The power 457 maps resulting from the time-frequency decomposition applied to the clustered components (8 to 30 Hz) are shown in Fig. 2.B. The detailed time 458 459 course of Mu (8 - 13 Hz) and Beta (15 - 30 Hz) bands power and significant ERD/ERS are highlighted in Fig. 3. Overall, Mu and Beta power show the ex-460 461 pected dynamics, that is, an ERD during the movement execution. This ERD appeared transient in the context of a discrete movement execution and sus-462 tained when the movement was rhythmic. The Mu/Beta ERD were followed by 463 464 an ERS (Fig. 3). Notably, the ERS significantly exceeded the baseline level in 465 the STOP_R condition only, evidencing of a post-movement Mu and Beta rebound in this condition. 466

467 The Mu and Beta time-series were then compared between the experimental conditions in a pairwise fashion (non-parametric permutation proce-468 dure, see Method). The detailed result of these comparisons is provided in Ta-469 470 ble 1. Importantly, Mu power did not vary significantly between the three con-471 ditions of the discrete experiment: there was no significant difference the be-472 tween movement-executed conditions (GO_D and fail-STOP_D) and the no-actual-movement condition (success-STOP_D). In the rhythmic experiment, the 473 474 significantly higher Mu power in the STOP_R condition characterized a postmovement Mu ERS that was not present in the GO_R and CONTINUE conditions. 475 476 When comparing the two experiments, the Mu power increase was stronger 477 after the forced rhythmic-movement stop in the STOP_R condition as compared to all the other conditions, including the GO_D and success-STOP_D conditions, 478 479 which are associated with a discrete-movement normal completion and can-480 cellation, respectively.

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481 Regarding the Beta power, the discrete conditions GO_D and fail-STOP_D 482 in which the movement was executed did not significantly differ. In contrast, 483 the success-STOP_D condition exposed a higher Beta power than GO_D , from 1,161 to 1,287 ms, and than fail-STOP_D, from 559 to 1,328 ms. In the rhyth-484 485 mic experiment, the significantly higher Beta power in the STOP_R condition related to a post-movement Beta ERS that was not present in the GO_R and CON-486 487 TINUE conditions (Fig. 3.). When comparing the two experiments, the pattern of differences was similar to the Mu power, with the post-movement Beta 488 power increase being stronger in the $STOP_{R}$ than the GO_{D} or the success-489 490 STOP_D. Additionally, the exploratory analysis of individual's motor impulsivity 491 indicated significantly a higher PMBR amplitude for the more impulsive partic-492 ipants in the STOP_R conditions (details in Appendix C.).



Fig.2: Component dimension time-frequency power analysis

Panel A: Equivalent current dipoles of the clustered sensorimotor components in the discrete (15 participants, 20 ICs) and the rhythmic (15 participants, 19 ICs) experiments.

Panel B: Time-frequency power maps (ICs grand-average) computed in the discrete (GO_D and success-STOP_D) and rhythmic (CONTINUE and STOP_R) conditions. Black line: Primary (GO or CONTINUE) stimulus onset. Red line: STOP signal onset (the represented onset is based on the average of the obtained SSD, over all the participants). The blue scale represents desynchronization and the red scale (re)synchronization of the brain activity.



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Fig.3: Beta and Mu power time series

Power time series (ICs grand-average) averaged in the Beta (15 to 30 Hz) and the Mu (8 to 13 Hz) frequency ranges from the time-frequency power maps computed in the discrete (GO_D , success-STOP_D and fail-STOP_D) and rhythmic (CONTINUE, STOP_R and GO_R) conditions. Black line: Primary (GO or CONTINUE) stimulus onset. Red line: STOP signal onset (the represented onset is based on the average of the obtained SSD, over all the participants). Resulting from the non-parametric permutation comparison against baseline value, blue, yellow and red colors indicate time-ranges of significant ERD, ERS and power-rebound, respectively (see Method).

BETA po- wer MU power	GOD	success- STOP _D	fail-STOP _D	CONTINUE	STOP _R	GO _R
GOD	_	Higher success-STOP _D power from 1,161 to 1,287 ms z > 1.1473	N.S. <i>z</i> < 1.1911	Higher GO_D power from -1,500 to 154 ms and from 1,468 to 2,000 ms z > 1.2438	Higher GO _D power from -1,500 to 172 ms and higher STOP _R power from 748 to 1,860 ms z > 1.7282	Higher GO _D power from 1,374 to 2,000 ms <i>z</i> > 1.2392
success- STOP _D	N.S. z < 1.5210	_	Higher success- STOP _D power from 559 to 1,328 ms z > 1.1018	Higher success- STOP _D power from -1,500 to 10 ms and from 1,133 to 2,000 ms z > 1.1908	Higher success- STOP _D power from -1,500 to 154 ms and higher STOP _R power from 780 to 2,000 ms z > 1.5789	Higher success- STOP _D power from 1,091 to 2,000 ms z > 1.1954
fail-STOP _D	N.S. z < 1.4692	N.S. <i>z</i> < 1.4689	_	Higher fail- STOP _D power from -1,500 to 179 ms and from 1,447 to 2,000 ms z > 1.2893	Higher fail- STOP _D power from -1,500 to 167 ms and higher STOP _R power from 741 to 1,654 ms z > 1.7432	Higher fail- STOP _D power from 1,325 to 2,000 ms z > 1.2455
CONTINUE	Higher GO_D power from -1,500 to 397 ms and from 1,871 to 2,000 ms z > 1.6163	Higher success- STOP _D power from -1,500 to 664 ms and from 1,458 to 2,000 ms z > 1.6883	Higher fail- STOP _D power from -1,500 to 399 ms and from 1,804 to 2,000 ms z > 1.5852	_	Higher STOP _R power from 773 to 2,000 ms <i>z</i> > 1.7528	Higher GO _R power from -1,500 to 164 ms <i>z</i> > 1.1942
STOP _R	Higher GO _D power from -1,500 to 331 ms and higher STOP _R power from 958 to 2,000 ms z > 1.7832	Higher success- STOP _D power from -1,500 to 189 ms and higher STOP _R power from 979 to 2,000 ms z > 1.7575	Higher fail- STOP _D power from -1,500 to 175 ms and higher STOP _R power from 928 to 2,000 ms z > 1.7198	Higher STOP _R power from 888 to 2,000 ms <i>z</i> > 1.9067	_	Higher GO _R power from -1,500 to -395 ms and higher STOP _R power from 755 to 2,000 ms z > 1.8822
GO _R	N.S. z < 1.5813	Higher success- STOP _D power from 493 to 2,000 ms	Higher fail- STOP _D power from 1,152 to 2,000 ms	Higher GO _R power from -1,500 to 178 ms <i>z</i> > 1.6104	Higher GO _R power from -1,500 to -216 ms and higher STOP _R power	_

	<i>z</i> > 1.6655	<i>z</i> > 1.5310	from 865 to 2,000 ms <i>z</i> > 1.9595	
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497 Table 1: Pairwise condition comparison of Mu and Beta power time series

Mu and Beta power time series from the clustered ICs were compared between experimental conditions in a pairwise fashion using a nonparametric permutation procedure (see Method section). The resulting timeranges of significant difference between conditions are reported.

Z values indicate the threshold values corresponding to p < .05 (corrected for multiple comparisons, see Method) retained to assess significance.

N.S. Non-significant.

498 Brain sources reconstruction

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499 Based on the voxel-based sLORETA images, we searched for brain acti-500 vation using voxel-wise randomization *t*-tests with 5000 permutations, based on nonparametric statistical mapping. This procedure was performed sepa-501 rately for the ICs of the discrete and rhythmic clusters. Significant voxels (p < p502 .01, corrected for multiple comparisons) were located in the MNI-brain (Fig. 4) 503 regarding the engaged Brodmann areas (BA) and the voxels coordinates. In 504 the discrete experiment, the clustered ICs activity was related to the activa-505 506 tion of sensory regions such as the primary somatosensory (BA 1, BA 2, BA 3) 507 and the somatosensory association (BA 5) cortices, as well as M1 (BA 4). In the rhythmic experiment, activation was found in the primary somatosensory 508 cortex (BA 3), as well as pre-motor areas (BA 6), and M1 (BA 4) (detailed MNI 509 coordinates of the activation are provided in Table 2). 510



Fig.4: Brain sources reconstruction

The sLORETA images showing significant estimated activation pertaining to the discrete (**panel A**) and rhythmic (**panel B**) clustered ICs, for three orthogonal brain slices (horizontal, sagittal, coronal).

Only the voxels that passed the p value threshold (p < .01, corrected) are shown in color. The color represents t value. In the discrete experiment, activation was found in sensory (BA 1, BA 2, BA 3, BA 5) and motor areas (BA 4). In the rhythmic experiment, fewer sensory (BA 3) but (one) more motor regions (BA 4, BA 6) were involved. Detailed MNI localization of the significant activation is provided in Tab. 2.

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513 Discussion

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519 ERD/ERS pattern identified over peri-Rolandic areas closely overlap those reported in previous work ^{14,50,52,62}. Indeed, we identified both somatosensory 520 521 and motor cortical areas as generators of the observed ERD/ERS pattern, supporting the idea that both movement-related and sensory-related neural ac-522 523 tivity may be engaged. The inhibition mechanism triggered by the STOP signal affected the LRP in both the discrete and rhythmic experiments, and oc-524 curred before the end of the RT_{GO} , RT_{STOP-D} , or RT_{STOP-R} latencies. Additionally, 525 526 the measured RT_{GO} for movement generation and RT_{STOP} for movement sup-527 pression fell in the time range classically observed in stop-signal experiments across various movement responses 81-84. The similarity between the discrete 528 529 and the rhythmic RT_{STOP} values indicates that the processes engaged in aborting the two movement classes are of comparable duration. 530

531 Our first expectation dealt with the LRP dynamics. We hypothesized a large LRP following a GO stimulus to contrast with the absence of an LRP (i.e., 532 zero amplitude) following a CONTINUE stimulus, and that this LRP amplitude 533 534 would be reduced by the STOP signal occurrence only in the discrete experi-535 ment. For the discrete movements, an LRP was triggered by the primary GO 536 stimulus, and was subsequently impacted by the STOP signal in both success-537 ful-STOP_D and failed-STOP_D trials. These findings are consistent with the notion that an inhibition signal that arrives at M1 attenuates cortical motor out-538 flow, as reflected by the reduction of the LRP amplitude ⁴⁰; in the case of fail-539 540 STOP_D trials, this reduction is insufficient to restraint the response threshold to be reached ³³. For the rhythmic movements, the CONTINUE stimuli occur-541 ring during the ongoing movement also led to an LRP response, albeit weaker 542 543 than in the GO_D instruction. Rebutting our hypothesis, this LRP response indi-

cates that the presentation of the CONTINUE stimulus during the ongoing 544 545 movement triggers a non-negligible cortical motor activity. Thus, LRP might not index pre-movement processing only, but also any cortical motor activity 546 occurring before and during movement. <u>Alternatively, if the rhythmic move-</u> 547 ment is implemented as a concatenation of discrete units, the LRP might re-548 flect the cortical motor activity engaged in the initiation of each unit. Indeed, 549 previous studies have shown that the sensorimotor activity recorded in rhyth-550 mic movements suggested a discrete-units-concatenation when the move-551 ment frequency was ranging from 0.33 to 1 Hz, whereas this activity was 552 553 <u>'truly' continuous for above 1 Hz movement frequencies</u>^{31,32}. Nevertheless, as the rhythmic movements in the present study were, on average, performed 554 at 1.65 Hz, the LRP observed in the CONTINUE trials are unlikely to reflect 555 556 motor cortical activity related to the concatenation of discrete movements.

557 The LRP amplitude following the CONTINUE stimulus was reduced in the STOP_R condition. Notably, the amplitude of this "inhibitory effect", albeit 558 559 weaker, was strongly correlated to the GO minus STOP_D LRP difference mea-560 sured in the discrete experiment. Thus, the LRP reduction might index action 561 inhibition in the context of both prepared-discrete and ongoing-rhythmic 562 movement suppression. This interpretation is consistent with the notion that 563 LRP is a marker of the cortical motor activity as a common final pathway in the central control of movement and thus be the "site" where (frontal) execu-564 tive "agents" exert inhibitory control ⁸⁵. Note that the commonality of the mo-565 tor site of inhibition in discrete and rhythmic action inhibition does not pro-566 vide information about the inhibiting "agents" engaged in the two situations, 567 568 as the two levels of inhibition processing can be independent ⁴⁰. Notably, the 569 EEG markers of the executive agents engaged in action inhibition tended to 570 dissociate the processing of discrete action cancelling and rhythmic action stopping ⁴³. 571

572 Our second expectation that the Mu ERD/ERS observed pattern should 573 show a transient vs. sustained activity for the discrete and rhythmic experi-574 ments, respectively, was confirmed. This validates the discrete vs. rhythmic 575 nature of the performed movements and aligns with the understanding of the 576 Mu rhythm as a correlate of the interaction between sensory and motor infor-

577 mation processing: The sustained ERD during ongoing movement may corre-578 spond to a closed-loop control for the online control of the ongoing movement. In contrast, the transient Mu ERD/ERS pattern did not differ between 579 the performed discrete actions in the GO_D and fail-STOP_D conditions and the 580 cancelled ones in the success-STOP_D condition. This finding is in line with the 581 Mu rhythm being independent of the movement outcome, which may be the 582 583 case if the Mu rhythm encodes the processing of sensorimotor integration in an open-loop control of discrete actions. Notably, the reactive inhibition of 584 585 discrete actions has been coherently conceptualized as a dual-step process 586 encompassing attention reorientation (by the STOP signal) and prepared-587 movement cancellation ⁸⁶⁻⁸⁸. The reorientation of attention is not specific to action inhibition but generalizes to multiple situations implicating goal redi-588 rection, including the reaction to a GO stimulus⁸⁸. Following the hypothesis 589 that the Mu rhythm is an alpha-like oscillation that links perception and action 590 ^{49,50}, a Mu ERD is expected to occur when cortical motor activity is modulated 591 592 following attentional reorientation, which includes both discrete GO_D and 593 STOP_D trials. Hence, the absence of actual movement in successful-STOP_D tri-594 als should not modulate the Mu rhythm dynamics relative to Mu rhythm in 595 GO_D trials. Our results are in accordance with this expectation. A compatible finding is that the Mu ERD/ERS varies with attention ⁸⁹. 596

597 Confirming our third expectation, the Beta ERD appeared sustained for 598 the ongoing rhythmic movement whereas it was transient for the discrete movement, thus following the motor activation dynamics. Next, a Beta ERS 599 occurred following the action. This is consistent with the purported role of the 600 601 Beta ERS in evaluating the action sensory output, in that it was lower for dis-602 crete-movement failed cancellation compared to successful cancellation. Previous findings already reported this "error-related Beta rebound reduction", 603 which may relate to salient error/mismatch detection mechanisms ^{90,91}. Still, 604 some results diverged from our expectations. On the one hand, the PMBR 605 was higher following a forced rhythmic movement stop (STOP_R) than the Beta 606 607 ERS following discrete movement completion (GO_D). On the other hand, the 608 discrete-action Beta ERS was higher after a successful action cancellation 609 than following action completion in GO_{D} and fail-STOP_D conditions, which did

not differ in this regard. These two findings support the notion that a higher 610 611 Beta ERS is a correlate of active action suppression ¹⁴, here triggered by a STOP signal. Whereas Parkes et al. identified PMBR neural generators in post-612 Rolandic (sensory) areas, which they interpreted in favor of the notion that 613 PMBR reflects sensory reafference evaluation ⁵⁹, other studies suggested that 614 the PMBR was also related to pre-Rolandic (motor) activation ^{58,92,93}. Our re-615 616 sults are in line with the latter findings, with both a significant PMBR and pre-617 motor activation being reported for the rhythmic but not discrete actions. 618 This engagement of pre-motor cortices in the rhythmic movements is congru-619 ent with the previously reported pre-supplementary motor area activation in 620 PMBR ^{94,95}. Thus, our results do not exclude that Beta ERS is an index of action sensory outcome evaluation, but they also support the view that it is as-621 622 sociated with an active inhibition process of cortical motor activity.

623 Nonetheless, this active inhibition hypothesis of the PMBR functional role is silent on why the ongoing action-forced stop gave rise to a large PMBR 624 625 over contralateral sensorimotor cortical areas, whereas a much weaker Beta 626 ERS followed discrete action cancellation. A tentative explanation is that the 627 inhibitory process engaged in movement cancellation acts at the movement preparation level, as indicated by the LRP decrease and the ERD abortion in 628 the STOP_D condition ⁴¹. Thus, inhibition might lie in maintaining the cortical 629 630 idle state to cancel a discrete action, whereas it would force the return to this 631 idle state to stop a rhythmic movement. This explanation is also consistent with the notion that a discrete action, if controlled in an open-loop fashion, is 632 not associated with an online control based on sensory prediction evaluation, 633 634 as the PMBR is a correlate of the latter. In contrast, if controlled in a closed-635 loop fashion, the ongoing-rhythmic action requires the evaluation of the sen-636 sory predictions associated with the movement production, as indicated by a 637 significant PMBR. A distinction in the movement-suppression after-effect (i.e., PMBR) suggests that discrete-action cancelling and rhythmic-action stopping 638 may engage distinct inhibition processes ⁴³. As action inhibition operates on 639 both discrete 64,81 and rhythmic 4-6,42 movements, considering the distinction 640 641 between the two movement classes would undoubtedly contribute to a better 642 understanding of this complex process at the neurobiological level.

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643 Alternatively, the lower Beta ERS following discrete action completion 644 and cancellation compared to the large PMBR following rhythmic action stop, may reflect a PMBR that has been reduced due to the task uncertainty. In-645 deed, previous work suggested that beta power reflects the estimated uncer-646 tainty in the parameters of the forward models involved in motor control ⁹⁶. 647 Thus, the primary stimuli (blue or green) in the discrete experiment required 648 a two-choice reaction (i.e., trigger a discrete movement toward the left or 649 right side), whereas the same stimuli required a unique response in the 650 651 rhythmic experiment (i.e., continue the movement for both blue and green 652 stimuli). This discrepancy may introduce a modulation of confidence in the 653 predicted sensory outcome in the forward model of action control, resulting in a lower post-movement Beta modulation ^{54,96}. In contrast, the rhythmicity of 654 655 an ongoing movement may lead to a confident movement execution that increases the PMBR ⁹⁷. 656

657 Overall, our pattern of results regarding the Beta power dynamics ex-658 cludes an understanding of the PMBR neither as a correlate of the action sen-659 sory outcome evaluation nor as an index of active motor suppression. In fact, 660 both interpretations are not incompatible, and a tentative explanation is that the PMBR reflects the action control in forward models, with its amplitude be-661 662 ing modulated by the uncertainty and the engagement of an inhibition 663 process. Thus, the PMBR could be reduced when the uncertainty of the pre-664 dicted sensory output is high, whereas it would be strengthened in reaction 665 to an inhibition signal. This imperative action suppression might result in suppressing the motor plan execution and its predicted sensory outcome. It 666 667 could also lead to the interruption of the closed-loop processing of sensorimo-668 tor information itself, as indicated by the Mu rebound that followed the rhythmic action stop. Although this explanation remains highly hypothetical with-669 670 out studies manipulating sensory feedback and inhibition requirement, it globally fits well with a recently established framework in which Beta re-671 bounds reflect, at various cortical sites, a "clearing-out" of the motor plan and 672 the working memory ⁹⁸. 673

674 The present study focused on the movement performance and sup-675 pression in reaction to an external cue, so-called exogenous action control ⁹⁹.

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Adapted behavior also includes performing and suppressing movement in a self-initiated fashion, that is, endogenous motor control. Generalizing the present functional interpretation of neural sensorimotor activities requires

that future experiments study and contrast both situations. Especially, internal and external movement initiation require partially distinct sensorimotor activities ¹⁰⁰. Movement suppression mechanisms are also known to vary as a function of whether proactive vs. reactive inhibition is required, both for the suppression of discrete ^{101,102} and rhythmic ⁶ movements. These investigations are much needed to provide a complete comprehension of sensorimotor cortical activity.

The understanding of sensorimotor activity has implications for multi-686 ple clinical syndromes associated with movement disorders ¹⁰³. The abilities 687 to initiate and stop action are especially affected by impulsivity ³, which is an 688 689 essential dimension of several psychiatric disorders, such as attention deficit hyperactivity disorder (ADHD) and obsessive-compulsive disorder (OCD). 690 Evaluating neural sensorimotor activity through movement-related cortical 691 692 ERD/ERS, healthy participants have been distinguished from those with ADHD ¹⁰⁴ and OCD ¹⁰⁵. In the general population, sensorimotor activity is poorly in-693 vestigated in relation to individuals' impulsivity traits. A recent study sug-694 695 gested that sensorimotor ERD/ERS amplitude may relate to impulsivity ¹⁰⁶. The association reported in Appendix C. between motor impulsivity and lower 696 LRP amplitude in triggering a discrete action and higher PMBR when forced-697 698 stopping a rhythmic action suggests that cortical sensorimotor activity in the execution and suppression of action might depend on the individual's impul-699 700 sivity level. Still, further studies targeting the impulsivity dimension and in-701 cluding participants exhibiting a broad range of impulsivity levels are re-702 quired to test this hypothesis.

Finally, the present study provides new insights in understanding the cerebral sensorimotor activity by exploring EEG records of LRP and Mu/Beta rhythms associated with the performance and suppression of movement in the context of discrete and rhythmic classes of actions. Showing the distinct sensorimotor dynamics that operate in the two action classes, our findings are highly compatible with recent proposals that Mu and Beta rhythms might

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709 encode reciprocal interactions between motor and sensory cortices to enable movement monitoring ^{47,96}. Still, the PMBR may also reflect the engagement 710 711 of a clearing-out function to abort the sensorimotor processing when action has to be inhibited ¹⁴. At any rate, our findings support the notion that Mu and 712 Beta frequency bands play complementary roles in the sensorimotor control 713 714 of action and also converge with previous work showing that PMBR arises from a distributed network rather than a discrete cortical focus 52,107. Further 715 studies using imaging procedures with a better spatial resolution are required 716 to disentangle the Mu and Beta specific implication in the different cortical ar-717 718 eas that engage in action performance and suppression.

719 Data Availability

720 The data generated during and/or analyzed during the current study are

721 available from the corresponding author upon reasonable request.

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